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Optimization of Station-based Carsharing Networks: Increasing Sustainability through Heterogeneous Fleets and Emission Control

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Impact (ceteris paribus) of … on	**Number of stations**	**Number of vehicles**			**Profit**
		In total	**Electric**	**Petrol**	
Costs for stations ↑	→	→	→	→	↓
Costs for parking lots ↑	→	→	→	→	↓
Costs for electric vehicles ↑	→	→	↓	↑	↓
Costs for petrol vehicles ↑	→	→	↑	↓	↓
Demand ↑	↑	↑	↑	↑	↑
CO_2-emission limit ↓	→	→	↑	↓	↓
Price per kWh ↑	→	→	↓	↑	↓
Price per liter petrol ↑	→	→	↑	↓	↓
Max. distance ↑	↓	↓	↓	↓	↑

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Abstract

The positioning and dimensioning of carsharing stations have already been addressed in several optimization models applying homogeneous fleets. Yet, carsharing organizations increasingly apply mixed fleets of vehicles with different propulsion methods. We introduce a model, which permits a combination of differently powered vehicles and the option to include fleet emission constraints to satisfy customer expectations and governmental requirements. It supports decision makers in solving the challenge of fulfilling demands while maximizing profit. With an applicability check, the proposed model is evaluated. Extensive sensitivity analyses are presented and discussed indicating how a profitable operation of heterogeneous fleets can be established.

Keywords

Station-based Carsharing, Transportation, Urban Mobility, Network and Fleet Optimization, Sustainability.

1 Introduction and Motivation

A growing level of eco-consciousness in public as well as business sectors evokes a rethinking of car usage and personal vehicle ownership (Shaheen and Cohen, 2013). In this context, carsharing addresses both, the environmental and economic concerns of conventional vehicle usage (Alfian et al., 2014). This leads to reduced emissions and grants carsharing clients access to a fleet of relatively new and thus environmentally friendly vehicles on a pay as-needed basis (Shaheen et al., 2010). As carsharing profitability depends on demand, carsharing services are typically offered in urban areas where car ownership can (partly) be dispensed with. With an increasing percentage of the world population living in cities and a rapidly rising number of people using carsharing, new opportunities for carsharing organizations arise (Dedrick, 2010). Supported by technological progress and a variety of available optimization approaches, carsharing organizations are able to better plan their networks as well as their fleet sizes and offer simplified operational services at high service levels to their customers (Hayashi et al., 2014; Kaspi et al., 2014). The scope of literature dealing with the functionality of different carsharing concepts, the analyses of these concepts, and investigations of use and users is manifold. Introduced optimization models focus on diverse goals and support the creation or expansion of station-based carsharing networks. But even though potentially crucial to success, the implementation of a heterogeneous carsharing fleet has not yet been intensively researched on existing models. The option of installing a heterogeneous fleet is deemed important as it allows a carsharing organization to leverage the benefits of diverse propulsion methods and thus address a larger customer pool. While a pure electric fleet contributes towards environmental protection, it creates high costs for vehicle charging infrastructures and leads to idle times during charging cycles under present-day conditions (Speranza, 2018). While a combustion engine fleet allows for increased capacity utilization, this results in higher emissions. The positive effects of reduced emissions and reduced energy consumption can thus be reinforced by including alternatively powered vehicles in the carsharing fleet (Shaheen et al., 2013). In addition, many of these alternatively powered vehicles already meet the requirements of so far mostly voluntary environmental labelling programs, which in turn represent a beneficial marketing aspect for carsharing organizations (Millard-Ball et al., 2005).

Real-life application examples further support the concept of heterogeneity. Especially the combination of electric vehicles with petrol-powered vehicles is a growing mixture in today's carsharing fleets. Zipcar, the main provider in the U.S., already successfully applies a heterogeneous vehicle approach with vehicle type and propulsion method varying depending on the location of offer (Zipcar, 2020). Other providers follow suit and start to partially replace existing fleets with electric vehicles, e.g., ShareNow (ShareNow, 2020).

While increasing the flexibility and availability of vehicles, electric fleets require vehicle charging infrastructures. Consequently, the integration of electric vehicles makes round-trip carsharing (also called two-way) most feasible for a carsharing network. This means that vehicles have to be returned to their designated parking lot or, in the case of electric vehicles, their respective charging infrastructure. This is rather limited possible for one-way modes, in which vehicles can be driven between designated stations, as more charging infrastructure and relocation costs incur decreasing the profitability of a carsharing organization. Regarding free-floating carsharing, which allows a vehicle to be left at any allowed parking space within a designated area, these cost-effects are even higher. Based on the number of potential carsharing users, the three carsharing operation modes are typically established within different city sizes. As free-floating is usually operated in cities with at least 500.000 inhabitants, round-trip carsharing is also suitable for towns with more than 50.000 inhabitants as it is less cost-intense to install and no costs for relocation incur. A summary of the above is given in Table 1, which shows the specific characteristics of the carsharing modes.

Table 1: Advantages and disadvantages of different carsharing operation modes

	One-way	Round-trip	Free-floating
Network structure	Station-based; vehicle can be picked up and dropped off at any station	Station-based; vehicle needs to be returned to a designated station / parking lot	Vehicle can be picked up and dropped off at any allowed parking space in the area of operations
Advantages for the carsharing organization	• Relocation is predictable because of typically required pre-booking	• No relocation costs • Prevents crowded stations/areas • No operational management • Planning reliability (e.g., utilization, maintenance, cleaning)	• No station costs
Advantages for the customer	• Fixed location for vehicles • Pre-booking is limited possible • Cost reductions may be applied to support relocation • Spontaneous trips possible • Round trips possible	• Fixed location for vehicles • Pre-booking possible • Spontaneous trips possible • Predictable with regard to long-term scheduling	• Door-to-door service is possible • High flexibility
Disadvantages for the carsharing organization	• Station costs • Relocation costs (staff vs. user incentives) • Crowded/vacant stations	• Station costs • Loss of demand for door-to-door service	• Relocation costs (staff vs. user incentives) • Parking costs in some areas • Crowded/vacant areas
Disadvantages for the customer	• No vehicle available at nearest/preferred station • Preferred destination station may be occupied	• Lower flexibility than free- floating/one-way • Payment of idle times (e.g., for parking)	• No vehicle available in nearby area (limited availability) • No pre-booking possible • Search for parking lot
Typical field of application	• Cities up to metropolises	• Towns up to metropolises	• Large cities and metropolises
Implications regarding electromobility	• Unlimited suitability for pure electric fleet • Limited suitability for heterogeneous fleet → Limited availability of vehicle charging infrastructure → Relocation necessary	• Unlimited suitability	• Limited suitability → Ineffective and expensive → Relocations necessary for charging

With the goal of reducing the overall emissions of a carsharing fleet, while at the same time maintaining a customer friendly and yet profit maximizing approach, the above considerations favor a unified fleet deploying different propulsion methods, such as electric, hybrid, or combustion engine vehicles in a round-trip mode. Thus, the research questions of this paper is:

How can an optimization model for strategic and tactical station-based carsharing be designed to maximize profit while applying a heterogeneous fleet and obtaining a maximum CO_2-threshold?

The paper is structured as follows: work regarding carsharing networks and its optimization is described the following section 2. Section 3 introduces our optimization model and explains the underlying assumptions as well as the input parameters. Section 4 explains our approach towards dataset creation, provides benchmarks, and resulting evaluations and generalizations. We complete our article with conclusions and an outlook.

2 Related Work

Research on carsharing related topics and the number of respective publications have increased over the past years. Most of these address the history and development of carsharing organizations (e.g., Barth and Shaheen, 2002; Shaheen et al., 2009). Others analyze user characteristics, user habits, and the willingness to switch from private vehicles as well as the environmental and social benefits of this mobility service (e.g., Bardhi and Eckhardt, 2012; Clewlow, 2016; Juschten et al., 2019; Nakamura et al, 2019; Shaheen and Cohen, 2013; Shaheen et al., 2013; Webb et al., 2019). Besides, many articles deal with the description of different carsharing concepts, success factors, or analyses focusing on existing and running carsharing organizations (e.g., Costain et al., 2012; Celsor and Millard-Ball, 2007; Kek et al., 2009; Münzel et al., 2018; Stillwater et al., 2009; Remane et al., 2016). Publications regarding the planning and optimization of station-based carsharing are summarized in the following.

The planning of a carsharing network is divided into three different levels (Boyaci et al., 2015). The long-term or strategic perspective determines the allocation of stations regarding number, location, and size. A typical medium-term or tactical action is the designation of vehicles to these stations. The outcome of these planning stages is an established carsharing network. Following long- to medium-term objectives, operational strategies for daily business need to be considered. This includes elements such as pricing, re-fueling, or, if required, relocation techniques (Correia and Antunes, 2012). These three levels, especially long- and medium-term activities, overlap to a certain extent and are therefore often combined in existing models. This is feasible in many instances, but needs to be cautiously considered on a case-by-case basis. For instance, organizations tend to adjust their prices more often than closing or opening a station. The review given below therefore focuses on long- to medium-term strategies and considers operational aspects only as part of network planning and fleet assignment.

A first concept for the strategic selection of carsharing stations is presented by Awasthi et al. (2007). Their analytical hierarchy process consists of a three-stage approach and can be applied for one-way or round-trip modes. In a first step, decision criteria have to be selected and potential stations have to be identified. The suggested decision criteria are developed in cooperation with local planners as well as an established carsharing organization. These contain six indicators including demographic, geographic, and transportation elements. Secondly, the stations are scored by allotting weights to each decision criterion. Finally, the stations with the best overall weights are chosen, provided they exceed a predefined threshold value. Musso, et al. (2012) introduce a similar approach for strategic selection using decision criteria to expand an existing network. Three success factors are derived from the built environment forming the foundation of their approach. These factors are assigned to quarters without existing carsharing stations and compared afterwards. New stations are opened in the highest-rated regions. The concrete location, size, and vehicle assignment is not calculated. This approach is not limited to a specific mode of station-based concepts. Another article presents a framework determining the best expansion strategy for an existing carsharing network limited to the round-trip mode: El Fassi et al. (2012) develop a decision support system based on discrete event simulation. This combines strategic and tactical elements to react to demand variations. Possible strategies include the establishment of new stations, the expansion of existing stations, and the (de)merging of stations. The optimization objective is to minimize the number of vehicles and stations while maximizing user satisfaction. This is intended to lead to a high performance carsharing network with reduced vehicle idle times.

