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Cost-Effective Planning of Station-Based Car-Sharing Systems: Increasing Efficiency While Emphasizing User Comfort

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Highlights

What are the main findings?

- 217 to 949 people is the ideal group size to share a car fleet.
- The number of car-sharing cars needed is influenced the most by long-distance trips.

What are the implications of the main findings?

- To reduce further car-sharing costs, alternative mobility options are required for long-distance travel.

Abstract

Station-based car-sharing has been shown to reduce resource-intensive private car ownership. However, only a small proportion of the population uses station-based car-sharing, which could be improved by redesigning the service to reduce walking distances and increase availability. We developed a method for designing an efficient and cost-effective station-based car-sharing network for smart cities that emphasizes user comfort and convenience, while reducing the number of needed cars. To quantify the placements, we created a high-resolution synthetic population for Munich, Germany as a case study. The population was based on census and OpenStreetMap data, and each person was assigned to a suitable mobility plan derived from two mobility surveys. Since car ownership and station-based car-sharing are particularly associated with trips for vacations, we supplemented the mobility plans with long-distance travel data from a one-year tracking dataset. This allowed us to perform a spatial and temporal analysis of the theoretical potential of various station placements for station-based car-sharing. The tested station networks varied in user comfort, especially in the distance to the nearest station and the group size of car-sharing users. Our findings indicate that the best trade-off between convenience and efficiency is a station design with a group size of 217–949 people. We further found that the car-sharing fleet size is strongly influenced by long-distance trips, and that a substitution rate of 1:1.25 to 3.3 with private cars is possible.

Keywords: car-sharing; station-based; cost-effective; theoretical potential; planning; environment

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1. Introduction

Station-based car-sharing can be an important component of a sustainable mobility transition, as it is a substitute for private car ownership [1,2]. Reducing private car ownership is necessary to ensure more efficient resource use. Station-based car-sharing can make

a contribution particularly in reducing the space required for parking vehicles in densely populated areas and reducing greenhouse gases globally [3]. In its current, common form, however, station-based car-sharing only appeals to a small group of users, as the user-friendliness of the system, in particular, is still considered insufficient [4]. Since free-floating car-sharing has no clear effect on car ownership rates [1,2], we focus exclusively on the placement of station-based car-sharing in this publication.

A promising approach to improving the user comfort of station-based car-sharing is residential car-sharing [5,6]. In this case, the sharing station is located close to the users' residential building and, depending on the system's design, can only be used exclusively by a group of residents. In most cases, this significantly reduces the distance to the nearest sharing station, which, in turn, is presumed to increase usage rates [7,8]. This might result in a conflict of objectives, in which a smaller user group leads to lower vehicle efficiency. To find the most efficient and cost-effective station network emphasizing user comfort, we developed a placement methodology using Munich, Germany as a case study. For this, we created a synthetic population based on high-resolution census data [9] and combined it with two detailed survey-based travel diaries. The matching was based on sociodemographic parameters. To include seasonally variable long-distance journeys, such as vacations or weekend trips, in the car-sharing design, we supplemented the dataset with findings from a long-term GPS tracking dataset.

2. Literature Review

Car-sharing has three main forms. These include station-based car-sharing, where the car is rented at one location and returned there at the end of the booking. Free-floating car-sharing is the second form, in which vehicles are rented and returned within a business area, and the third form is peer-to-peer car-sharing, in which vehicles are provided by private providers [10]. In this paper, we focus on station-based car-sharing, as free-floating car-sharing does not necessarily lead to a reduction in private car ownership [1,2] and peer-to-peer car-sharing is still rarely used in Germany.

2.1. Sustainable Potential of Car-Sharing

The exact amount of CO_2 savings achieved through car-sharing depends heavily on various factors. These include the substitution rate, the type of car-sharing vehicles used, and changes in mobility patterns resulting from the use of car-sharing [11]. The extent to which this is due to a reduction in private car ownership varies from just a little effect [12], to over 66% of total savings due to private car ownership reduction [11], to the statement that a real reduction can only be achieved by reducing the use of private cars [13]. This makes reducing the number of private cars an important part of the sustainability of car-sharing. Furthermore, the benefits are not limited to saving resources in production, but also extend to saving resources in mobility, as households with fewer cars make more use of active mobility [14].

The car-reduction rate for station-based car-sharing users is a subject of controversy in the research literature. Multiple studies completed surveys in different countries with car-sharing users, finding the substitution effects of one car-sharing vehicle to include replacing five private cars [15], nine to 13 private cars [16], eleven private cars [17], and up to 23 private cars [18]. All the studies have in common that they are survey-based, involved active car-sharing users, and calculated the replacement rate based on their responses. The calculated substitution rate, based on the car registration data of several cities in Germany which offer station-based car-sharing, came to nine private cars replaced by a car-sharing vehicle in [1]. All these substitution rates are limited to existing car-sharing services and do not account for the potential a new car-sharing offer can theoretically unlock.

A calculation of the technical potential of free-floating car-sharing using telematic data as a proxy for car-sharing demand was conducted by Strada et al. [19] for a case study in Milan, Italy. They calculated the potential reduction rate to one car-sharing vehicle replacing 1.3 private cars [19] showing a difference from the survey-based replacement rates of six [20] or even 15 private cars [21]. To the best of our knowledge, the technical potential of station-based car-sharing has not yet been researched.

2.2. Car-Sharing User

Car-sharing users differ across car-sharing systems and the time since their introduction. Overall, the group of people who use car-sharing is shifting from early adopters to late adopters. Among other things, the diversity of age, gender, and income among these groups is increasing [22]. Car-sharing users are, in comparison to bike-sharing and ride-hailing users, more likely to live with a partner, have children, lack access to their own car, and live in a neighborhood designed for commuters [23]. Station-based car-sharing users are, in comparison to the users of peer-to-peer car-sharing, wealthier and older [24]. However, it is not the mere use of car-sharing that is important for a sustainable transport transition, but rather the decision to give up one's own car.

2.3. Residential Car-Sharing

Residential car-sharing has not yet been extensively researched, but it is attracting increasing attention in the scientific community. In an analysis of existing systems in Stockholm, sharing vehicles within a closed user group—in this case, the residents of the building—was rated particularly positively [6]. These findings were also confirmed by a case study in Munich [5]. The latter study also found that this system appeals to broader segments of the population than traditional car-sharing services. Neighborhood car-sharing thus opens up opportunities for new business models for car-sharing operators, but also for construction companies, as many municipalities in Europe are already waiving the requirement to build private parking spaces that would otherwise be mandatory [6]. To our knowledge, there are no studies dealing with the placement of stations for this new type of car-sharing. Although there are studies, e.g., from Switzerland [25], that show the potential of known station-based car-sharing services in great geographical detail, it is important, especially for residential car-sharing, to know how many vehicles can actually be saved to correctly estimate the need to build parking spaces. In our opinion, this must be done under the requirement that individuals' familiar mobility remains feasible, including long-distance trips, because otherwise people will not be willing to give up their private vehicles. To the best of our knowledge, the impact of long-distance trips on the design process of car-sharing has not been researched before, even though station-based car-sharing is often used for it [26]. This leads to the question: How many people should share a fleet of vehicles so that walking distances to the next car-sharing station remain short, ensuring that the vehicles are used as efficiently as possible and that the total number of vehicles required is as low as possible? We develop a methodology to answer this question and provide recommendations to municipalities, car-sharing operators, and real estate developers based on our case study in Munich, Germany.

