Estimating savings in parking demand using shared vehicles for home-work commuting*

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Abstract

The increasing availability and adoption of shared vehicles as an alternative to personally-owned cars presents ample opportunities for achieving more efficient transportation in cities. With private cars spending on the average over 95% of the time parked, one of the possible benefits of shared mobility is the reduced need for parking space. While widely discussed, a systematic quantification of these benefits as a function of mobility demand and sharing models is still mostly lacking in the literature. As a first step in this direction, this paper focuses on a type of private mobility which, although specific, is a major contributor to traffic congestion and parking needs, namely, home-work commuting. We develop a data-driven methodology for estimating commuter parking needs in different shared mobility models, including a model where self-driving vehicles are used to partially compensate flow imbalance typical of commuting, and further reduce parking infrastructure at the expense of increased traveled kilometers. We consider the city of Singapore as a case study, and produce very encouraging results showing that the gradual transition to shared mobility models will bring tangible reductions in parking infrastructure. In the future-looking, self-driving vehicle scenario, our analysis suggests that up to 50% reduction in parking needs can be achieved at the expense of increasing total traveled kilometers of less than 2%.

1 Introduction

Traffic caused by privately owned vehicles presents major challenges in urban environments around the world, with pollution and congestion being serious concerns. Part of the problem of congestion is the high amount of space cities need to dedicate to roads, parking lots and garages, posing problems in high-density downtown areas and having a huge impact on shaping suburban communities, where planning is often centered around cars and parking spaces. As an example, in car-dependent Los Angeles county, roads take up about 140 square miles, while parking spaces in total take up 200 square miles; this latter area is equivalent to about 14% of all incorporated area in the county [1]. Apart from a variety of regulatory and development policies governments use in response to challenges associated with urban transportation [2, 3], it has been shown that specific policies on parking have substantial effects on urban areas [4, 5, 6, 7].

After rapid technological developments especially over the past decade, autonomous vehicle (i.e., *self-driving*) technology is expected to be ready for wide deployment in the near future with large implications for urban mobility [8, 9, 10, 11]. It is generally accepted that one of the main benefits of self-driving cars could be reduced road congestion, as current roads are expected to have much higher capacity if the majority of traffic is autonomous vehicles [12]. On the other hand, the convenience of autonomous vehicles can generate significant further traffic, both from people who currently are not able or prefer not to drive, and more generally as well, similarly to how increasing road and parking capacity often leads to increased traffic [10, 13, 14, 15].

Further gains are expected from using shared autonomous vehicles instead of private ones, with people buying *mobility-as-a-service* instead of cars [16]. A major expected benefit of a shared car system is better economics: the cost of owning and maintaining vehicle can be distributed proportionally among the per-trip costs, allowing people to make more informed choices about their transportation mode and vehicle type on a much more granular level. Furthermore, as private cars are parked most of the time, it is expected that a smaller fleet of better utilized shared vehicles could service the same mobility demand,

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offering reductions in need for parking as well [17, 8, 18]. On the other hand, since per-trip costs are expected to be significantly lower than current costs of trips made with either a private car or with a taxi service, the availability of a fleet of shared autonomous vehicles can again lead to significant increase in total traffic volume as people currently not being able to afford a car can switch from alternative modes of transportation [18, 19, 15].

Apart from the expectations from autonomous vehicles, car-sharing has been proposed as a more efficient alternative to private car ownership decades ago, while large-scale deployment only occurred in the past 15-20 years, mainly due to advances in smart technologies [20]. Proponents argue that many benefits of sharing can be achieved with conventional shared cars, while there are practical challenges limiting adoption, including user anxiety about finding a nearby vehicle or parking and the problem of rebalancing if one-way trips are allowed [21, 22]. These problems could be easily solved with autonomous vehicles; thus we expect that in the future the distinction between taxi, ride-sharing, car-sharing services and even transit will blur and new, integrated solutions will become possible, providing services similar to personal rapid transit systems proposed but never implemented in the previous century [23, 19]. Consequently, we find it important to characterize the expected performance of transportation solutions based on the sharing of vehicles.