Focusing on round-trip optimization approaches, Rickenberg et al. (2013) introduce a mathematical model for an optimal selection of number, location, and size of carsharing stations and the subsequent fleet assignment. Their model includes a maximum distance constraint between stations and demand points to satisfy customer needs. With the aid of a stochastically distributed demand, the costs for the installation of such a carsharing network are minimized. In addition, and to support local planners, a decision support system is presented. Sonneberg, et al. (2015) extend this approach to establish a carsharing network consisting of an all-electric vehicle fleet. These are charged via selectable infrastructures with variable charging cycles. In order to satisfy customers, the demand has to be fulfilled completely. As an operational element, time windows throughout the week are introduced to simulate peaks and off-peaks. A mixed-integer model maximizes the profit of a carsharing organization. While annual leasing costs for vehicles, stations, parking lots, and different charging opportunities are incorporated in the model, expenses for staff or office spaces are not considered.

The following models tackle the optimization of one-way modes and thus integrate to some extent the simulation or optimization of arising relocation procedures. Boyaci et al. (2013a) suggest an approach to optimize station locations and sizes as well as vehicle assignment. Their model is limited to electric vehicles operating in a one-way carsharing scheme and balances the trade-off between profit maximization and level of service. Relocation shifts are required (but not optimized) to satisfy both customer demand and customer satisfaction. Despite the use of electric vehicles, charging times are not taken into account, even though they negatively influence profit. Boyaci et al. (2013b) extend this work by splitting the objective function into two discrete objectives in order to simplify the optimization procedure. Cepolina and Farina (2012) provide a cost minimization model for the distribution of small city-accessible electric vehicles used within pedestrian areas in the city of Genoa, Italy. Their concept includes a fully user-based relocation strategy. Stations are spread over the investigation area and located in densely populated areas or at access points to local public transportation or tourist attractions. A simulated annealing process determines the tactical fleet optimization of small electric vehicles. The user-based relocation is guided by operators offering different pick-up and drop-off locations determined by micro-simulations. The focus of these simulations is to minimize operator costs while not exceeding a maximum waiting time threshold limit. Correia and Antunes (2012) conducted an integration approach that optimizes network design, fleet assignment, and operational vehicle relocation. The authors present a mixed-integer problem, which employs a branch-and-cut algorithm to maximize the revenues of a carsharing organization operating in one-way mode. The relocation procedure is conducted by supervisors and is only possible after an entire period, for example one day. A relocation is carried out on the basis of reservations for the next period, thereby representing a non-dynamic relocation process. This approach is extended by Jorge et al. (2012) by including dynamic relocations throughout the day. This results in a mixed-integer linear problem with the objective of profit maximization. A further refinement by Jorge et al. (2014) considers different scenarios regarding operational relocation. Their model simulates user behavior based on information about intention to use other pick-up and drop-off locations. Boyaci et al. (2015) present an optimization framework refining their previous work concerning electric vehicles in one-way mode.

This approach introduces an operative planning level and the inclusion of charging requirements additional to the previous ones. A multi-objective mixed-integer linear problem is developed to maximize the profit of a carsharing organization while at the same time maximizing the user net benefit as a monetary function. As the model is not found to be efficiently solvable for real-world situations, they derive an aggregated model. This model is solved via a branch-and-bound algorithm and optimizes an organization's profit. Subsequently, the model is validated by an existing carsharing network in Nice, France. Brandstätter et al. (2017) present an article to determine optimal locations for charging stations of electric carsharing systems under stochastic demand. Introducing a two-stage optimization problem, the utilization of electric vehicles is maximized. For larger problem instances, a heuristic algorithm is developed.
Reviewing these approaches, none of them permits the implementation of heterogeneous fleets. Another aspect not yet considered is the inclusion of maximum emission levels to fulfill customer expectations or potential future pre-requirements for carsharing fleets. The mathematical model introduced in the following solves the present problems relating to carsharing organizations. It supports the network generation of a mixed fleet and tackles the necessary planning horizons regarding station-based round-trip carsharing.

3 Problem description and optimization model

3.1 Problem specification and assumptions

Before a mathematical model for carsharing network optimization can be introduced and applied, several requirements need to be considered. Preconditions for successful carsharing are related to demographic as well as geographic factors. The typical carsharer is thereby described as young to middle-aged, well-educated, and preferably lives in small non-family households in apartment buildings with an average of less than one vehicle per household (Burkhardt and Millard-Ball, 2006; Firnkorn and Müller, 2012; Morency et al., 2011; Habib et al., 2012; Stillwater et al., 2009). Geographic factors include high population density as well as walkable and mixed-use urban areas (Cohen et al., 2008; Celsor and Millard-Ball, 2007). These considerations include elements such as accessibility and distance to users' homes as well as a shortage of parking possibilities (Celsor and Millard-Ball, 2007). In addition, good coverage of local public transport plays an important role for the success of carsharing organizations and increases the ability to dispense with a car (Celsor and Millard-Ball, 2007; Cohen et al., 2008; Stillwater et al., 2009).
If these requirements are met, the key to a thriving carsharing organization is the optimum access, availability, and distribution of vehicles (Barth & Todd, 1999). All of these aspects are addressed in our mathematical model. Our model concentrates on strategic and tactical network optimization, allows for a heterogeneous fleet, and considers operation in the round-trip mode. Throughout the investigation area, demand and supply points in the form of potential stations are assigned and characterized by geographical coordinates. Local conditions have to be considered for both demand points and potential stations. This includes, for instance, the limited capacity of parking lots. This is influenced by different parking conditions such as bilateral, parallel, and transverse parking as well as on-street and off-street parking. Furthermore, a demand level is assigned to each demand location. These levels are discretely modeled

using the Poisson distribution, allotting a number of arrival processes within a timeframe. The complete process of dataset creation and assignment of supply and demand points is described in Section 4.1.
To avoid the establishment of unprofitable stations, the assigned demand is not required to be completely fulfilled. The model allows some demand points to be served only partially or even not at all, while others may be served completely. In order to achieve this, the optimization allows a minimum service level to be inserted. To delimit the optimization, this service level can be set to zero. To reach a maximum of fulfilled demand, the service level can be set to 100 percent. Furthermore, a maximum allowable distance between a built station and an assigned demand location is adjustable so as not to exceed a specific span and ensure customer satisfaction (Morency et al., 2008; Costain et al., 2012; Celsor and Millard-Ball, 2007).
In addition, vehicles with various propulsion methods, such as combustion engine, hybrid, or electric vehicles can be implemented. These vehicles have to be differentiated with respect to costs, consumption, range, emission, charging process, and resulting charging time, if applicable. Vehicles operated with other than electric consumables are expected to be filled-up by carsharers, which is an efficient approach most carsharing operators adopt (e.g., Zipcar, 2020). Annual leasing costs incur for each vehicle, station, and parking lot. These include expenses for acquisition, depreciation, amortization, administration, taxes, insurance, service, maintenance, repair, cleaning, and marketing. If electric vehicles are included, charging infrastructure also incurs expenses for grid connection. Trips are simulated based on a normal distribution regarding duration and distance driven. Respective durations are subdivided into driving time and parking time. The calculation of trips and the resulting consumption further considers local conditions in the investigation area, such as average speed.
In addition, an option is included to implement time windows to simulate demand peaks and off-peaks. If desired, these could be set per week, day, or a combination of both. Special attention must be paid to the Poisson distributed demand, which must be suitable for the time window selection. This means that when choosing a demand per week, time windows need to be set per week and must not be set per day. To fulfill local environmental labelling programs, a maximum average amount of CO_2-emissions in g/km over the entire carsharing fleet can be set. This results in a confinement of vehicle selection during the optimization process and leads to more vehicles with low emissions and lower allowable CO_2-emission levels.