3. Materials and Methods

To evaluate the efficiency and user comfort of the new station placement, we needed to know the corresponding car-sharing demand. To this end, we created a synthetic population for our case study region, the city of Munich, using the proposed process of Hörl and Balac [27], based on the 2022 census [9] and OpenStreetMap data [28]. We added mobility plans using data from two survey-based travel diaries (Mobilität in Deutschland

2023 (MiD) [29] and Mobilität in Städten 2023 (SrV) [30]) and one GPS-based mobility survey (Mobilität.Leben [31]). The schematic process is shown in Figure 1. The mobility plans used are all collected from Munich residents. For the MiD dataset, the sample size is n = 13,387, and for the SrV dataset, n = 40,366.

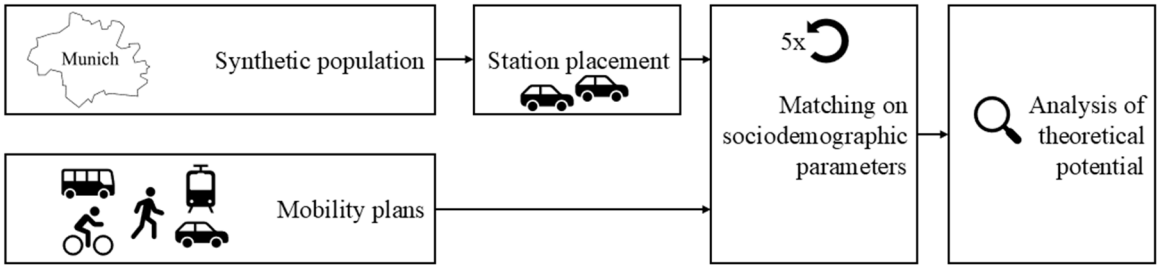


Figure 1. Procedural model for the synthetic population with mobility plans.

3.1. Synthetic Population

To determine whether sociodemographic parameters are necessary for predicting daily vehicle use, we performed a feature analysis of the MiD data using a random forest approach. Ranked by importance, the features can be derived as the number of cars in the household, employment, accessibility of the place of residence by public transport, gender, and age. We obtained information on the number of people, gender, household sizes, and age from the German 2022 census with a quadratic resolution of 100 m edge length [9]. Additional information on employment distribution by age group and gender was collected at the municipal level from census data. The distribution of the synthetic population within the squares was based on building data from OpenStreetMap [28]. We extracted residential building data via an API interface based on the tags from [32], interpolated missing floor information weighted by distance, and later assigned people to buildings based on relative living space. Households were assigned to buildings using greedy optimization, assuming that each household lived in only one building. The household size was taken from the census data. Individuals were randomly assigned to households located in each 100 m times 100 m square. The public transport (PT) accessibility score for each building was calculated by summing the distance-weighted number of PT stops in the surrounding area. The data used is from OpenStreetMap. The assignment to discrete accessibility classes, as specified in the MiD, was then carried out proportionally based on the population distribution known from the MiD. Based on accessibility and household size, the number of vehicles per household was then allocated proportionally according to the findings from the MiD. These values were calibrated using the registration figures for the city of Munich according to the allocation of households to city districts [33] as of the reporting date in January 2023. The resulting synthetic population is outlined in Figure 2.

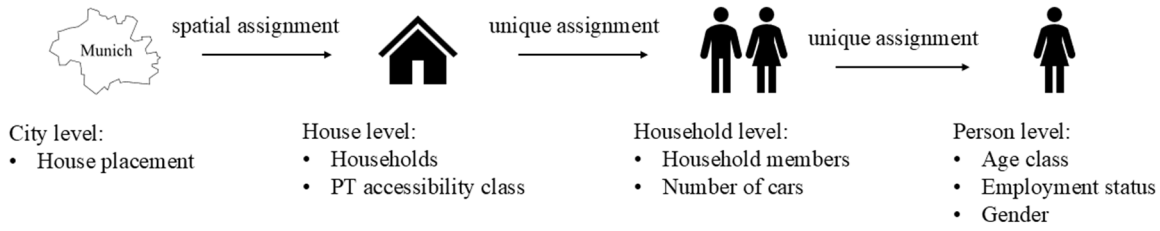


Figure 2. Parameter assignment of the synthetic population.

3.2. Fusion with Mobility Plans

The mobility plans for each individual person in the synthetic population were assigned from the mobility plans recorded either in the MiD or SrV. It was a random decision

for each person in the synthetic population which data set was used. We used the parameters age, employment, gender, household size, number of cars in the household, public transport accessibility, and district assignment as a parameter set to identify direct equivalents in the datasets. If several people in the mobility datasets shared the same parameters, the final mobility plan was assigned at random. Each person in the synthetic data set was thus assigned a corresponding mobility plan.

Long-distance trips are often inadequately captured in survey-based mobility data collections [34], but they can be decisive for the design of car-sharing systems [5]. We therefore supplemented these separately. Long-distance trips vary greatly in frequency depending on the time [35,36]. Consequently, we defined three time periods: weekdays, weekends, and peak holidays. The proportions of the population who travel by car were calculated using a correction factor from [35] and distinguish between households with and without car ownership. The proportion of the population who undertake long-distance travel is independent of car ownership [35]. The values used are shown in Table 1 and based on [35]. In the MiD and SrV, participants were asked whether they were outside their usual living environment at the time of the survey. This group of people was primarily classified as long-distance travelers. Further classification was done randomly if necessary. In the synthetic population, only one vehicle was used if there were several long-distance travelers per household.

Table 1. Share of people on long-distance trips (values based on [35]).

	Weekday	**Weekend**	**Public Holiday**
People on long-distance travel by car:	13.7%	20.6%	37.7%
Non-car owners	27.3%	31.7%	33.2%
Car owners	54.7%	62.6%	65.3%

The assignment of a mobility plan represents the mobility of one average day. As information for a single day might not be sufficient to design a car-sharing offer, we ran the assignment five times to collect data from five random samples. The mobility plans were reassigned in each iteration.

3.3. Placement of Car-Sharing Stations

The synthetic population was spatially distributed in Munich. To offer a car-sharing service to all inhabitants, we analyzed five station placement methods, ranging from a dense to a loose network.

The analyzed car-sharing station placement methods are:

- House-based (PH): Each residential building has its own car-sharing station.
- Square-based (PS): Symmetrical placement of the stations in the center of each census square with an edge length of 100 m.
- Distance-based (PD): Placement based on maximum air distance from a residential building to the next car-sharing station. We used a classic greedy algorithm with distance clustering [37] and capacity, as well as distance limitations, to place the stations. We varied the maximum air distance within a cluster from 50 m to 425 m, which represents a maximum walking distance of 70.5 m to 600 m with a detour factor of 1.41 [38]. A distance of 600 m is the maximum distance people are willing to walk to a car-sharing station [39].
- Mixed method (PM): Does not place new stations but uses the stations of PH and PD simultaneously. This idea is based on findings from [5], which suggested designing different car-sharing fleets for different use cases. In this concept, a small car-sharing

fleet, technically ideal for short-distance journeys—which are all journeys below 200 km [35], like commuting, grocery shopping, and other errands of daily life—was placed based on the PH method. A second fleet of larger cars, ideal for long-distance trips such as holidays, was placed using the PD method. The decision on which fleet to use is based on the journey length (<200 km PH, >200 km PD).