1.1 Contributions

In this paper, we focus on commuting between home and work, and investigate the possible gains from car-sharing and self-driving on the number of parking spots and vehicles required. Contrary to previous studies, we focus specifically on commuters who contribute a major portion of road traffic and parking demand, yet are not the typical target of car-sharing or even taxi services. A reason for this is that commuting flows are typically imbalanced and traffic demand is highly concentrated in rush hours. These factors make regular commuters a difficult target for current commercial car-sharing solutions, ride-sharing and taxi services; on the other hand, due to the large amount of traffic associated with commuting, even moderate gains in efficiency can have large benefits for cities. Additionally, as there are well established methods to estimate commuting flows from mobile phone usage data, our methodology can be easily applied to provide baseline estimates of possible efficiency gains, in contrast to more detailed case studies which would require accurate data on general purpose trips. We specifically focus on parking, as the decrease in parking needs is expected to be a clear positive outcome; we note that an estimate of decrease in the total number of cars is less meaningful, since each vehicle is expected to travel more, potentially giving rise to similar levels of congestion as private cars today. On the other hand, focusing on parking captures a potential benefit from smaller total fleet sizes.

We use data from mobile phone network logs to estimate home and work locations for a large sample of the population in Singapore and simulate their daily trips assuming private, shared and shared self-driving car usage. In the case of shared cars driven by their users, a main limiting factor for sharing is that the car needs to be parked at a comfortable walking distance from the origin and destination of their users. In the case of self-driving, this limitation is removed as the car can be allowed to travel longer distances to a parking spot or their next customer, at the expense of higher total vehicle miles traveled (VMT); we explore the implications of this trade-off by varying the distance self-driving cars are allowed to travel without a passenger. Furthermore, we repeat simulations with varying presumed adoption rates to estimate which rate is required to gain sizable benefits.

We note that a main limitation in our approach is that, beside taking note of any additional distance traveled, we do not explicitly model any effect on congestion as that would require a detailed microsimulation of traffic and assumptions on the actual performance of autonomous vehicles in real traffic conditions. Furthermore, while we expect that people's behavior will change in response to availability of shared and self-driving vehicles, we do not aim to model this in our current work yet; we only assume that a certain share of commuting is made with shared vehicles.

Summarizing, the novel contribution of this paper is the development of a methodology that, starting from extensive real-world mobility traces, provides an accurate estimation of parking needs in a variety of sharing scenarios, including the effect of self-driving vehicles.

1.2 Related work

In accordance with the growing adoption of car sharing and the potential impact of self-driving, there is a significant research interest in assessing potential effects with regards to usage patterns, traffic and emissions. Survey-based methods find that car ownership among car-sharing users decreases significantly, up to 40%, depending on the study and the parameters used to correct for sampling effects [24, 16]. Still, drawing conclusions for the more widespread adoption of shared vehicles is not straightforward, since current car-sharing users are probably not a representative sample of the general population. Further studies try to estimate public attitude toward mobility options represented by self-driving vehicles and estimate the potential for adoption based on these [9, 10, 11]. Several studies then try to estimate the fleet size which could serve a certain population given some operational parameters, and the associated costs for travelers. Studies based on randomly generated trips find that about 10% – 15% of cars could serve mobility demands compared to private vehicles, with significantly reduced costs when compared to either privately owned cars or taxi rides [17, 18, 19]. This also prompted some concerns about the possibility of shared self-driving cars inducing significantly more traffic since they offer much cheaper and more convenient means of transportation [15, 10]. A more recent study based on re-

alistic origin-destination flows obtained from travel surveys in Singapore and a theoretical derivation for fleet size finds that a fleet which has a size of about 38% of the number of privately owned vehicles can satisfy mobility demand with a bound of 15 minutes on passenger waiting times [25]. Further work in the central area of Singapore focused on the trade-off between fleet size and utilization using a detailed simulation of people's mobility [26].

Concentrating on parking, a recent study has shown that by utilizing space much more efficiently, AVs have the potential to significantly reduce to spatial footprint of parking facilities [27]. Regarding shared vehicles, our work is most similar to studies by Zhang et al. [28, 29], who find that parking demand could be reduced by up to 90% for people switching to shared autonomous vehicle usage. The main difference is that the authors in [29] focus on the use of *existing* parking infrastructure, while in the current study we aim to calculate minimum parking requirements based only on basic assumption about commuter behavior, thus our methodology does not require any previous knowledge of available parking which can be difficult to obtain, especially on large scales [29, 1]. Furthermore, our simulation includes a significantly larger target population and more than 100 times larger fleet size (while the authors in [29] only consider 5% of the population of the city of Atlanta, i.e. about 22 thousand people in total, we consider a sample of over 1 million commuters in Singapore). A further recent study investigating the operational characteristics of a shared autonomous vehicle system in Lisbon, Portugal also considered potential reductions in parking needs with estimating that all on-street parking and a significant amount of off-street parking could be eliminated [30].