3.2 Input Parameters

Sets and indices:

$i = (1, \dots, I)\colon potential\ station\ location$

$j = (1, \dots, J)\colon demand\ location$

$p = (1, \dots, P)\colon propulsion\ method$

$w = (1, \dots, W)\colon time\ windows$

Decision variables:

$d_{ijpw}\colon satisfied\ demand\ at\ station\ i\ for\ demand\ location\ j\ of\ propulsion\ method\ p\ at\ time\ window\ w\ [\#]$

$v_{ip}\colon number\ of\ vehicles\ with\ propulsion\ method\ p\ at\ station\ i\ [\#]$

$y_i\colon 1, if\ station\ is\ built;\ 0, else$

$z_{ij}\colon 1, if\ demand\ location\ j\ is\ served\ by\ station\ i;\ 0, else$

Parameters:

C_p: $leasing\ cost\ of\ charging\ infrastructure\ for\ propulsion\ method\ p\ [US\$\ p.a.]$

e_p: $energy\ price\ per\ propulsion\ method\ p\ [US\$/kwh]\ or\ [US\$/l]$

f_p: $average\ energy\ consumption\ per\ propulsion\ method\ p\ [kwh/km]\ or\ [l/km]$

k: $expected\ distance\ driven\ [km]$

L_i: $leasing\ cost\ of\ a\ parking\ lot\ at\ station\ i\ [US\$\ p.a.]$

n_i: $maximum\ number\ of\ lots\ at\ station\ i\ [\#]$

Q: $maximum\ distance\ between\ station\ i\ and\ demand\ location\ j\ [km]$

q_{ij}: $distance\ between\ station\ i\ and\ demand\ point\ j\ [km]$

r^{km}: $revenue\ for\ renting\ per\ distance\ [US\$/km]$

r^{min}: $revenue\ for\ renting\ per\ duration\ [US\$/min]$

S_i: $leasing\ cost\ of\ station\ i\ [US\$\ p.a.]$

t: $expected\ duration\ of\ a\ rent\ [min]$

U: $average\ maximum\ carbon\ dioxide\ emission\ per\ vehicle\ [g/km]$

u_p: $carbon\ dioxide\ emission\ per\ vehicle\ with\ propulsion\ method\ p\ [g/km]$

V_p: $leasing\ cost\ per\ vehicle\ with\ propulsion\ method\ p\ [US\$\ p.a.]$

Θ_{jw}: $Poisson\ distributed\ demand\ per\ time\ window\ w\ of\ demand\ location\ j\ [rents/time\ window]$

α: $considered\ demand\ period\ account\ for\ one\ year\ [\#]$

β: $minimum\ level\ of\ service\ to\ satisfy\ [\#]$

γ_p: $possible\ trips\ per\ vehicle\ with\ propulsion\ method\ p\ [\#]$

3.3 A MILP for Network Generation and Fleet Assignment

$$Max. F\,(\mathrm{v}, y) = \overbrace{\alpha * \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{p=1}^{P} \sum_{w=1}^{W} d_{ijpw} * \left(\left(t * r^{min} \right) + \left(k * r^{km} \right) \right)}^{revenue\ [US\$\ p.a.]}$$

$$- \overbrace{\alpha * \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{p=1}^{P} \sum_{w=1}^{W} d_{ijpw} * \left(k * e_p * f_p \right)}^{variable\ costs\ [US\$\ p.a.]} \tag{1}$$

$$- \overbrace{\sum_{i=1}^{I} \sum_{p=1}^{P} \left(v_{ip} * \left(V_p + L_i + C_p \right) + y_i * S_i \right)}^{leasing\ costs\ [US\$\ p.a.]}$$

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

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

$$\sum_{i=1}^{I}\sum_{p=1}^{P} d_{ijpw} \leq \Theta_{jw} \quad \forall j, w \tag{4}$$

$$\sum_{p=1}^{P} d_{ijpw} \leq z_{ij} * \Theta_{jw} \quad \forall i, j, w \tag{5}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P} d_{ijpw} \Big/ \sum_{j=1}^{J} \Theta_{jw} \geq \beta \quad \forall w \tag{6}$$

$$v_{ip} * \gamma_p \geq \sum_{j=1}^{J} d_{ijpw} \quad \forall i, p, w \tag{7}$$

$$\sum_{p=1}^{P} v_{ip} \leq n_i * y_i \quad \forall i \tag{8}$$

$$q_{ij} * z_{ij} \leq Q \quad \forall i, j \tag{9}$$

$$\sum_{i=1}^{I}\sum_{p=1}^{P} v_{ip} * u_p \Big/ \sum_{i=1}^{I}\sum_{p=1}^{P} v_{ip} \leq U \tag{10}$$

$$y_i \in \{0, 1\} \quad \forall i \tag{11}$$

$$z_{ij} \in \{0, 1\} \quad \forall i, j \tag{12}$$

$$v_{ip}, d_{ijpw} \geq 0 \quad \forall i, j, p, w \tag{13}$$

The objective function (1) maximizes the annual profit of a carsharing organization. This is carried out by calculating the revenues and subtracting the resulting variable and leasing costs; all of the leasing costs are on an annual basis. In detail, the revenue equals the product of the sum of minutes of rent and the sum of kilometers driven at every established station in each time window and for each vehicle type over the number of satisfied trips at each demand location. This enables a carsharing organization to generate the revenue on either a time-dependent and/or distance-dependent basis in the calculation. Aggregated time windows depict one whole week. Hence, we need to multiply one week of revenue by the number of operating weeks during one year, which is expressed by a. The subtracted variable costs incorporate the resulting vehicle consumption for these satisfied trips, while allowing for different propulsion methods. This leads to the requirement for variations of the type of consumption, the average consumption per kilometer, and the costs for one unit of the respective consumption for each propulsion method again multiplied by the number of weeks. In addition, annual leasing costs for different kinds of vehicles, required charging infrastructures, parking lots, and stations are subtracted.

The constraints (2) and (3) are necessary for the proper creation of the carsharing network and constitutional assignments. Constraint (2) ensures that every demand point is served by one or more dedicated stations. The interconnection of (3) denotes that a station has to be built before a demand location can be assigned to it.

The constraints (4) to (7) deal with demand-related characteristics and the resulting supply aspect. In constraint 4), the calculation of the satisfied demand per station has to be equal or smaller than the existing demand, which is modeled by a Poisson distribution. Constraint (5) ensures the assignment of demand to only established stations in compliance with the demand location assignments. As described in Section 3.1, the existing demand is not required to be completely fulfilled. Thus, constraint (6) expresses a share as an adjustable minimum service level, which implies a minimum percentage of demand that has to be satisfied. Based on the number of trips that need to be satisfied, a respective number of vehicles is necessary to fulfill this demand, as stated in constraint (7). Therefore, the parameter γ_p defines the maximum number of trips possible for a vehicle powered by each propulsion method. This parameter is characterized by the following equation (14):

$$\gamma_p = \frac{duration\ of\ a\ time\ window}{t * \left(1 + \frac{maximum\ charging\ time_p}{\left(\frac{range_p}{average\ speed}\right)}\right)} \tag{14}$$

The maximum number of trips within a time window is calculated using the range per propulsion method, the average speed within the investigation area, the maximum charging time (if applicable), and the duration of a trip proportioned according to the duration of a time window. Furthermore, a number of threshold variables limit the optimization process, as expressed in equations (8) to (10). A limited number of parking lots for vehicles (8) is allocated to every station in order to account for local parking conditions around each potential station. Further, the constraint guarantees the existence of at least one vehicle per established station. Constraint (9) ensures that a maximum distance between a demand point and an associated station is not exceeded. To ensure sustainability aspects, an average emission limit regarding carbon dioxide assumed over the whole fleet is covered in constraint (10). Constraints (11), (12), and (13) set the specific value range of the decision variables of the underlying model.

4 Application, Results, and Sensitivities

4.1 Parameter Definition and Dataset Development

The described MILP is developed to establish a profitable carsharing network at highest possible service rates. When applying the optimization approach, the quality and level of the input values strongly affect the results of the underlying model. This not only includes cost-related parameters, such as vehicle and station costs, but also the assumed demand, which considerably influences the solution. Accurate input values and realistic demand estimates are therefore crucial to the success of the carsharing network and fleet planning with the introduced model. Various approaches regarding demand and station dataset creation, as well as the choice of input parameters are explained and discussed in the following.

The establishment of a new carsharing network is often difficult due to missing data of acceptance and demand in the chosen investigation area. Many existing approaches, e.g., Boyaci et al. (2015), Lee and Park (2012), or Nourinejad and Roorda (2014), estimate the demand based on empirical values of carsharing organizations already in operation to evaluate and validate new optimization models. While accurate for a specific area, such procedures are not transferable to other areas or different carsharing approaches. This similarly applies to different network structures. Even though the approach helps to validate a model, a method to adapt this model to a new area is lacking. We therefore conclude that these approaches are neither flexible nor adequate enough for practical applications. In order to realize a model with wider applicability, we hence developed a new estimation approach to generate demand values irrespective of existing carsharing services.

Our demand estimation is based on carsharing user characteristics identified in the scientific literature. This refines and extends the approach of Sonneberg et al. (2015) by providing calculation models with an accurate derivation and description of these calculations. While many attributes of a typical carsharer differ between publications, five characteristics are consistently supported by the investigations. These serve as predictor variables for our demand estimation and describe the typical carsharer as young to middle aged, well-educated, living in small non-family households, in apartment buildings, with less than one vehicle per household (see section 3.1). Other characteristics, such as (household) income, marital status, or gender are excluded due to inconsistent investigation results (e.g., Jorge and Correia, 2013).

The first step in our demand estimation approach is to subdivide the investigation area into smaller parts. Census criteria, such as the American classification into blocks by the US Census Bureau may be used to support this step. Such a block typically involves several buildings, which results in smaller subdivisions of approximately 500 to 3,000 individuals. The most densely populated point of each block is used as its center and serves as a demand point described by geographical coordinates. As a result, the whole investigation area is covered with demand points. The five characteristics of the typical carsharer are used to estimate the demand level per block. The respective values for these characteristics should be based on (forecasted) data published by governments or independent institutes. Before the potential user group of each block can be calculated, shares for each chosen characteristic need to be identified (equations (15) – (19)). These shares are determined for each block individually and then form the basis for calculating the potential user group per block.

$$\frac{\#\, inhabitants\ aged\ between\ 21\ and\ 44}{\#\, inhabitants} = \Delta\, age \tag{15}$$

$$\frac{\#\, inhabitants\ with\ at\ least\ a\ Bachelor's\ degree}{\#\, inhabitants} = \Delta\, education \tag{16}$$

$$\frac{\#\, small\ non-family\ households}{\#\, households} = \Delta\, household\ type \tag{17}$$

$$\frac{\#\, households\ with\ one\ or\ no\ vehicle\ available}{\#\, households} = \Delta\, vehicles \tag{18}$$

$$\frac{\#\, apartment\ buildings\ with\ more\ than\ 5\ housing\ units}{\#\, apartment\ buildings} = \Delta\, housing\ units \tag{19}$$