- Original placement (PO): This placement method took an existing station network [40] from the largest and only comprehensive station-based car-sharing provider in the study region as the status quo.

Each car-sharing station was equivalent to one car-sharing fleet. An overview of the resulting parameters of the placement methods is listed in Table 2.

Table 2. Car-sharing station placement methods.

Method Description	Acronym	Resulting Station Amount	Resulting Average Walking Distance
House-based	PH	139,069	~0 m
Square-based (100 m × 100 m)	PS	15,699	~57 m
Distance-based (e.g., 300 m)	PD	1596	~231 m
Mixed method	PM	139,069 + 1596	~0 m–231 m
Original placement	PO	106	~1161 m

The placement method PM was the only one where two car-sharing stations were associated with each household. With all other placement methods, each household used only one car-sharing station which corresponded to a closed user group within each car-sharing fleet. Each household was assigned to the closest car-sharing station. The resulting catchment areas for each station, differentiated by placement method, are shown in Figure 3.



Figure 3. Resulting catchment areas for different station placement methods.

3.4. Usage of Cars

For round-trip car-sharing, it is crucial to know when the vehicle is not available at the station. Therefore, we grouped the car trips from the created synthetic population into

journeys. A journey might contain multiple car trips; the first trip starts at home, and the last trip of a journey ends there again. The trips in between do not start or end at home. We assumed in our study that these car journeys should be fulfillable by car-sharing vehicles to provide a real alternative to private cars.

We used different parameter sets to quantify the theoretical potential of the placed car-sharing stations, listed in Table 3. The default values were used to generate the results, unless otherwise specified.

Table 3. Parameter set (the default values were used to generate the presented results unless specified differently).

	Default Values	Unit	Set
General parameter:			
Mobility dataset	mixed		{SrV, MiD, mixed}
Placement method	-		{PH, PS, PD, PM, PO}
Sharing ratio	100	percent	[5, 100]
Substitution ratio	100	percent	[0, 100]
Electric cars	False	-	{True, False}
Switch time	15	minute	[5, 15]
Distance threshold for long-distance tour	200	kilometer	
Journey substitution	False	-	{True, False}
Tour distance until substitution with dif. mode	0	kilometer	[0, 10]
Long-distance share	weekdays	-	{Weekdays, weekends, public holidays, none}
Placement parameter:			
Max. walking distance	300	meter	[50, 425]
People capacity per station	Inf	-	[20, inf)

To generate a diverse mobility data set, the two mobility data sets (MiD and SrV) were combined to expand the range of mobility plans.

We varied the proportion of households using car-sharing between 5% and 100% and the ratio of car-sharing users who surrender their private cars between 0% and 100%. The calculated fleet design enables all car-sharing users to complete all car trips with the provided car-sharing system. Therefore, the optimal case would be that all car-sharing users surrender their private cars, which would represent the upper bound for the possible reduction in car numbers.

We assumed a high share of cars will be electrified in the future and examined the impact of electric cars on the required fleet size, assuming that the energy used for the distance traveled must be recharged at the car-sharing station upon completion of the journey. Here, we used an average charging power of 11 kW, which corresponds to typical market values, and an average consumption of 0.15 kWh/km [41].

As a buffer between two rentals, we assumed a changeover time of 5 to 15 min during which a car cannot be rebooked, which is called the switch time.

The potential effect on the car reduction rate of changing the mode of transport from cars to other modes was examined by excluding car journeys of up to 10 km, unless they served a business or people transport purpose.

Due to the large number of possible parameter combinations, we chose a partial factorial design for evaluation. In the evaluation, we focused on the calculated utilization of the car-sharing vehicles and the resulting fleet sizes, which are primarily relevant for car-sharing operators. For the public sector, we analyzed the calculated potential reduction rate of private cars and their spatial distribution in Munich, and for users, we analyzed the

number of other people sharing the vehicle fleet with them and the distance to the nearest car-sharing station.

4. Results

To verify the plausibility of the mobility data generated with the synthetic population, Figure 4 compares the average time a person spends driving per day and the average distance traveled per day as a driver. All differences between the original data sets and the values determined from the synthetic population are less than ±3%, which is significantly lower than the differences between the mobility data sets used, which exceed 10%. To compensate for these differences and increase the diversity of the mobility data, we used the combined values from the MiD and SrV for further evaluations.

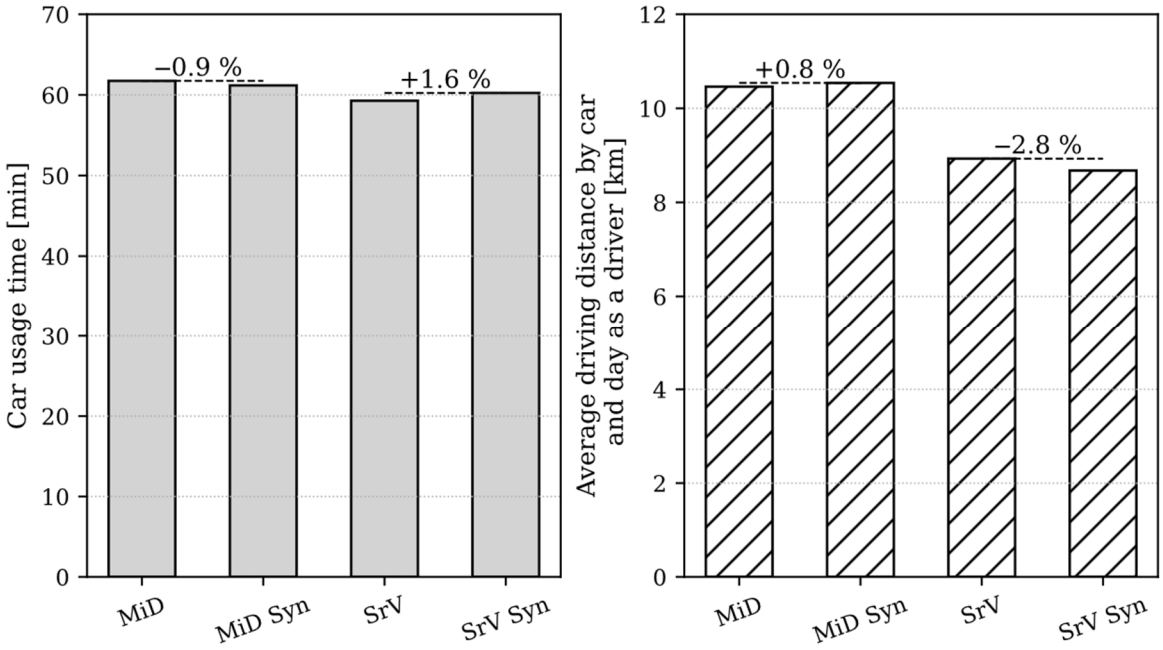


Figure 4. Evaluation of mobility plan distribution in synthetic population (Syn).