2 Methods

2.1 Home and work location detection

For the purpose of this work, we use call record detail records (CDRs) provided by Singtel, the largest mobile network operator in Singapore. The data includes records of several million subscribers for a period of eight weeks. The data includes a record when a user places or receives a call, or sends or receives a text message; data connections or handover information is not included. Each record includes the location of the antenna handling the event; with the high density of antennas in Singapore, spatial accuracy is estimated to be around a few hundred meters. Our dataset does not allow the reconstruction of individual trip data, but can be efficiently used to detect home and work locations of mobile phone users; this is considered standard and well-established practice [31, 32, 33].

Clustering people's locations and identifying the main nighttime and daytime clusters result in our estimates on home and work locations. To ensure the quality of the results, we use the criteria that the clusters identified as work or home locations should have at least 20 records during working hours or during evenings and at night respectively. Furthermore, for the following work, we only include people whose identified home and work locations are at least 1 km distance apart (using simple geodesic distance) and thus are possible candidates for commuting by car. There are a total of 1,992,950 people in the dataset whose home and work locations could be reliably detected, and 1,066,504 of these fulfill the criteria that the two locations are more than 1 km apart. We show the obtained spatial distribution of home and work locations in Fig. S1 and the distribution of commute distances in Fig. S2 in the Supplementary Material. Furthermore, we display the difference between home and work locations in Fig. 1; as unbalanced flows in the morning and evening present a fundamental challenge to sharing cars and parking spaces, this will pose an inherent limit to the possible gains in efficiency from them. Since the granularity of detected locations is that of antennas in the network (i.e. each location corresponds to an antenna), we add a random noise of the magnitude of 166 m to users' locations so that these will be less clustered. We note that the main assumption behind the current work is that the home and work locations obtained from this dataset will be a representative sample of people who would choose commuting by car.

2.2 Travel times

In order to better estimate commute times, we calculate the travel times between people's home and work locations based on real-world data as well. In the case of Singapore, average travel times between a set of road intersections were provided by the Land Transport Authority, measured at different times of the day and week. There are a total of 11,789 intersections, providing a good coverage of the area. For each user in the dataset, we located the closest intersection to their home and work location and use the travel time between these points as an estimate. We use estimates for times between 7AM and 8AM in the morning for travel from home to work and estimates for times between 4PM and 5PM as for travel from work to home. We display the distribution of these (as compiled for the list of people in the dataset) in Fig. S3. The travel time distributions have a mean of 1199 s and 1027 s respectively for the morning and afternoon case, while the medians are 1090 s and 983 s. Note that these seem relatively low when comparing to typical values people spend by daily commuting. We speculate that this is the effect of Singapore's highly restrictive policy on private car ownership, but highly car-centric road infrastructure, resulting in cars being a highly efficient means of transport for those who can afford them[1].

[1] In 2010, there were about 780 thousand private cars in Singapore, a city with a population of about 5 million (3.2 million citizens and 1.8 million permanent residents and visitors), giving a ratio of only 154 cars per 1000 population (241 per 1000 when only counting citizens); this is significantly lower than the value of 500 – 800 found in other developed countries. This is mainly achieved by the government setting quotas on newly registered vehicles and auctioning spots to potential buyers. In October 2017, as the result of the auctioning, the levy to register a new car for a 10-year period was about S$41,000 (US$31,000).

Figure 1: Distribution of difference of number of work and home locations (red means more work locations, while green means more home locations); these differences set a limit on the minimum needed parking spaces.

2.3 Simulated scenarios

In this work, we focus on a set of commuters as described in the previous section and estimate the number of parking spaces and vehicles needed to satisfy their mobility demand. In the following, we denote the number of users in our dataset by N_U, the number of required parking spaces by N_P, and the number of required cars by N_C. Furthermore, we measure the total distance traveled by commuters, denoted by d_{tot}. We employ several scenarios for their commuting habits and compare the results and quantify the improvement due to sharing vehicles and self-driving:

1) No sharing Each person uses a private car and has a private reserved parking space at their home and work location. In this case, it trivially follows that $N_C = N_U$ and $N_P = 2N_C$, while d_{tot} is simple the sum of distances between people's home and work locations.