For the share of carsharers within the typical age range, equation (15) divides the number of inhabitants per block of the corresponding age group by the number of total inhabitants per block. Similarly, the comparatively high level of education of the typical carsharer is accounted for in equation (16). For the shares of vehicle availability and household type, the number of households per block serves as a basis for the calculation. Carsharers tend to live in small non-family households, as stated in equation (17). As indicated by equation (18), these households are equipped with one or no vehicle. As expressed by equation (19), these types of households are typically embodied into larger apartment buildings with more than five housing units. Certainly, there is also a minor percentage of additional carsharers who do not fall into the typical

profile described above, e.g., with regard to age structure. As this number is deemed negligible, however, it is not expected to significantly affect the overall demand estimation and is therefore not considered.
As shown in equation (20), the potential user group participating in carsharing services for each block is then determined by multiplying these five shares. As every potential user does not actually participate in carsharing, the absolute number of carsharers is much lower. This ratio (λ) depends on various regional aspects such as the infrastructure of the investigation area or attitudes towards the sustainability of inhabitants. Therefore, the assumed λ should be varied based on these conditions; in our calculations we assume a default λ of 0.05, which is varied between 0.01 and 0.10 in section 4.2.5.

$$\begin{gathered} potential\ user\ group = \\ \lambda * (\Delta\ age * \Delta\ education * \Delta\ household\ type * \Delta\ vehicles * \Delta\ housing\ units) \end{gathered} \tag{20}$$

Depending on the result obtained from equation (20), the potential user group can drop to zero in blocks with a majority of family households or elderly population, and the demand points can be eliminated. Based on the resulting potential user groups per block, the actual demand levels can be calculated. Diverse analyses of the behavior of carsharing users conclude that a carsharer requests three trips per month on average (Habib et al., 2012; Morency et al., 2011; Millard-Ball et al., 2005). When applying this value to the above user groups, a certain demand level results for each block. Our approach incorporates these demand levels on a weekly basis with the option to simulate peaks and off-peaks throughout the week. If required, a planner can adapt the demand structures and focus on different time spans via time windows. To simulate varying arrival processes of carsharing customers, the inputs are then calculated following the Poisson distribution within the optimization process. To satisfy the resulting demand levels, supply points need to be established which represent potential station locations. Due to the proven correlation between public transport and carsharing, possible station locations should be set close to public transportation access points (Celsor and Millard-Ball, 2007). The parking situation around each potential station location has to be considered as this limits the possible number of parking lots. Existing parking lots can be used as a basis for this determination.
In addition to the demand levels and potential station locations, parameters such as vehicle costs as well as vehicle consumptions or emissions are required for the optimization process. Representative input values are preset in the optimization model to facilitate completion of the optimization process. These values are summarized in Table 2 and explained in the following.
The composition of cost elements is described in Section 3.1. The values for the annual leasing costs of a vehicle, the related CO_2-emissions, and consumption are chosen on the basis of manufacturer's data (official brochure data). For the following calculations, we choose identical annuals costs for each station and parking lot. To allow for comparability between the different propulsion methods, the Renault CLIO (petrol-driven) and the Renault ZOE (electrically powered), which are otherwise constructed identically, are chosen. The range of the electric vehicle is used for calculating the required charging cycles and therefore does not apply to the petrol-driven variant.
Values for trip duration in terms of time and distance are based on previous investigations (e.g., Cervero and Tsai, 2004; Duncan, 2011; Morency et al., 2011), as is the chosen maximum distance (e.g., Celsor and Millard-Ball, 2007; Costain et al., 2012; Morency et al., 2008).

Table 2: Chosen Values of Input Values

Parameter (vehicle-related)	Value	Parameter (operational)	Value
Petrol vehicle [US$ p.a.]	2,400	Revenue per minute [US$]	0.04
Electric vehicle [US$ p.a.]	4,200	Revenue per km driven [US$]	0.26
Parking lot [US$ p.a.]	2,400	Price per kWh [US$]	0.20
Cost per station [US$ p.a.]	600	Price per liter petrol [US$]	0.80
Charging infrastructure [US$ p.a.]	6,000	**Parameter (trip-related)**	**Value**
CO_2-emission (Petrol) [g/km]	127	Average trip duration [min]	120
CO_2-emission (Electric) [g/km]	0	Std. dev. trip duration [min]	60
Max. average CO_2-emission [g/km]	75	Average trip distance [km]	35
Parameter (demand-related)	**Value**	Std. dev. trip distance [km]	20
Monday [%]	10	Energy consumption per km [kWh]	0.07
Tuesday [%]	10	Petrol consumption per km [l]	0.1
Wednesday [%]	10	**Parameter (other)**	**Value**
Thursday [%]	10	Max. distance [km]	0.75
Friday [%]	15	Max. range of electric vehicle [km]	210
Saturday [%]	25	Charging time [min]	30
Sunday [%]	20	Average speed [km/h]	25
Potential user group λ [%]	5	Min. level of service [%]	75

The revenues per minute and kilometer driven result from a web-based comparison of different existing round-trip carsharing organizations (Greenwheels, 2020; Stadtmobil carsharing, 2020). Similarly, the costs for a fast-charging infrastructure and the resulting charging times result from a market analysis. Consumptions for operational business are at current market price. Parking lot and station costs as well as average speed are adjusted to local conditions. The average CO_2-emission limit for the entire fleet is adjustable to fulfill local environment labelling programs. Our pre-set value of 75 g/km can only be attained when using a combined fleet of electric and petrol-driven vehicles. We selected seven time windows (Monday to Sunday; each 24 hours long) to depict peaks and off-peaks during a week. The demand-related distribution is determined from the real data of a German carsharing organization.

4.2 Benchmark and Sensitivities

4.2.1 Investigation Area of San Francisco

The developed optimization model for the strategic and tactical planning of a heterogeneous carsharing fleet is applied and validated in this Section. Using the case example of San Francisco, the annual profit of a carsharing organization is optimized, compared, and elucidated for different scenarios. San Francisco is chosen due to its high population density of over 6,500 inhabitants per square kilometer, its parking shortage, the mix modes of transportation, and the resulting ability to dispense with a vehicle. The city consists of eleven districts, which form the basis for the comparison of differently populated areas in our benchmarks. It is further divided into 573 blocks in accordance with the U.S. Census Bureau based on census data. The positioning of demand locations was set analogous to the subdivision of blocks, as suggested in Section 4.1.

Each block is characterized by a particular demand location at its center of settlement with assigned geographical coordinates. In addition, a total of 1,448 potential carsharing stations are distributed over the whole investigation area, likewise using precise geographical coordinates. Due to the well-developed public transport system covering the majority of the city, close proximity of potential stations to public transportation access points is easy to ensure. Our benchmarks are established using single districts and combinations of districts of San Francisco, which differ in size and population, as shown in Fig. 1 and quantified in Fig. 2 as well as in Table 3.

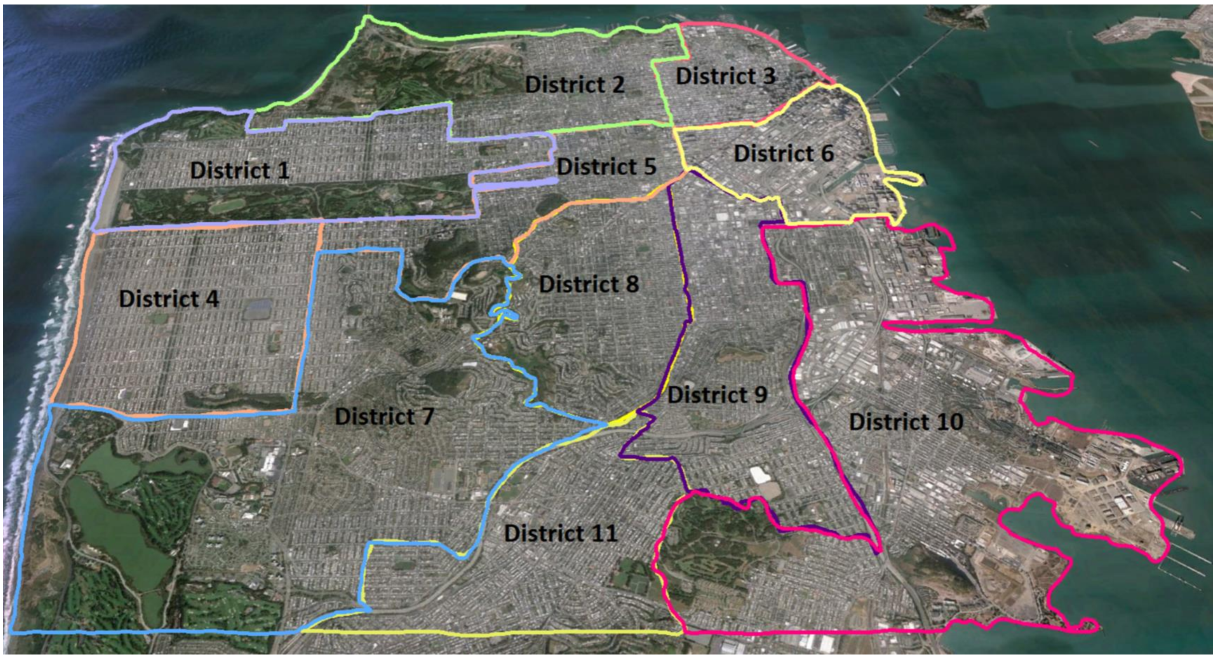

Figure 1: Visualization of Eleven Districts of the Investigation Area of San Francisco

As shown in Figure 1, some areas such as districts 1, 2, and 7 include parks, lakes, or countryside areas, whereas others, such as districts 8 and 9 are completely urbanized. This leads to differences between the districts regarding demand points, demand level per week, and potential stations per district. An overview of the number of demand points, potential stations and expected demand levels per week in the various districts is given in Figure 2.