We first conducted the analysis at the station level to develop recommendations for further station placements and then provided an overview of the theoretical potential of station-based car-sharing on the city level for our case study area.

4.1. Analysis on Station Level

For user convenience in car-sharing, the distance to the car-sharing station and the user group with which the vehicles are shared are important factors. For different sharing ratios, we varied the maximum permissible distance to a car-sharing station from 50 m to 425 m and analyzed the resulting parameters. The evaluation is shown in Figure 5 on the right-hand side. On the left-hand side, the resulting parameters from the other station placement methods are plotted for comparison. In addition to the mean values, the range of one standard deviation is shown. The reduction rate does not increase linearly with increasing distance to the next station but approaches a limit that depends on the sharing rate. The mean reduction rate per station clearly increases up to a maximum air distance of 300 m to the next station and remains constant with higher distances. The reduction rate at a maximum air distance of 300 m is 5.1% with a 10% sharing rate, 28.7% with a 50% sharing rate, and 60.1% with a 100% sharing rate. The rates remain almost constant at greater distances, but the standard deviation decreases further.

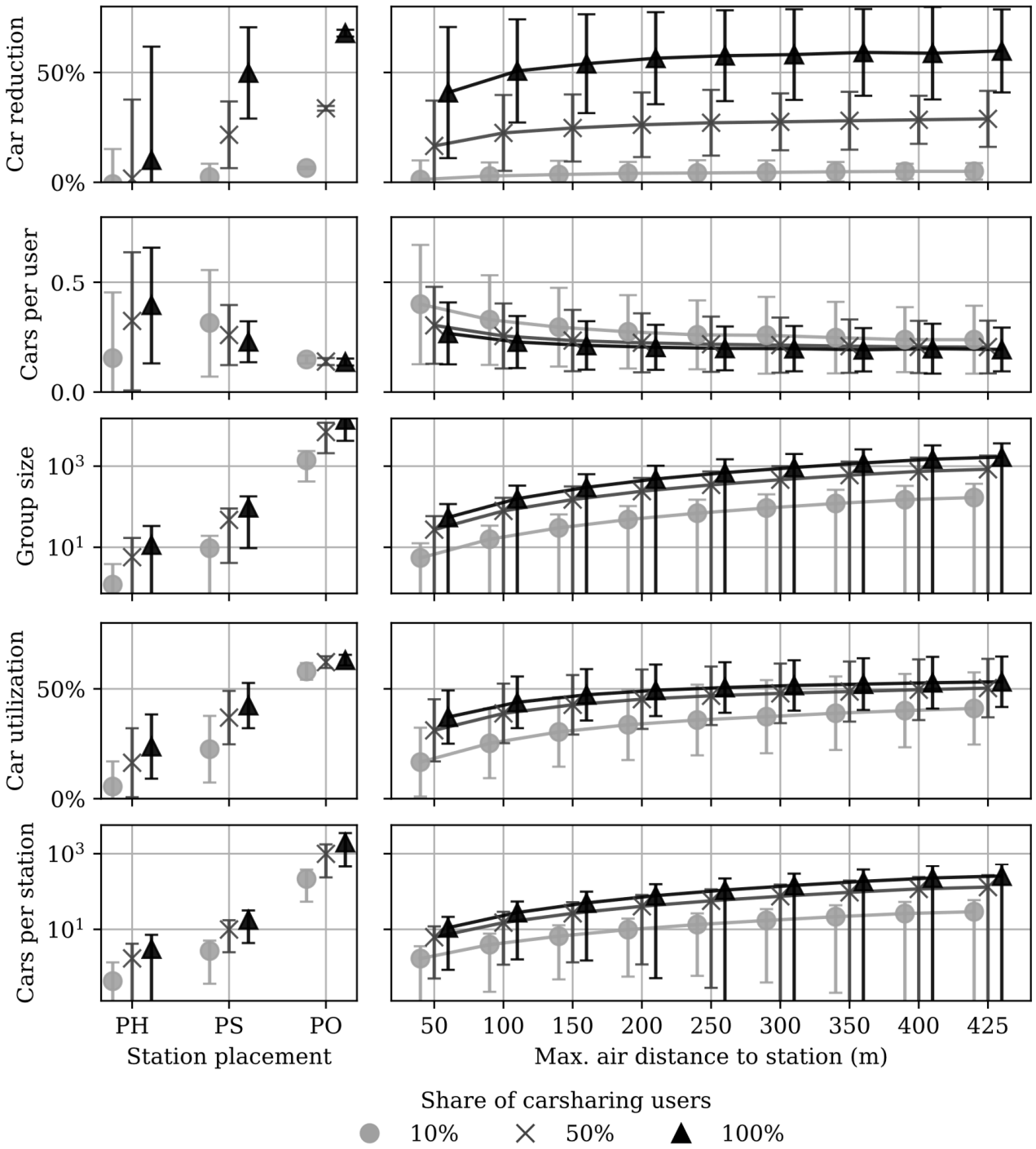


Figure 5. Mean values and first standard deviation for different key parameters for car-sharing station sets placed by different methods.

The results show a similar behavior for the number of vehicles needed per user. These decrease with increasing sharing rate and station distance. Here, the negative limit value is almost reached at a maximum air distance of around 350 m with 0.23, 0.19, and 0.18 for the different sharing ratios. The average number of people sharing one car-sharing fleet and the number of cars needed for a car-sharing fleet increase continuously with increasing maximum air distance to the next station. For 300 m, the group sizes are, on average, 93, 463, and 927, and the number of cars needed per station is, on average, 17, 73, and 141 for the three different sharing ratios. The average vehicle utilization also approaches a limit as the maximum air distance to the station increases. This value is almost reached at around

300 m with 37.3%, 47.9%, and 51.5% for the three different sharing ratios. The standard error continues to decrease as the distance from the station increases. This illustration shows that a station placement that focuses on fewer, more distant stations is better across most parameters, but that there is a limit value that is almost reached at an air distance of around 300 m.

In addition to the distance to the car-sharing station, the group of people with whom users share the vehicles is also a decisive factor. To determine the effect of different group sizes on the number of cars needed per person, we applied the mobility plan association 15 times to obtain samples for 15 random working days. All types of placement mechanisms were used, but they were plotted by group size. We evaluated the average number of cars we need per person to meet mobility requirements. The result is shown in Figure 6. Each gray dot represents a station on a random day. The aggregation steps are calculated for a bin size of 50 people. These values include the mean, one standard deviation, and two standard deviations. We fitted a decreasing hill equation through the mean values. The result is shown in Figure 6. As the number of people in a sharing group increases, the required vehicle-per-person ratio converges toward a limit. With a group size of 217, 105% of the limit value is reached. This implies that from a group size of 217 people onwards, the number of cars needed per person does not decrease notably further.