2) Private cars, shared parking In this scenario, all parking is shared, with people taking the closest available spot to their destination at the end of each trip. Furthermore, we require that everyone is able to find parking closer than a given r_{max} to their destination, which is the main parameter in the simulation. In this case, $N_C = N_U$, $N_C \leq N_P \leq 2N_C$, while the total distance traveled (d_{tot}) will increase as people have to reach their actual parking spot from their destination.

3) Shared vehicles In this case, we assume that everyone is using shared cars to commute to work. This means that people always take the closest available car at the origin of their trip and park it at the closest available spot at the destination of their trip, with the requirement that cars and parking have to be available closer than r_{max} to the origin and destination of each trip, respectively. The main gain in this case is that one vehicle can potentially complete more than two trips per day, thus $N_C \leq N_U$, while we still have $N_C \leq N_P \leq 2N_C$.

4) Shared self-driving vehicles In this case, it is assumed that the shared cars are capable of self-driving, thus they can pick up and drop off passengers at their exact home and work locations and then find an available parking spot in the neighborhood. Computationally, this case can be modeled in exactly the same way as the previous one, but an important difference is that r_{max} now represents the distance self-driving cars are allowed to travel without a passenger. Thus, much larger values for r_{max} are possible with the trade-off of adding extra traffic and further increasing d_{tot}.

We note that currently most cities have a mix of scenarios #1 and #2. Curb parking typically contributes to #2, while most larger employers who provide on-site parking contribute to #1, i.e., their garages are not utilized in any manner beside employee parking. Furthermore, many car owners prefer to have their designated spot at home if they can afford it (either a private garage, driveway or a reserved space in a parking lot or garage), which is then left underused during the day, but guarantees convenient parking when they arrive home in the evening. While our current work only assumes commuting between work and home, and thus the number of parking spaces per car is maximum two, in real cities the number of total available parking per car can be as high as 3.3 [1].

In contrast to scenario #1, the use of shared parking with conventional vehicles (scenarios #2 and #3) present additional anxiety to users about finding parking close to their destination to avoid excess walking. On the other hand, scenario #4 presents the convenience of picking up and dropping off passengers at their exact preferred locations, which can be a substantial advantage over both private or shared conventional vehicles.

2.4 Computational implementation

We run simulations to determine the demand for parking spaces and the opportunities for sharing in scenarios #2 – #4 and compare results to the constant values in the case of scenario #1. We show the simulation algorithm in the case of private vehicles (#2) as Algorithm 1 and for shared or self-driving vehicles (#3 or #4) as Algorithm 2. In both cases, the input is a set of trips (generated from the home and work locations) and potentially a set of free parking spaces and available shared vehicles (only for Algorithm 2).

In the case of private vehicles (#2) in Algorithm 1, we start the simulation with assuming that everyone has a parking spot at their home location and do not assume any more parking spaces at work locations yet. In accordance with this, we set the total number of parking spots in the city to be $N_P = N_C = N_U$, and the set of available parking (L_P) is empty. At first, as people leave home in the morning, their home parking spots become available for other to use. We keep track of free parking spots in the list L_P (employing a spatial index for efficient searches later).

Algorithm 1 Main algorithm to calculate parking demand for private vehicles with shared parking for a set of trips generated for one day (scenario #2 above). The event list E is generated with assigning random start timestamps to every person's home-work and work-home trips.

```
E = { list of trip events; one event is either the start or
end of a trip }
r_max = maximum distance people are willing to walk
N_P parking spaces required (initially one per person)
L_P = { list for free parking spaces }
process all events in E in time order:
for all e ∈ E do
    if e is the start of a trip then
        add to L_P a new empty parking space
         with e's the coordinates
    else e is the end of a trip
        find closest free parking space p ∈ L_P
         s.t. dist(e, p) < r_max
        if found then
            remove p from L_P
            (i.e. user occupies p)
            start the user's next trip from p
        else
            assume there is a more parking
            increase N_P by one
            start the user's next trip from e
        end if
    end if
end for
Result: N_P total number of parking spaces needed to
satisfy mobility demand
```

When someone arrives at their work location, they search for free parking spots in L_P within a $r_{\max}$ radius. If such a parking spot is found (i.e., someone's home spot that is unused), it can be occupied; in case of more than one parking available within the search radius, we always select the closest one. If there are no free parking spots close to an arriving person's work location, we add one more which they occupy. Thus, we increase the number N_P of parking spots by one. We can assume that this parking spot was there all the time, but no one needed it yet. When moving people back home, we repeat the same procedure: everyone takes their car from where they parked it in the morning (adding that spot to L_P), drives home and tries to find a free spot. Since leaving from work and arriving at home happens stochastically, it can happen that a person finds their "home" spot occupied. In this case, they again search for the closest available alternative spot, or if none is found within an $r_{\max}$ radius, we again add a further parking space to the city, again increasing N_P. Depending on the timing of commutes, people leaving and arriving at either their home or work locations happens interleaved, meaning that not all parking becomes available. This way, the timing of trips plays a significant role in the result as well. See the next subsection for assigning trip timings.