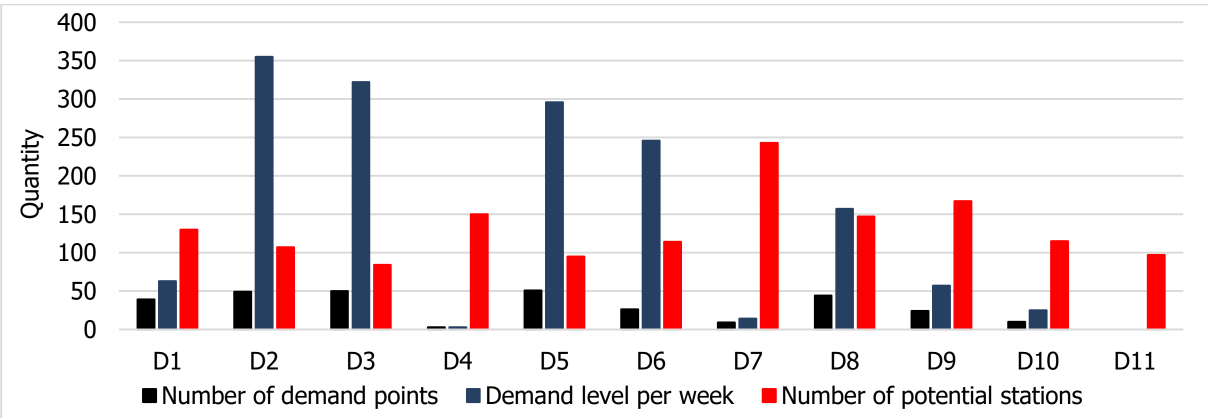

Figure 2: Number of Potential Stations, Demand Points, and Demand Levels per District

Due to its relatively large area (measured on the basis of the surface occupied) with a combination of apartment blocks and the lake area, district 7 has a high number of potential stations assigned to it, while the overall demand is comparatively low. In contrast, districts 2 and 3 have a high estimated demand per week compared to their overall size due to their larger number of apartment buildings, which is typical for high carsharing demands.
Our benchmarks and sensitivity analyses are carried out using so-called clusters consisting of different combinations of districts. These clusters are defined in Table 3 with their respective overall numbers of demand points and potential stations. For classifying and allocating districts to the clusters, we follow the demand levels beginning with the most distinct ones. The objective of this procedure is to visualize to what extent the choice of the investigation area influences profit and service level of the carsharing organization. The first cluster consists of district 2 due to its highest existing group of potential users and the resulting high level of demand. The second cluster additionally includes district 3. Clusters 3 and 4 are similarly augmented. Cluster 5 finally contains all eleven districts representing the entire city of San Francisco. An overview is provided in Table 3. By adjusting diverse input values in the optimization model, these clusters are examined and compared to each other in the following in order to validate our optimization model.

Table 3: Distribution of Clusters and Contained Districts

Dataset	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Contained districts	D2	D2 & D3	D2, D3, D5, & D6	D2, D3, D5, D6, D1, D8, & D9	D1 – D11
# Demand points	49	99	176	283	305
# Potential stations	107	191	400	844	1,448

4.2.2 Comparison of Different Clusters

Our initial set of benchmarks for all five clusters is based on the preset input parameters introduced in Table 2. The results are presented in Table 4 and include the overall profit, number of stations, electrically powered as well as petrol-driven vehicles, average CO_2-emissions, demand satisfaction, computing time in total (accumulated calculation times of all cores) and calculation time. Calculations were performed on a Linux cluster system (16 cores each @ 2.4 GHz CPU with 64 GB RAM) using GAMS 24.5.6 with CPLEX 12.6.2 and a set optimization gap of 3%.

Table 4: Initial Benchmarks for All Clusters

Clustered districts [3% gap]	Profit [US$]	# Stations	# Vehicles		Av. CO_2-emission [g/km]	Demand satisfaction [%]	Computing time in total [mm:ss]	Calculation time [mm:ss]
			Petrol	Electric				
Cluster 1	165,567	5	4	3	72.57	99.7	00:10	00:05
Cluster 2	337,500	8	8	6	72.57	99.8	01:06	00:50
Cluster 3	611,785	18	15	11	73.27	99.8	08:15	04:06
Cluster 4	665,355	27	21	15	74.08	98.9	16:54	08:38
Cluster 5	629,405	36	25	18	73.83	99.6	18:49	10:06

Although profit increases with larger investigation areas, this only applies if the relation between demand and supply is balanced. In cluster 5, stations also need to be built for areas with lower demand levels, which implies a decrease in profit compared to cluster 4. When examined in more detail, the profit is found to almost double between the first and second as well as the second and third cluster, meaning that districts 2, 3, 5, and 6 are similarly profitable. This is in line with the demands shown in Table 3. The profit in cluster 4 increases less, as demands are lower, and eventually decreases in cluster 5. From an economic perspective, this implies that adding the last districts D4, D7, D10, and D11 is not worthwhile for carsharing organizations due to low expected demands in these areas.

The number of stations and overall vehicles increases with larger clusters, as this involves a larger operating area and hence more demand points are satisfied. The composition of the heterogeneous fleet changes with more included districts since the annual leasing costs are much lower for petrol-driven vehicles than for electrically powered ones. The electric vehicles are preferably deployed with a high occupancy rate because of the comparatively low operating costs (less consumption and less energy costs). With more included districts and reduced occupancy rates, more petrol-driven vehicles are selected due to lower fixed leasing costs and no costs for charging infrastructures.

The CO_2-emission limit depends on the shares of electric and petrol-driven vehicles and is set at 75 g/km as an initial value. The actual average CO_2 limit in all clusters is only slightly below this maximum level. This implies that electric vehicles are merely used to keep within the CO_2-emission limit. Although electric vehicles (including the necessary charging infrastructure) are indeed more expensive than petrol-driven vehicles, they use cheaper energy than petrol-driven ones and have a lower consumption. It is more cost-efficient to use electric vehicles at a high demand profile due to the above-mentioned energy price and consumption advantages of this propulsion method. The demand satisfaction is highest in clusters 2 and 3 (99.8%) and is less in clusters 4 and 5 due to the addition of comparatively less economical districts. As expected, the computing time in total increases in larger clusters. This can be explained by the larger operating area with an increase in demand locations and more possibilities to install stations and vehicles. Our model is solved by CPLEX, which uses multi-threads to calculate the solutions. The results of our strategic and tactical optimization computations were obtained within a few minutes depending on the sizes of the underlying cluster and respective number of contained demand points and potential stations.

4.2.3 Comparison of Heterogeneous and Homogeneous Fleets

To ascertain the impact of our mixed fleet composition (M), we compare the initial benchmark of each cluster with calculations involving solely petrol (P) and electric (E) vehicles; CO_2-emission levels are ignored for these cases. The calculation findings for the number of necessary vehicles as well as the expected profit and demand satisfaction are visualized in Figure 3.

The number of vehicles for the three considered fleet options is found to increase when more districts are added (see also Table 4 and its description). The number of used vehicles is the lowest in all clusters when a pure electric fleet is applied. The profit and demand satisfaction are lowest when compared to the other two fleet compositions. This is due to the higher initial costs of an electric vehicle and the required charging infrastructures compared to a petrol-driven one.

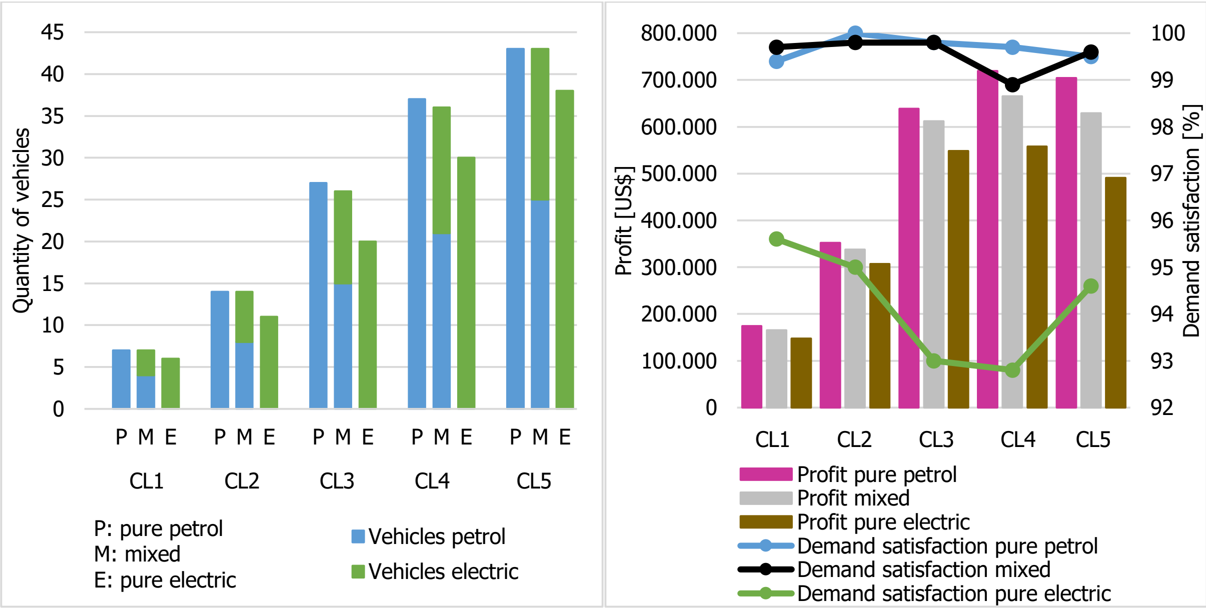

Figure 3: Impact of Fleet Composition on Number of Vehicles, Profit, and Demand Satisfaction

Another aspect is the necessary charging cycle, which has to be considered as an additional operating factor. If electric vehicles have high occupancy rates, they are cheaper regarding the operation business owing to less and cheaper consumption and thus become worthwhile for a carsharing business.