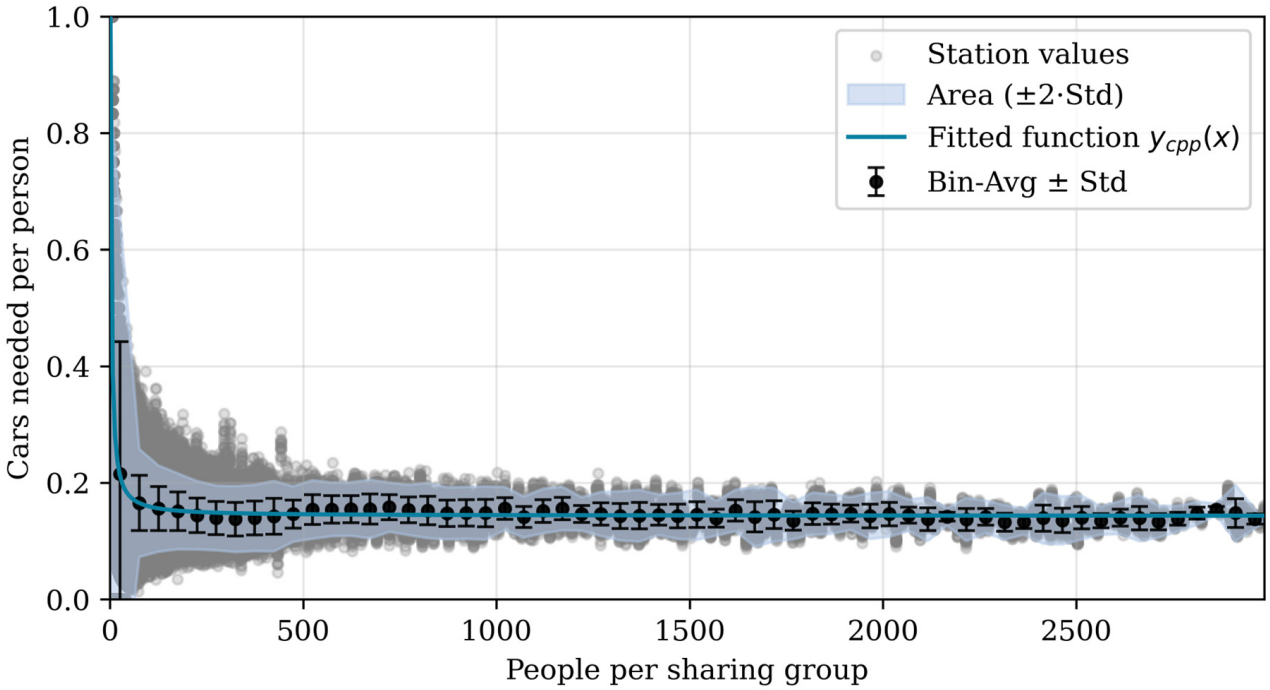


Figure 6. The correlation between the group size of a car-sharing station and the resulting number of needed cars.

The calculated average utilization rate for five random weekdays at each station, relative to group sizes, is shown in Figure 7. Each gray dot represents the average utilization rate for a station. The calculation methods for the mean and standard deviation are equivalent to those shown in Figure 6. Instead of a decreasing hill equation, an increasing hill equation is used. It is evident that the utilization rate increases with the size of the user group but approaches a limit of around 61.2%. The 95% value of this limit is reached with a group size of 949 people. This implies that a larger group size does not notably increase the potential utilization rate of the car-sharing fleet.

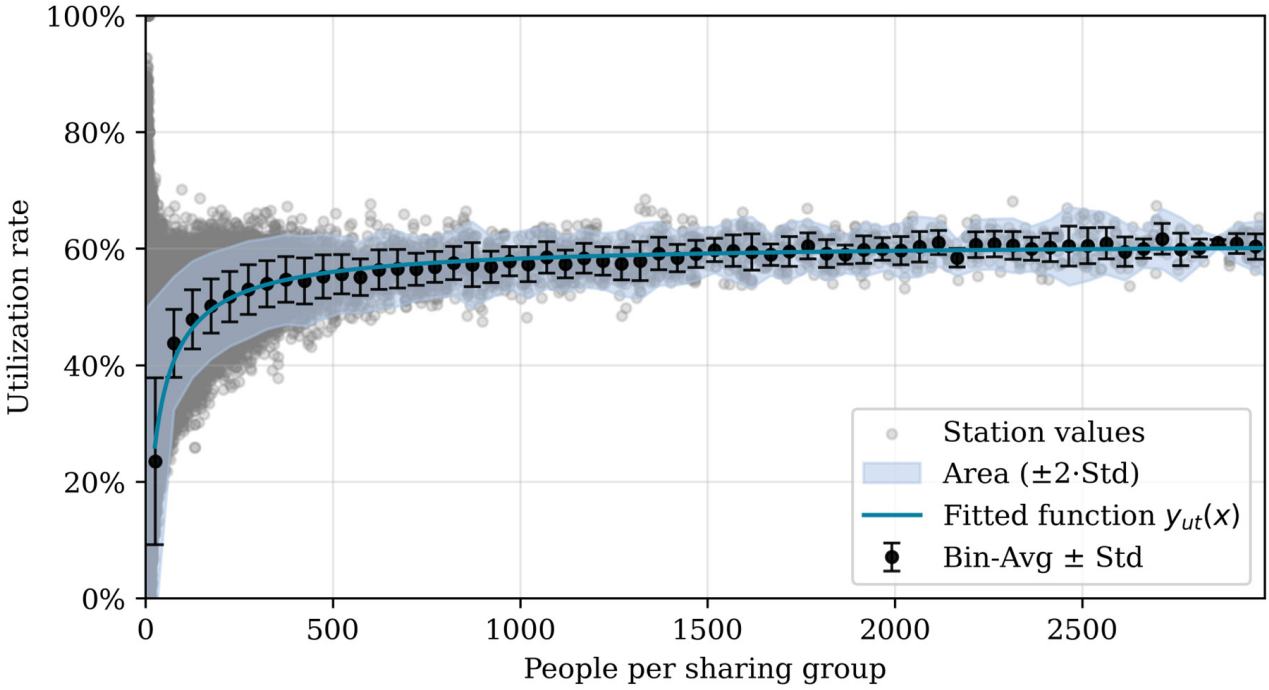


Figure 7. Average utilization rate during five random weekdays of car-sharing vehicles in relation to group size.

4.2. Analysis on the City Level

The different placement methodologies for car-sharing stations yield different potential for reducing the number of needed vehicles. These also vary with the assumed proportion of car-sharing users and the substitution ratio of them. The results of this sensitivity analysis are shown in Figure 8. The analysis shows that the city's overall car fleet would increase if fewer than 25% of all car-sharing users surrendered their private cars (substitution ratio). For the placement methods of PH and PM, even a 50% substitution ratio would not be enough to reduce the overall number of cars. PD and PO show a reduction potential in overall car numbers for a 50% substitution ratio and all sharing levels, whereas PS requires a sharing level above 30% to exhibit a reduction potential. If the substitution ratio were to reach 100%, which corresponds to all car-sharing users surrendering their private cars, the car reduction rate for all placement methods is positive. In this case, the car reduction rate in the whole case study region increases with the share of sharing in the population. However, this rate is higher with fewer, larger stations than with more stations, for the same share of people using car-sharing. With placement according to PH, the sharing rate would have to be about twice as high as with placement according to PO to achieve the same reduction rate. Even with the PD and PS methodologies, the sharing rate must increase by about 50% compared to PO. The achievable values according to PM are comparable to the achievable car reduction rates with PH. The more efficient use of individual vehicles within a smaller fleet, along with an additional fleet for long-distance trips, does not result in a smaller overall fleet size in comparison to the PH placement method in our results.