In the case of car-sharing (#3) and self-driving vehicles (#4), as displayed in Algorithm 2, we not only maintain a list of free parking spots (L_P), but also of available vehicles, again including the coordinates where they are parked (L_C). When someone starts a trip, we first search in the list of available cars (L_C), and if a suitable car c is found within $r_{\max}$ distance of the origin of the trip, we select the closest such car c, remove it from L_C and add its location to L_P as a free parking spot. On the other hand, if no such cars are found, we add one more car to the system at the trip origin location, increasing the total number of cars N_C. We also increase the number of parking spaces N_P as we assume the newly added car to have been parked in that location, which again becomes a free parking spot and is added to L_P. In this case, at the beginning of the simulation, we do not place any parking spaces or cars in the system, i.e., we start with $N_P = N_C = 0$ and the L_P and L_C lists being empty. This way, during the course of the simulation, only the necessary number of vehicles and parking spaces are added. In this case, we also take into account the extra trip time due to traveling between the origin or destination of a trip and the parking location. This quantity can become significant for self-driving vehicles, especially if we consider a relatively larger $r_{\max}$ radius.

In all cases, it is assumed that the agents are able to find the closest available parking and closest available car when using shared cars. While searching for parking is complex problem by itself [34, 35], our assumption basically means that all drivers use an efficient navigation system which also receives real-time updates on parking availability. Implementing such a system is possible already with today's technology; also, we expect that shared autonomous vehicles will be able to communicate with a "controller" that directs them to the closest available parking.

Since the actual timing of morning and afternoon trips can affect the results – see subsection below –, in case of both algorithms we run the simulation for multiple days in a row with different, randomly generated trip timings each day. It is important to note that we start with empty L_P and L_C lists only on the first day of the simulations; on subsequent days, we start the simulation with the L_P and L_C lists and N_P and N_C values obtained by the end of the previous day. This way, we are testing if the same number of parking, vehicles and actual spatial configuration of parking is sufficient to satisfy the travel demand on the next day, or if further parking and cars need to be added to the system to account for a different sequence of trips. In the experiments reported below, we ran the simulation for $n_d = 30$ days in each case.

2.5 Simulation parameters

For all scenarios #2–#4, the main parameter that will affect the results is the bound $r_{\max}$ on the distance between trip origin and destination and the sought parking spot. In the case of scenarios #2 and #3, this bounds represents the distance people are willing to walk from their parking location and their destination. In case of shared

vehicles (scenarios #3 and #4), $r_{\max}$ is also the upper bound to the distance to the closest available shared car. For scenario #4, this is the distance that self-driving cars are allowed to travel without a passenger before the start or after the end of a trip to reach their parking location.

The second main parameter in the simulation is the method used to generate commute timings. This is represented by a *commute window* of length t_W; all trips are assumed to start inside this window (see below). Furthermore, results are affected by the penetration ratio of shared mobility, i.e., the number of people who use shared or self-driving cars among the group of commuters considered.

Algorithm 2 Main algorithm to calculate parking demand for shared or self-driving vehicles with shared parking (scenarios #3 and #4 above) for one day. Again, the event list E is generated with assigning random start timestamps to every person's home-work and work-home trips.

E = { list of trip events; one event is either the start or end of a trip }
$r_{\max}$ = maximum distance that
  people are willing to walk (#3 case) or
  self-driving cars travel empty (#4 case)
$N_P = 0$ parking spaces required
$N_C = 0$ number of cars required
L_P = { list for free parking spaces }
L_C = { list for available cars }
process all events in E in time order:
for all $e \in E$ **do**
  if e is the start of a trip **then**
    find closest $c \in L_C$ s.t. $dist(e, c) < r_{\max}$
    if found **then**
      remove c from L_C
      add c's location to L_P
      add travel time between c
       and e to the total trip time
    else
      assume there is a free car at e
      increase both N_P and N_C by one
      add e's location to L_P
    end if
  else e is the end of a trip
    find closest $p \in L_P$ s.t. $dist(e, p) < r_{\max}$
    if found **then**
      remove p from L_P
      add travel time between e
       and p to the total trip time
      add p's location to L_C
    else
      assume there is a more parking
      increase N_P by one
      add e's location to L_C
    end if
  end if
end for
Result: N_P total number of parking spaces and N_C total number of cars needed to satisfy mobility demand