The number of petrol-driven vehicles and the total number of vehicles within a mixed fleet are approximately equal over the five considered clusters, which is also reflected in demand satisfaction. When analyzing the distribution of vehicles, petrol-driven vehicles are found to be slightly predominant compared to electric ones in all clusters.

Profit is found to be slightly less for a mixed fleet composition due to the higher costs for electric vehicles. Nevertheless, when considering the pure electric fleet, demand satisfaction is found to be highest in the first cluster (95.6%) before it decreases (to below 92.8%) and finally rises again in cluster 5. The highest value in cluster 1 is associated with high expected demands and the resulting high occupancy rates for electric vehicles. The subsequent decrease depicts the weaker districts in terms of demand, and hence less demand is sufficient to still maximize the profits of the carsharing business. In cluster 5, demand satisfaction again rises to realize higher profits, even though less worthwhile districts are included. The impact of the less worthwhile districts can also be seen in the profit development. For a pure electric fleet, the profit is reduced by approximately US$ 60,000, but only by ~US$ 15,000 for a pure petrol vehicle fleet and ~US$ 36,000 for a mixed fleet. To conclude, cluster 4 is most profitable for heterogeneous and homogeneous fleets. For this reason, cluster 4 is chosen for the following benchmark calculations and sensitivity analyses performed for heterogeneous fleets.

4.2.4 Impact of Various Maximum Distances

Ceteris paribus, we vary the maximum allowed distance between a demand point and the assigned carsharing station to demonstrate the impact on the number of stations and vehicles as well as on profit and demand satisfaction using cluster 4 due to its most profitable characteristics. The respective results are shown in both parts of Figure 4, which is divided into five parts with 0.5 km, 0.75 km, 1 km, 1.25 km, and 1.5 km as the maximum allowed distance. For each distance, the corresponding annual profit, number of stations, and the number of vehicles are shown in the left part of Figure 3. In the right part of the figure, the same is carried out for profit (primary vertical axis) and demand satisfaction (secondary vertical axis).

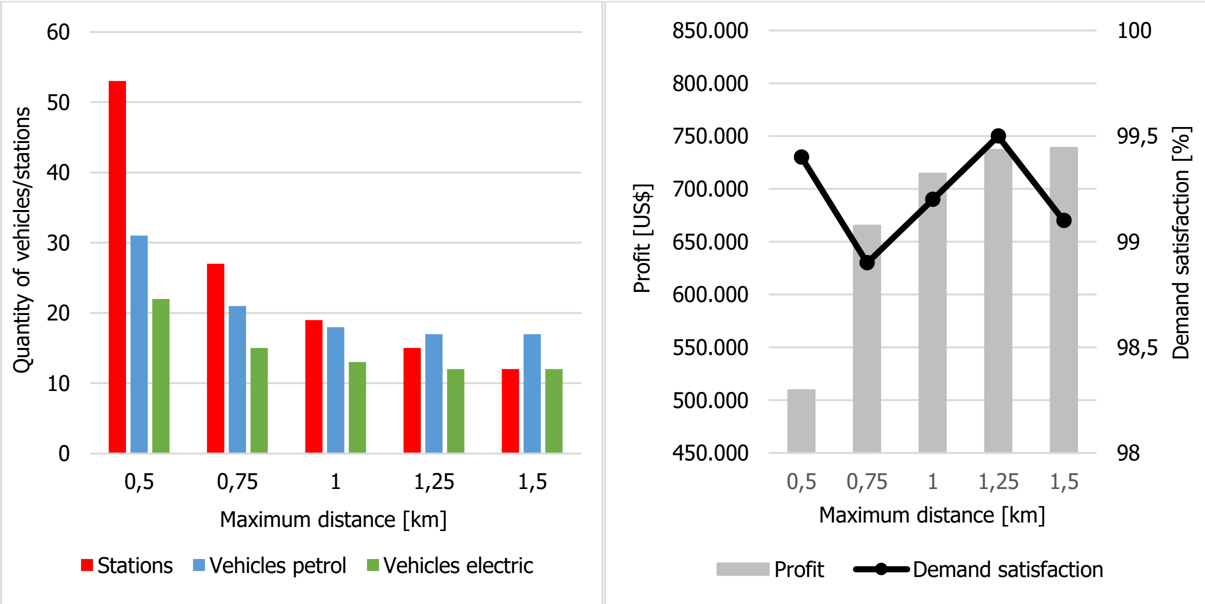

Figure 4: Variation of Maximum Distance and Impact on Stations, Vehicles, Profit, and Demand Satisfaction (Cluster 4)

In general, with an increasing maximum distance, a tendency towards fewer overall vehicles and less established stations can be observed while demand satisfaction does not vary significantly. A lot more stations and vehicles must be provided within shorter distances to satisfy customer needs. Therefore, the occupancy rate of vehicles is less with lower distances and hence reduces profit. Correspondingly, a trend to an increase in profit with larger maximum distances is evident, as especially less stations as well as fewer vehicles are required to satisfy customer needs. However, higher distances can negatively impact customer satisfaction due to greater effort and more time required to reach the nearest station. These aspects are not considered in our approach. At a maximum distance of only 0.5 km, more than 50 stations equipped with just one vehicle per station have to be installed to generate a dense network of stations throughout the investigation area. The number of stations rapidly decreases with an allowed maximum distance of 0.75 km. The customer satisfaction of demanded trips is fairly high and slightly varies between 98.9% and 99.5%.

These benchmarks are in line with expectations, as less stations and vehicles are required with larger maximum distances accompanied by an increase in profit. This results from the assignment of more demand points to one station due to the fact that customers are compelled to accept longer distance to the next station which increases the occupancy rate of vehicles. Regarding demand satisfaction, no clear trend is visible. It should be noted, however, that the overall demand might decrease if no carsharing station is available nearby.

4.2.5 Impact of Various Demand Levels

This section examines the ceteris paribus impact of varying demand levels at a maximum distance of 0.75 km using cluster 4. Besides the impact on the required number of stations and vehicles, the significant influence of demand on overall profit and hence the success of a carsharing organization is visualized. The demand ratio λ of 5%, which was initially chosen for the city of San Francisco, may not apply to cities with less public transport, lower public interest in carsharing, or a high number of competitors. λ is therefore varied between 0.01 and 0.10. The respective results are presented in Figure 5.

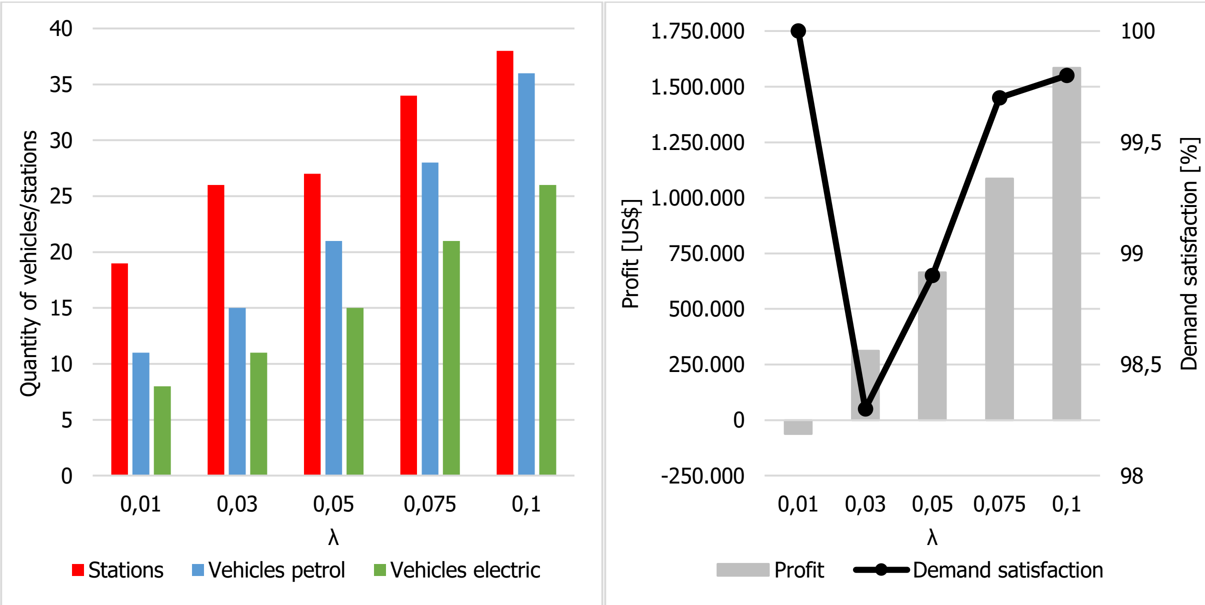

Figure 5: Variation of Demand Levels and Impact on Stations, Vehicles, Profit, and Demand Satisfaction (Cluster 4)

As evident in Figure 5, the demand level strongly influences the expected profit as well as the number of stations and vehicles required. A λ of 0.01 results in a negative outcome of US$ 62,400, which means that a carsharing business is not worthwhile at this low demand value; for a λ of 0.1, however, the profit increases to more than US$ 1,500,000. This growth in profit is almost linear and in line with the rising demand profile. Similarly, the number of stations and vehicles almost linearly rises, starting with 19 stations and 19 vehicles for a λ of 0.01 and increasing to 38 stations and 62 vehicles for a λ of 0.1, also resulting in an increase of the vehicle per station ratio. The demand satisfaction fluctuates around 99%. With a λ of 0.01, the existing demand is fulfilled completely to avoid even more negative outcomes owing to unsatisfied trips. A λ of 0.03 results in a decrease of demand satisfaction but in an increase in profits. At subsequent demand levels, the demand satisfaction rate is found to increase.
This increase in profit with higher demand is in line with expectations. It highlights the importance of correctly assessing the habits of potential users in order to realistically evaluate demand. Small misjudgments in this regard can easily make the difference between business success and failure of a carsharing organization.