The use of cars is not limited to everyday mobility. Traveling on vacation or for a weekend trip must also be possible with the car-sharing service. However, these trips occur infrequently. We capture this sort of trip in the following analysis of what we call long-distance travel. The influence of these trips on the design of a car-sharing fleet is shown in Figure 9 using the PH placement method and a substitution rate of 100%. These findings show that the potential car reduction rate decreases as long-distance travel events are included in the fleet design process. If the car-sharing fleet is adjusted to the demand expected on a particularly busy holiday, the maximum possible car reduction rate is halved

compared to not accounting for long-distance travel demand (for the other placement methods and 100% sharing rate, these reduction rates remain: PS: 39%; PD: 48%; PO: 50%). If only the demand expected on an average weekend is considered, the maximum possible savings rate is eleven percentage points higher than designing a fleet for public holidays.

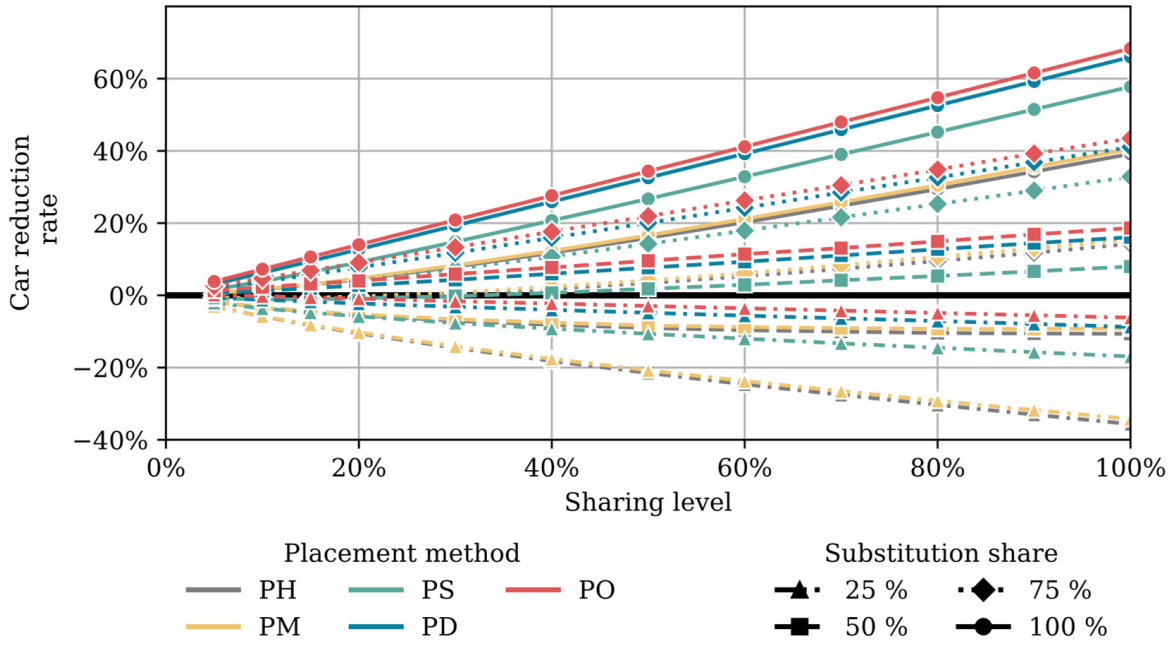


Figure 8. Variation in the share of the population using car-sharing and the resulting theoretical car reduction rate with different station placement methods.

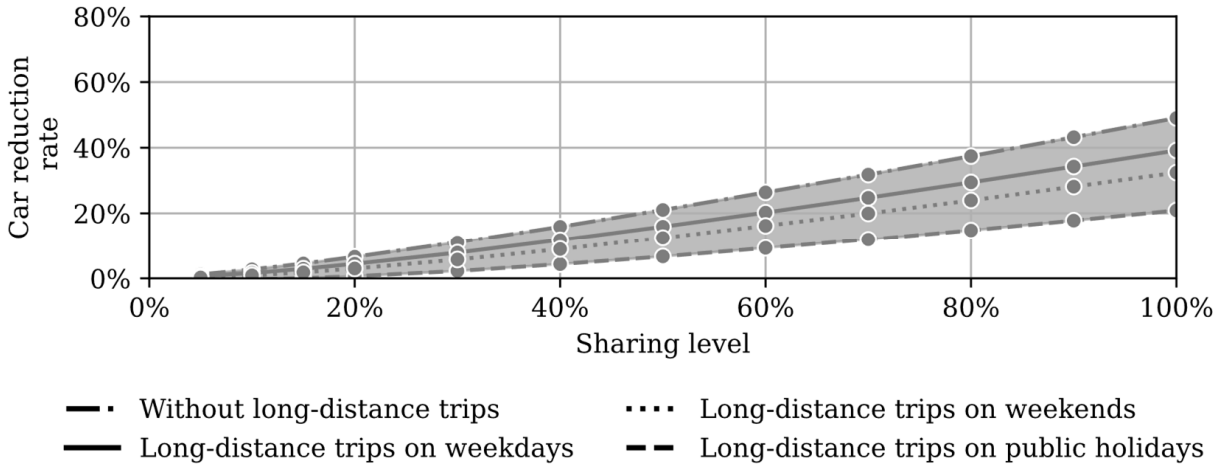


Figure 9. Variation in share of population using car-sharing in relation to the theoretical car reduction rate by PH, and differentiating the share of long-distance trips.

If long-distance trips are not taken into account in the fleet design, the fleet can be reduced by 27–35% for PH, 22–31% for PM, 31–45% for PS, 43–51% for PD, and 50–53% for PO, depending on the sharing level (5–100%).

The population distribution in Munich is not homogeneous, nor is the distribution of private cars and connections to public transport. This is also reflected in the potential distribution for station-based car-sharing shown in Figure 10. The left-hand side shows the potential for vehicle reduction, and the right-hand side shows the expected utilization. The two top figures show the area inside, commonly known as the extended city center, and outside the main ring road in Munich. The lower figure differentiates between the Munich districts. In particular, the calculated vehicle reduction rate does not follow any

immediate apparent pattern. Inside the ring road, the replacement rate is 66.9%, nearly equivalent to 66.3% outside. Vehicle utilization, on the other hand, is generally higher and decreases with increasing distance from the city center. The calculated utilization rate in the area inside the ring road is 5.7 percentage points higher than outside, with 57.9%.