2.6 Generating trip starting times

As we commented above, a main determinant on the possible efficiency gains is the sequence and timing of individual trips, since it determines if a specific shared vehicle or parking spot is available at the time when a commuter would want to start or finish their journey. Since timings of individual trips on a large scale are hard to obtain, and are still subject to daily variations, we generate these randomly for each person in the simulation. To test for variations in different realizations, we run the simulations for $n_d = 30$ consequtive days and then repeat the whole process 100 times for better stochastic accuracy. Each day in a single simulation run presents a different realization of random trip start times. Running the simulation for several days helps establish the robustness of spatial configuration of parking and vehicles, while repeating the simulation allows us to test for statistical variations. We find that random variations are very small: standard deviation are less than 1% in all cases, and less than 0.1% in most cases. We report the effect of these variations in the Supplementary Material, in Figs. S5, S7, S8 and S9 and in Table S1[2].

For the main results of the current work, we generate the start time of each individual trip uniformly at random in a time window of length $t_W = 1$ hour, from 7AM to 8AM for morning commutes and between 4PM and 5PM for afternoon commutes. Beside the main results, we further explore several options for t_W and also an option where we generate trip start times based on a dataset of public transportation usage in Singapore.

3 Results

3.1 Reduction in parking spaces and cars required

The main result of the presented estimation methodology is the number of cars and city-wide parking spaces needed to cope with the travel demand. We display the required number of parking spots in the different scenarios as a function of $r_{\max}$ in Fig. 2. We see that for reasonably small values of $r_{\max}$ (i.e., between 100 m and 500 m), around 23% of parking spaces can be saved by using private cars and sharing parking spaces, as in scenario #2 (we note that a real city will be between #1 and #2, but we expect that most people still have reserved parking). If we introduce shared cars as well (scenario #3), the reduction in parking demand approaches 40%. Just comparing the case of private and shared cars (#2 and #3), we see that introducing shared cars saves around 20% of parking spaces from an already highly optimized system with shared parking (see the inset in the right panel of Fig. 2).

For private or shared cars driven by their users, the $r_{\max}$ distance is essentially the maximum distance people are willing to walk from their parking spot to their final destination. In our main simulations, we considered

[2] Available as a separate download `https://www.dropbox.com/s/s410s74oxh28h07/parkefficiency_si_table_S1.ods?dl=0`

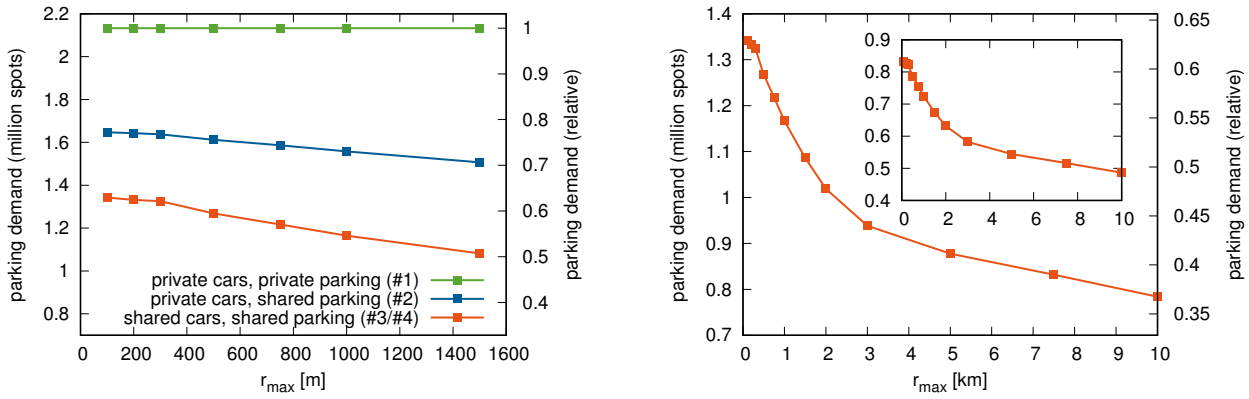

Figure 2: Comparing demand for parking in different scenarios. Left: Parking demand in scenarios #1-#4 up to $r_{\max} = 1.5\,\text{km}$. The number of parking spaces required is displayed on the left y-axis, while relative numbers (compared to case #1, i.e. private parking spaces) are shown on the right axis. Right: parking demand in scenario #4 with $r_{\max}$ values up to 10 km. The inset shows relative numbers compared to scenario #2, i.e. private cars with shared parking (with a fixed $r_{\max} = 500\,\text{m}$).