4.2.6 Impact of CO_2 Levels as well as Energy and Petrol Prices

In the following part of our sensitivity analysis, we vary the prices of petrol and energy for different CO_2-emission limits to demonstrate the respective influence on network structure. On the one hand, this takes into account recent developments on the energy market, leading to uncertainty of energy and petrol prices. On the other hand, it also includes potential future limitations regarding the maximum allowed emissions of a carsharing fleet, which can either be self-motivated and as a competitive advantage or externally required by way of a city or country directive.

The sensitivity analysis is again run on cluster 4. We include calculations on three different maximum levels of average CO_2-emissions (50, 100, and 150 g/km) for two possible energy price levels (US$ 0.10 and US$ 0.30 per kWh) and for four possible prices of petrol (US$ 0.50, US$ 1.00, US$ 1.50, and US$ 2.00 per liter). The results of these calculations are presented, compared, and discussed in the corresponding diagrams of Figure 6 for all six scenarios. Bars in the diagram illustrate the number of petrol-driven as well as electric vehicles. Additionally, the shift of the average CO_2-emissions is shown on the secondary vertical axis. The number of overall stations is not illustrated as this only varies marginally between the different scenarios with a minimum of 27 and a maximum of 33 stations and with no observable relation to price variations. Our most important consideration concerns the change in composition of the heterogeneous fleet. Regarding the benchmarks, this means that the varying number of electric and petrol-driven vehicles in combination with different CO_2-emission levels is a focus of attention in the following.

At a first glance, it is apparent that the number of electric vehicles exceeds the number of petrol-driven vehicles for the lowest maximum average CO_2 level of 50g/km, irrespective of energy and petrol prices. In addition, the number of electric vehicles increases with rising petrol prices and a corresponding decrease in petrol-driven vehicles. In detail, we notice that in most scenarios with low petrol prices (0.50 US$/l), the CO_2 limit restricts the number of petrol-driven vehicles since electric vehicles are less profitable as long as the price of petrol is comparatively low. With a rising price of petrol, the number of electric vehicles is found to increase. Consequently, a tendency towards reduced average CO_2 levels can be observed. It is notable that even with a high maximum CO_2-emission level, electric vehicles are selected (with the exception of a petrol price of US$ 0.50 per liter) for the carsharing fleet, as these appear to be a profitable alternative in certain areas. Petrol-driven vehicles are deployed in every scenario of the sensitivity analyses with a tendency towards fewer vehicles for a rising petrol price, even though this tendency is only weak for the lower CO_2-emission level. Although average CO_2-emissions strongly depend on the maximum limits, these also show a clear decrease with rising petrol prices due to the deployment of more electric vehicles. In scenarios 3 to 6 and a price of petrol of only US$ 0.50 per liter the number of petrol-driven vehicles strongly dominates, since the maximum average CO_2 limit allows for this composition. Electric vehicles are almost eliminated at this petrol price within a limit of 100 g/km and are completely eliminated in the scenarios with a limit of 150 g/km. This indicates that the CO_2 limit has a significant impact on the composition of the carsharing fleet as long as the price of petrol is low. In this case, electric vehicles are unattractive in terms of profitability and are only selected to comply with CO_2 restrictions. Nevertheless, the distribution is found to change with higher petrol costs. Electric vehicles become more attractive due to the increasing gap between petrol and energy price as well as the lower consumption of an electric vehicle.

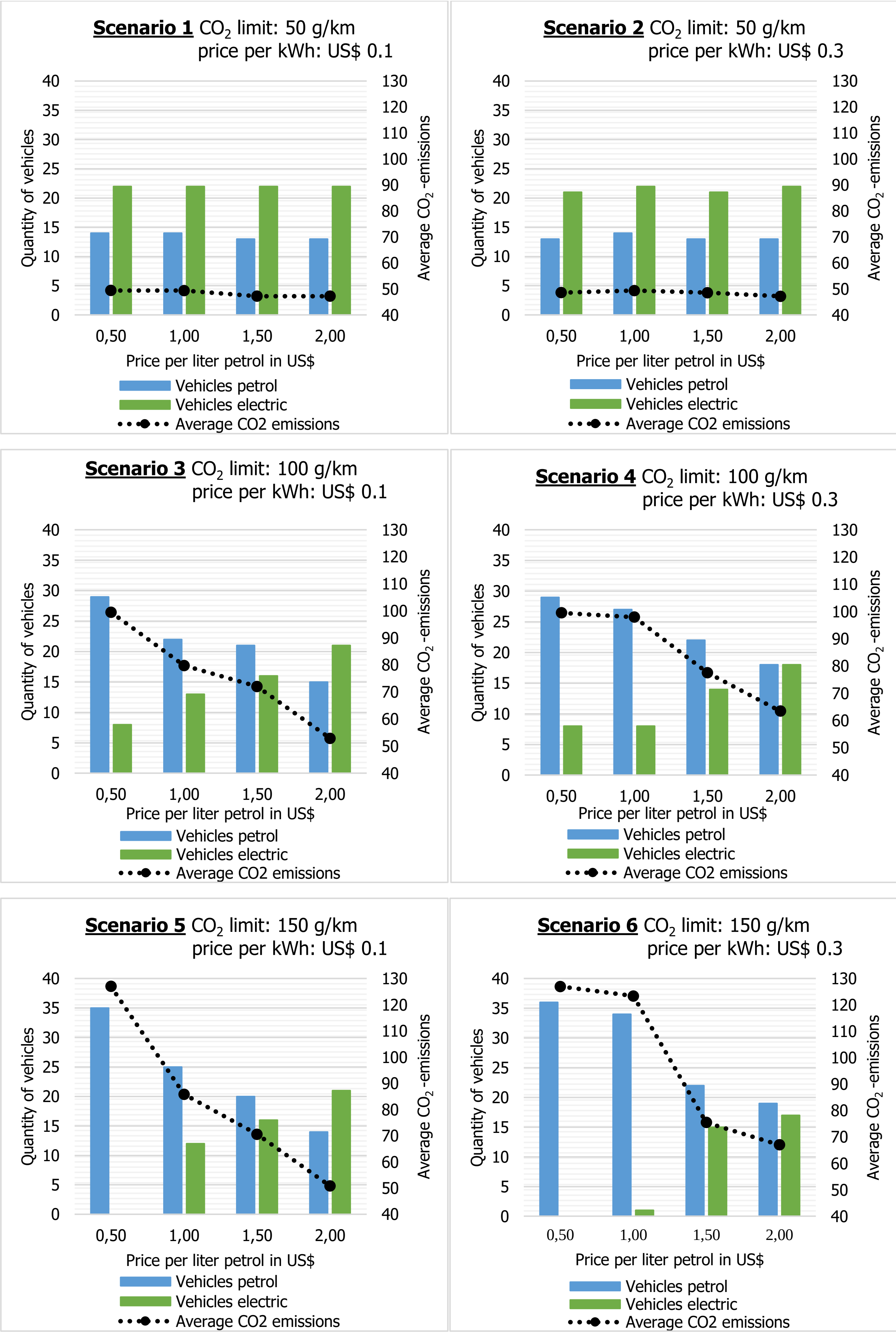

Figure 6: Impact of Various CO_2 Levels and Prices on Fleet Structures (Cluster 4)

For an energy price of only US$ 0.10 per kWh and a high petrol price of US$ 2.00, electric vehicles even comprise the majority of the fleet regardless of the maximum allowed average CO_2-emissions. The high number of electric vehicles is primarily governed by the CO2 limit while the price impact becomes negligible. However, in all other calculations, petrol-driven vehicles dominate due to their lower annual leasing costs and no costs for charging infrastructure. Some minor exceptions to the general tendencies exist and can again be explained by a combination of a varying demand satisfaction, normal variance of the calculation, and the set gap of 3%.

In the following, we consider the impact of different CO_2 levels as well as petrol and energy prices on the expected annual profit for a carsharing organization. Similar to the above benchmarks, we compare three different maximum CO_2 levels and vary the prices of energy and petrol. The resulting expected profits are illustrated as two lines for the two different energy prices and show the development of four possible petrol prices. Figure 7 shows the sensitivity analysis results for the six mentioned scenarios combined in three diagrams.

The lines within the same maximum CO_2 level scenario show similar patterns. Additionally, the yellow lines for energy costs of US$ 0.10 per kWh (scenario 1, 3, and 5) are above the green lines for energy costs of US$ 0.30 (scenario 2, 4, and 6), as a higher profit can be achieved when energy costs are lower.