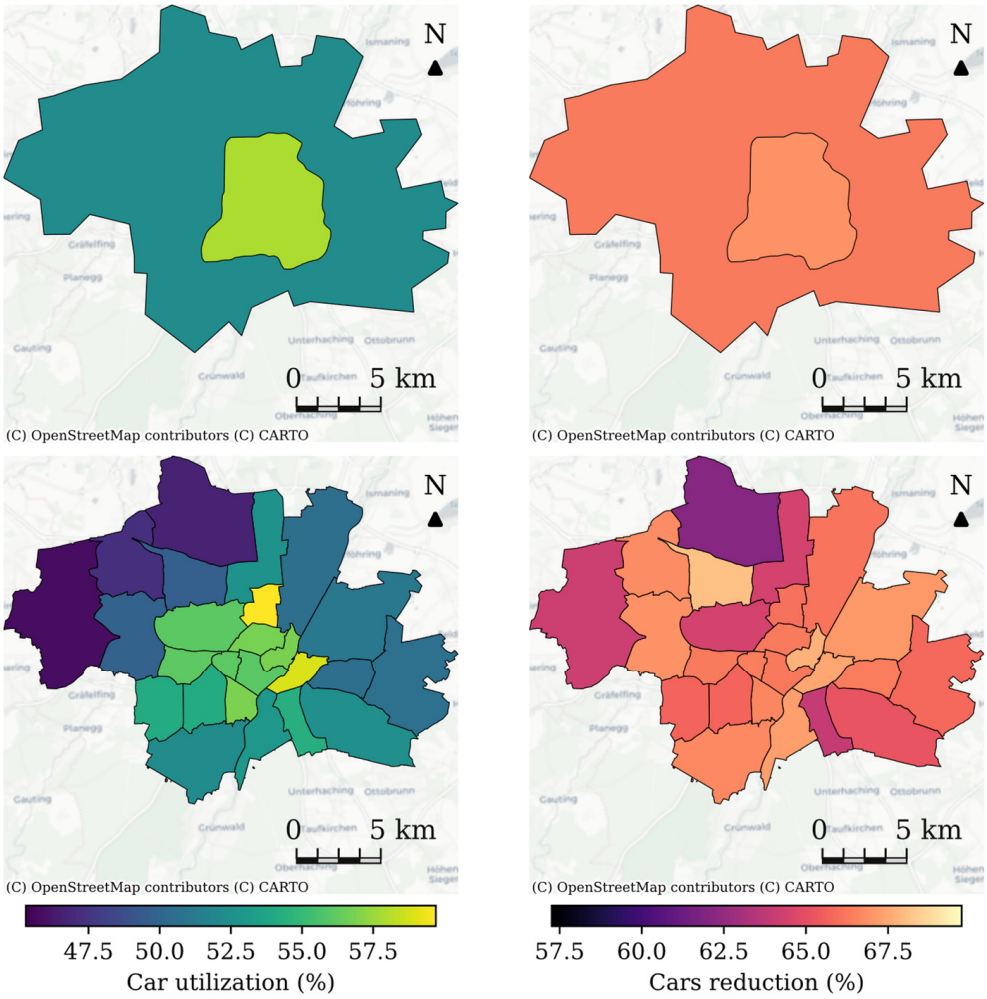


Figure 10. Resulting car utilization rate (**left**) and car reduction rate (**right**) differentiated by Munich townships (**bottom**) and extended city center (**top**) when using a distance placement method with 300 m and 100% car-sharing usage.

Future car-sharing services will primarily use electric vehicles, so it is important to estimate how charging times will affect the required fleet size. Our analysis indicates that when using electric vehicles, the vehicle reduction rate falls by 2–3 percentage points, depending on the placement methodology, if long-distance transport demand on an average working day is taken as a basis.

If shorter journeys are no longer taken by car in the future, corresponding to a change in mode choice, this could also reduce the car-sharing fleet size needed. The impact of not using a vehicle for trips of 0 to 10 km, with the exception of trips for which a vehicle is necessary, is shown in Figure 11. The station placement method does not seem to have a significant impact on the additional substitution rate. The biggest potential is for the placement method PM with an additional substitution rate of 12.5% if all journeys below 10 km do not use a car in the future. All other placement methods vary between 10.4% and 11.2%. The sharing rate does not have a significant effect on the additional car reduction rate. It varies the additional car reduction rate by less than 1.3 percentage points.

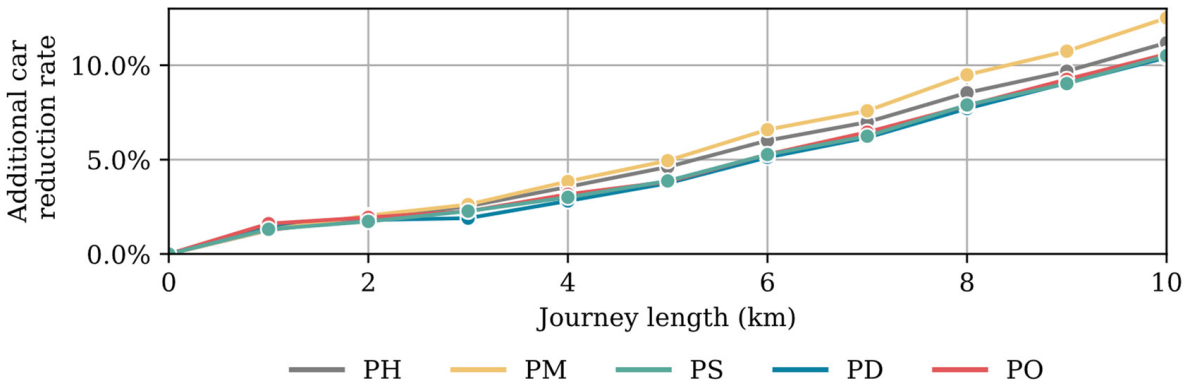


Figure 11. Additional effects on the theoretically possible car reduction rate by not using cars for journeys of different lengths and an assumed sharing rate of 80%.

5. Discussion

The calculations deliver important insights for designing station-based car-sharing services as a substitute for private cars and provide a starting point for determining which input parameters influence car-sharing potential. The results shown demonstrate the theoretical potential of residential car-sharing under idealized, simplified conditions for the case study region of Munich and cannot be directly applied to real-world car-sharing operations.

5.1. Discussion—Methodology

The calculations were based on the creation of a synthetic population. The most spatially accurate and up-to-date values were used for this, but these are subject to certain restrictions. In particular, the composition of households does not reflect reality because individuals are randomly assigned. However, the assignment is necessary because, without it, it is not possible to realistically assign existing vehicles to households, and vehicles are usually shared within households. The random assignment means that the mobility behaviors of individuals within households do not influence each other, which would be especially true on weekends [42]. The proposed methodology reduces the impact by assuming a shared car-sharing vehicle for long-distance trips. We assume that the remaining simplification will likely lead to a small overestimation of the number of car-sharing vehicles needed for everyday mobility. Further research is needed to quantify the impact of intra-household mobility behavior when using car-sharing.

Since the census data does not include household income, it would be possible to add it only by using additional external data. However, this would introduce further uncertainties into the population, which is why we decided not to consider it. The official population figures for the city and the census population figures differ by approximately 100,000 inhabitants. Since the census data is recognized in Germany, we decided to use this data. When matching the sociodemographic characteristics between the census data and the mobility surveys, there were slight differences, e.g., in the distribution of age groups and employment. This leads to further inaccuracies in the synthetic population. The absolute number of vehicles in the synthetic population does not correspond to the official registration figures for the city of Munich. This is due to the different survey methods. A vehicle registered in Munich does not necessarily have to be used in Munich, and conversely, not all vehicles permanently used in Munich are registered here. However, since vehicle availability is decisive for mobility behavior, we used the distribution from the mobility surveys and calibrated it with the distribution of registered vehicles by city district. This approach reduces the uncertainties in vehicle availability but cannot completely eliminate them. Overall, our chosen approach leads to a whole series of uncertainties. However, since

our study aims to compare different station-based car-sharing station networks, all of which are based on the same uncertainties, we believe these uncertainties can be disregarded. Our evaluations have also shown that the population's mobility characteristics match those of the mobility data sets used, with minor deviations. The differences are significantly smaller than those between the two mobility data sets used, which is why the resulting mobility data is more strongly influenced by inaccuracies in the mobility surveys than by inaccuracies in assigning mobility plans to the synthetic population.