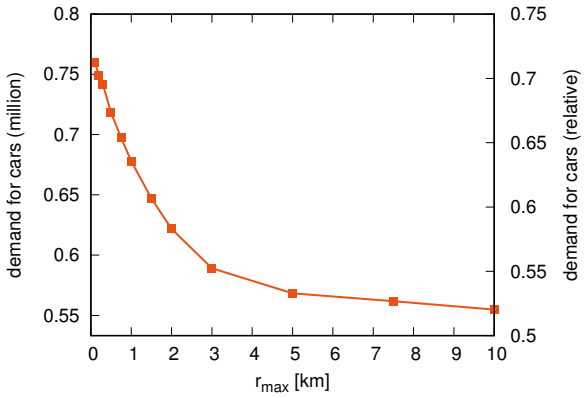

Figure 3: Number of shared cars needed to serve the given mobility demand in scenarios #3 and #4, as a function of $r_{\max}$. Absolute numbers are displayed on the left y-axis, while relative numbers compared to the case of private cars (scenarios #1 and #2) are displayed on the right y-axis.

$r_{\max}$ between 100 m to 1.5 km for scenarios #2 and #3 and $r_{\max}$ up to 10 km for scenario #4 as shown in Fig. 2. We believe that actually only the smallest values of $r_{\max}$ are realistic for walking; while previous studies for transit usage typically consider 500 m as an acceptable walking distance [36, 37], empirical studies on parking usually reveal distance to the destination as the main factor when deciding where to park (more important than price, time spent searching for parking, etc.) [38, 39, 7]. For this reason, only the leftmost values in Fig. 2 can be considered significant in these cases. We present larger values mainly for comparison between Algorithms 1 and 2.

On the other hand, in the case of self-driving vehicles, much larger $r_{\max}$ values are feasible. The results of our analysis show that, already with $r_{\max} = 1.5\,\text{km}$, parking needs reduction is above 50% compared to scenario #1, and around 33% when compared to scenario #2 with $r_{\max} = 500\,\text{m}$, a realistic upper bound on walking. When considering larger values of $r_{\max}$ up to 10 km, savings in parking demand increase up to 63% (50% compared to scenario #2). However, these savings would come at the expense of increased traffic, as discussed in the next section. We note that actual walking or extra travel distances can be smaller than $r_{\max}$, which only specifies the upper bound. In Fig. S6 in the Supplementary Material, we display the distribution of actual walking distances in a few typical cases of $r_{\max}$. For most trips, we find that the actual walking distance is much lower than the $r_{\max}$ parameter used for the simulation; on the other hand, a relatively small chance of having to walk excess distances could be still highly discouraging for potential users.

The fleet size resulting from our estimations is reported in Fig. 3; we see that we can achieve about 30% reduction with shared cars and small $r_{\max}$ values suitable for walking, while these gain increase to over 45% for larger $r_{\max}$ values achievable with self-driving.

3.2 Varying simulation parameters

So far, we have presented results for a limited set of parameters modeling commuting in Singapore. To estimate the robustness of the presented results to changes in the simulation parameters, we repeated the experiments for several different parameter combinations.

First, we considered different penetration rates of shared mobility, repeating the simulations for scenario #3/#4 while varying the number of commuters, out of the total number of commuters considered, who use shared vehicles. The results are reported in Fig. 4. We see that the possible relative gains (in terms of parking spaces) barely change when at least 25% (i.e. about 267,000) of people participate in a shared mobility scheme; a smaller sample of only 10% of people (107,000 people) would instead result in noticeably smaller gains (about 5% difference) when using a radius of $r_{\max} = 300\,\text{m}$, which we consider a reasonable value for walking. On the other hand, for radii of at least