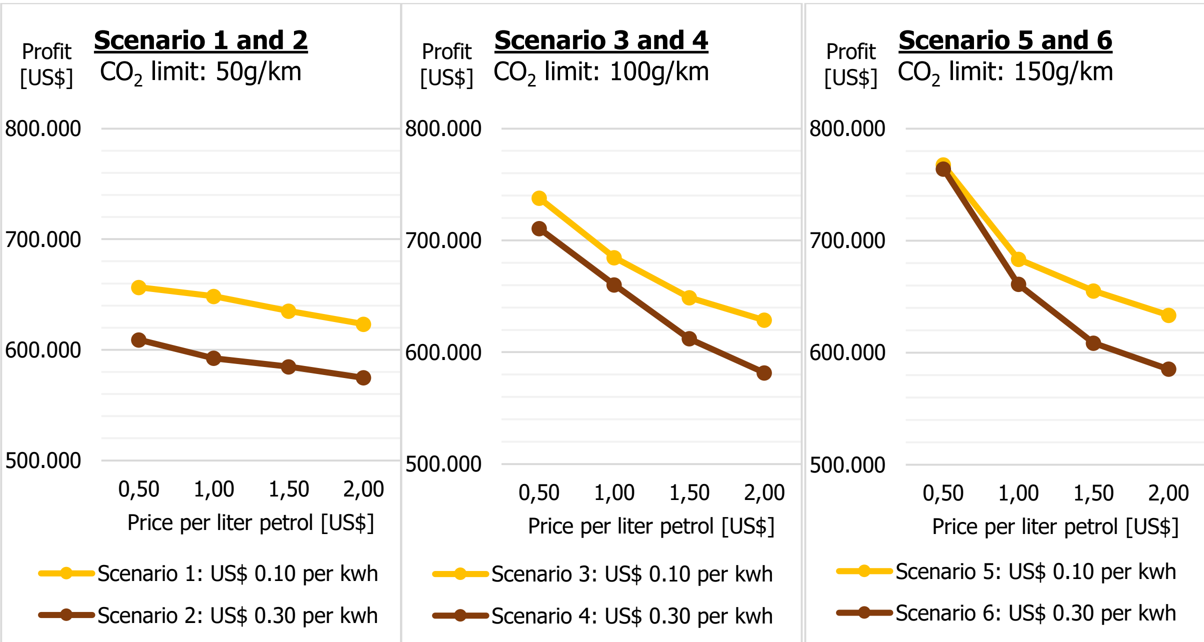

Figure 7: Impact of Various CO_2 Levels and Prices on Expected Profit (Cluster 4)

A general tendency can be perceived for decreasing CO_2 limits, which reduce the overall profit. Depending on the application area, electric vehicles appear to be less profitable compared to petrol-driven ones even though they represent the majority of the fleet. Thus, profit depends on the composition of the fleet when CO_2 limits restrict the number of petrol-driven vehicles. Profits for different CO_2 limits correspond approximately to higher petrol costs. This is most evident for the highest assumed petrol price of US$ 2.00 per liter in every scenario, where the profit is almost identical for all CO_2 limits. A plausible reason for this is that the changing composition of the fleet is influenced rather by energy and petrol prices than by the CO_2 limit. This allows an optimization of profit independent of CO_2 requirements, implying that electric vehicles are deployed for economic reasons. It can be inferred that the consumption of each propulsion method as well as variable and fixed costs also have an influence on the composition of the fleet and the profit for carsharing organizations. This might influence single values, however, but not the overall tendencies presented.

4.3 Generalizations of Results

From the above benchmarks of the city of San Francisco, generalizations can be derived regarding the influence of various selected parameters ceteris paribus. As Speranza (2018) points out, electric vehicles are available on the market that now feature in several optimization approaches. Based on monetary and efficiency drawbacks compared with conventionally powered vehicles, a homogeneous electric fleet is not favorable for suppliers, e.g., carsharing organizations. When implementing a heterogeneous fleet, the advantages of conventionally powered vehicles (lower costs and a higher level of service) and electric vehicles (lower emissions) can be combined. If electric vehicles become affordable and the required charging cycles decrease in duration and range-dependent necessity, a fleet could be replaced gradually up to a prospective pure electric (carsharing) fleet.

Table 5 summarizes modifications with respective impacts on network, fleet, and profit of the carsharing optimization approach for a heterogeneous fleet. A generalization regarding different clusters in the investigated area is not reasonable because the number of demand points and demand levels vary per analyzed cluster, as indicated in Figure 2, Table 3, and Table 4. In general, many demand points lead to a larger network, while high demand levels result in more vehicles for customer satisfaction.

Table 5: Generalizations of Variations regarding Network, Fleet, and Profit

Impact (ceteris paribus) of … on	Number of stations	Number of vehicles			Profit
		In total	Electric	Petrol	
Costs for stations ↑	→	→	→	→	↓
Costs for parking lots ↑	→	→	→	→	↓
Costs for electric vehicles ↑	→	→	↓	↑	↓
Costs for petrol vehicles ↑	→	→	↑	↓	↓
Demand ↑	↑	↑	↑	↑	↑
CO_2-emission limit ↓	→	→	↑	↓	↓
Price per kWh ↑	→	→	↓	↑	↓
Price per liter petrol ↑	→	→	↑	↓	↓
Max. distance ↑	↓	↓	↓	↓	↑

The cost increase of stations and parking lots does not impact the network structure but decreases profit. Similarly, a cost increase for a particular type of vehicle does not influence the number of stations but decreases the number of vehicle types subject to increased costs and increases the number of vehicles with unaltered costs. A higher demand has an increasing impact on all of the above variables. With a lower average CO_2 limit, the number of stations and overall number of vehicles does not change, whereas the number of electric vehicles increases and the number of petrol-driven vehicles as well as profit decrease. A rise in the price of petrol or energy has a comparable effect on the increase in costs for the designated vehicle type. A higher maximum distance between supply and demand points eventually decreases the number of stations, increases profit, and slightly decreases the number of both types of vehicles. Computing and calculation times increase with larger clusters; thus, a generalization based on single parameters is not feasible. The demand satisfaction does not show clear tendencies; variations can be explained by the preset optimization gap and the underlying network differentiations.

4.4 Discussion of Critical Considerations

The preceding benchmarks demonstrate the applicability of the introduced optimization model for the profit maximization of a round-trip carsharing service equipped with a heterogeneous fleet. The model permits the integration of the characteristics of a city to solve the complex problem of determining optimal locations, vehicle compositions, and assignment to carsharing stations. As a result, the model provides a precise, practically applicable recommendation of station allocations within a city.

Despite the latter, certain limitations and potential enhancements need to be considered. Our optimization model can be used for any city worldwide with the restriction of data availability for necessary demand estimate. The city should fulfill the described geographic and demographic characteristics for appropriate and successful application. In this paper, the evaluation of the model and its applicability was limited to the city of San Francisco. Additional tests for cities of different size, structure, and population are required to further validate transferability and generalizability.

Our demand estimation based on demographic data supports realistic assumptions regarding the profitability of carsharing and can be adopted to other cities if the required data is available. Especially for cities with no actual carsharing data, this method allows carsharing organizations to evaluate the feasibility of offering their services in a designated area. Yet, the approach is simplified as it only considers the demand of the habitual abode of potential users and not the demand in business areas or at public transport stations due to a lack of data and research in this domain. Demand also depends on variables other than those discussed, including e.g., the price of carsharing, the structure of the city concerned, and the competitive market situation. While our model does not explicitly consider these aspects, a variation of λ can indirectly adjust the demand to lower values, e.g., when competitors are present. In addition, our model permits adjustments regarding the percentage of the demand, which has to be fulfilled to eliminate unprofitable stations due to low expected demands.

Differently powered vehicles can be included in the optimization model with respective average emissions. A maximum limit of overall CO_2-emission for the fleet can then be set to control the latter and achieve a certain sustainability level. This limit plays a crucial role in the calculations as it strongly influences the required number of alternatively powered vehicles and thus the overall profit of the carsharing organization. If the limit is set to a high value, only few alternatively powered vehicles are included in the fleet. In the future, it is expected that low emission levels will be supported or even required when offering a carsharing service. Today, such an emission limit is voluntary and typically used to support the environmentally friendly image of an organization.

In our benchmarks, we use the two extremes of possible propulsion methods, namely petrol-driven and electrically powered vehicles. We limit our analyses to only two methods to allow comparability of varying vehicle compositions. In addition, we assume 0 g/km CO_2-emission

for electric vehicles, which require renewable energy not only for the charging process but also for the production of the vehicles. This represents a simplification of real life situations.
Due to the requirement of charging infrastructures for electric vehicles, a station-based round-trip carsharing approach is considered which takes into account all the advantages and disadvantages given in Table 1. One-way trips generate significantly more costs due to the requirement of additional charging infrastructures at each station as well as staff or user incentives for relocation. However, the implementation of a one-way option with higher prices to cover the additional costs could increase flexibility and attract additional users. This option may be limited to non-electric vehicles, as already offered by Zipcar (Zipcar, 2020).
Further improvements of the set optimization gap of 3% are possible with additional computing time. As our model addresses strategic and tactical planning, computing time is not a critical aspect. However, the set optimization gap used in our benchmarks may lead to small biases between the results.

5 Conclusions and Outlook

Carsharing organizations offer their services in an increasing number of cities worldwide. With a growing public environmental awareness, the number of carsharing users continues to rise rapidly and the aspect of sustainability becomes more and more important. As a consequence, the integration of vehicles with alternative propulsion methods such as electric vehicles into existing fleets depicts an ongoing trend in this business sector. To successfully integrate differently powered carsharing vehicles in a city, station locations, their sizes, and an optimal number of different types of vehicles have to be determined. Round-trip modes are especially advantageous as they can be used in almost any city regarding their requirements concerning population density.
We introduced a MILP to support the challenging task of network and fleet planning as well as optimization for heterogeneous fleets with the overall objective of profit maximization under consideration of ecological sustainability. We evaluated our model using the example of San Francisco. Our benchmarks reveal that the identification of realistic demand levels has a significant influence as to whether carsharing is profitable or not. They further show that slight adjustments in parameters can have a notable impact on how to optimally disburse the carsharing network of a heterogeneous fleet. In doing so, we contribute to station-based carsharing and its planning as well as its optimization. Further, we present a possibility to estimate the demand without having actual user data on hand. Although certain limitations have been identified, it was possible to verify the applicability and usefulness of the optimization model.
Benefit could be drawn from more detailed empirical evaluation in this field; as demand represents the most crucial factor to success, additional information regarding typical carsharer and support for the currently used aspects could further validate and enhance our approach. The optimization model itself could be refined by adding aspects not yet considered, such as the implementation of additional multi-mobility constraints, demand-related prices, or a one-way option including relocation procedures. We emphasize that the potential of including alternative propulsion methods in carsharing applications is considerable, as this approach serves to increase sustainability while maintaining profitable installation. In conjunction with further enhancements, our work can therefore contribute to supporting a cleaner environment and a greener future.

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