5.2. Discussion—Results

Demand estimates for car-sharing are already available in a much more precise geographical resolution than our analysis can offer, but these are designed for an existing car-sharing service [25]. The demand we use represents a theoretical upper-bound scenario, which is not realistic. The advantage of our approach is that it allows us to compare car-sharing services that do not yet exist under different demand conditions. Realistic demand depends heavily on the design of the car-sharing service, including the cost structure and vehicle selection [5], as well as other parameters, such as participants' mode choice. However, estimating real demand for existing services was not the goal of this study, and such an investigation should be pursued in future studies.

The theoretical potential of residential station-based car-sharing depends on numerous parameters. The sharing rate and the substitution ratio have the greatest influence on the actual savings potential of private cars. Since the design of the offering was not the subject of our study, it is not possible to predict the willingness to share or the willingness to reduce private car ownership across individual groups. Nevertheless, it naturally makes a difference which segment of the population uses car-sharing [43]. The worst outcome of introducing a car-sharing system is when many people use it but the substitution ratio is too low to reduce the overall car fleet. This would result in an even larger car fleet in the city than today. However, the first case studies with residential car-sharing show an increasing willingness to reduce car ownership [5,6]. Further research is needed to quantify and maximize this behavior. This study presents only the theoretical potential of car reduction.

The values we have calculated for the benefits of car-sharing are theoretical estimates. Nevertheless, in a case study with 24 people testing residential car-sharing in Munich [5], 0.17 cars per person per day are needed for a group of 24 people, which is in the range of our results.

If all Munich residents' car mobility were to switch to car-sharing and the substitution ratio is 100%, around 20–70% of the fleet could be saved, corresponding to a substitution rate of 1 to 1.25–3.3 private vehicles. The exact ratio mainly depends on station placement and whether the fleet dimension covers long-distance trips. This is significantly lower than the values reported in the literature, which range from 5 to 23 [1]. One explanation could be the gap between stated and revealed preferences, and the literature values have been collected based on existing offers and among active users. Our calculated ratio is highly dependent on the number of long-distance trips included in the car-sharing offer design. The more weekend trips and journeys are made with car-sharing vehicles, the lower this ratio will be. During the transition, this ratio can also be improved if car owners who drive little are the first to use car-sharing [43]. This can be controlled by considering the needs differences between frequent and rare users when designing a car-sharing system [44,45].

The calculated impact of long-distance travel is significant at up to 50%, but it may be somewhat overestimated, as the data used is based on only a small sample size, and our calculation also includes the arrival and departure days of long-distance trips, which block vehicles entirely, as well as the fact that vacation plans within a household are not

synchronized. Nevertheless, the impact of long-distance travel is significantly greater than that of potential short-distance substitutes, reaching a maximum fleet-reduction potential of 12.5%.

The impact of electrification on fleet size is relatively insignificant, at just a few percent, compared to long-distance transport.

Another interesting finding in our results is that the benefits of car-sharing quickly approach a threshold value as the group size increases. This behavior is to be expected because mobility plans complement each other well above a certain group size, but to our knowledge, it has not yet been quantified.

When transferring the calculated data to another city, note that Munich is relatively affluent, has a dense public transport network, and is close to the mountains. This, in turn, affects mobility patterns. The everyday mobility by car in Munich, compared to other cities, is quite low [29], while the amount of long-distance travel is most likely higher [46]. This might lead to a higher impact of long-distance travel on the car-sharing design than in other cities.

5.3. Recommendations

Our findings lead us to make several recommendations regarding residential station-based car-sharing. Our calculations clearly show that the interests of all stakeholders cannot be reconciled without contradiction. Although the shortest possible distance and a small group sharing a car-sharing fleet are convenient for users, they cannot unlock the same potential as larger groups, probably because their mobility plans do not complement each other well enough. Therefore, closed car-sharing groups should not be too small and, according to our calculations, should comprise more than 217 people. It could be exciting for car-sharing operators that, according to our calculations, groups larger than 949 people no longer drive significant increases in utilization. If, on the other hand, the distances to the nearest car-sharing station become shorter, this could appeal to groups of people who were not previously open to the existing offer [39]. For residential car-sharing, this means that more than one apartment building is likely needed to achieve high vehicle availability while also maximizing vehicle and cost efficiency. At the same time, it does not have to be an entire neighborhood that shares a vehicle fleet. Given high utilization, it also makes sense for car-sharing operators to locate their station networks closer to the city center. However, this is not necessarily in the public sector's interest, as the potential to reduce the vehicle fleet is constant across the entire city. Overall, the question arises as to which kind of mobility the car-sharing vehicles should be used for. If the goal is to cover all mobility, including the peaks around Christmas and Easter, then the theoretically achievable potential of car-sharing is significantly lower. Even outsourcing long-distance mobility to a fleet shared by a larger group of people did not provide a solution in our analyses.

6. Conclusions

We proposed a new approach to planning cost-effective residential station-based car-sharing systems and tested it through a case study in the city of Munich, Germany. We focused in particular on the influence of long-distance travel behavior on the required fleet size and the number of people sharing a car-sharing fleet.

Our results suggest that the car-sharing user group should not be too small for each sharing fleet. Based on the results of our case study, the ideal group size is between 217 and 949 people, ensuring vehicle availability and enabling the potential to reduce costs and increase vehicle efficiency while maintaining high user convenience. Placing car-sharing fleets exclusively for one residential building, as discussed in the literature for further car-sharing development, does not seem to be the best compromise between user comfort

and cost-efficiency, as the resulting group sharing the fleet is too small. The greatest impact on the required fleet size is the long-distance travel behavior of car-sharing users. The needed fleet size could be reduced by up to 50% if no long-distance trips are allowed. The effect of substituting trips of 10 km or less with other modes of transport on the required fleet size is less than 10%. Our results for Munich indicate that the potential substitution rate for station-based car-sharing is 1.25 to 3.3 private cars per car-sharing vehicle.

The results presented are calculated based on current mobility demand, assuming that mobility behavior with car-sharing remains unchanged and that car-sharing users give up their private cars. These assumptions yield a theoretical upper bound on car-sharing demand that overestimates actual demand. For more specific implementation guidelines for residential car-sharing, a more realistic car-sharing demand is needed. It is especially important to understand the steps needed to ensure that people give up their private cars to realize the possible substitution ratio. This could be achieved by analyzing different residential car-sharing fleets under real-world living-lab conditions.

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Abbreviations

The following abbreviations are used in this manuscript:

MiD	Mobilität in Deutschland
PD	Placement method distance-based
PH	Placement method house-based
PM	Placement mixed method
PO	Original placement
PS	Placement method square-based
PT	Public transport
SrV	Mobilität in Städten
Syn	Synthetic population

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