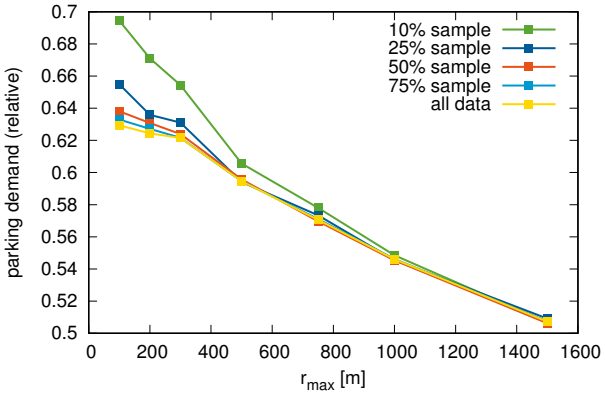

Figure 4: Relative parking demand, compared to scenario #1, for different adoption rates of shared mobility. A sample size (rate) of 10% results in somewhat less efficiency; above that, we observe gains similar to those obtained with full adoption of shared mobility.

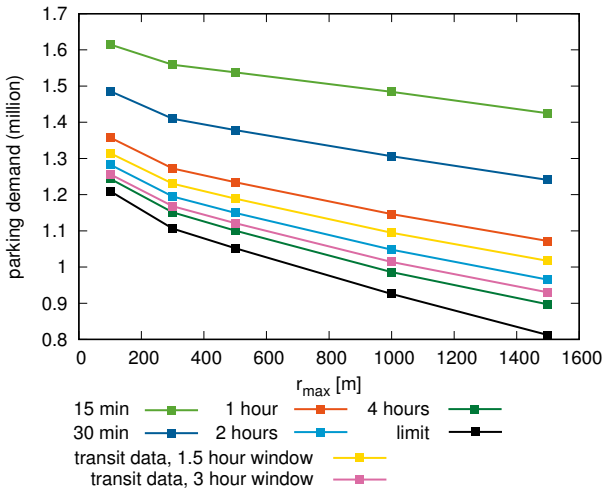

Figure 5: Parking demand for different values of the time window parameter t_W. The plot also reports values obtained when trip starting times are randomly generated according to probability distribution extracted from transit data.

500 m, the gains in parking efficiency are only slightly worse even in this case, suggesting that for self-driving cars, a relatively low adoption rate would already bring significant benefits. We note that actual gains might be even better as a smaller fleet could be occupied to a larger degree during the day outside commuting hours, performing taxi-like service as well.

Furthermore, we repeated the simulations using Algorithm 2 for several different commute lengths of the time window t_W. These results, reported in Fig. 5, indicate that t_W is indeed an important parameter as a commute windows value below one hour significantly decreases sharing opportunities. On the other hand, higher values of the commute window will only add moderate reductions in parking needs. Furthermore, using travel timings generated from the transit data does not alter the results significantly. We note that the one hour commute window used to obtain the main results of this paper can be still considered a conservative estimate (e.g. the activity peaks seen in transit data seem significantly longer as we show in Fig. S4 in the Supplementary Material).

We compute a further measure to characterize the inherent inefficiency due to unbalanced commute flows. This bound is obtained by applying the same model under the assumption of instanstaneouos travel (i.e. all trip times are set to zero, but trips are processed in a random order). Since no vehicles are in transit to their destination in this model, the result of this process can be intended as a measure of the inherent inefficiency in parking needs that arises from the mere spatial distribution of trip origins and destinations. This is displayed as the black line in Fig. 5; we see that there is about 20% – 30% difference between the main results (considering $t_W = 1$ hour) and this theoretical limit.

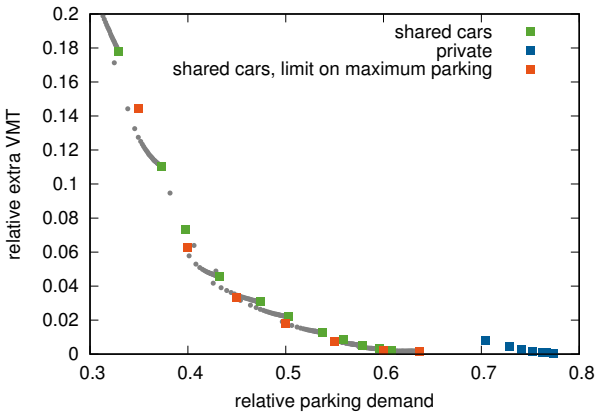

Figure 6: Relative extra traffic, measured as vehicle miles traveled (VMT) as a function of relative reduction in parking needs. The blue and green point are the results from the simulation run as Algorithms 1 and 2 for private cars (#2) and shared or self-driving cars (#3 or #4) respectively. The points displayed are the results obtained after running the simulation for 30 days. The grey points are the results for shared or self-driving cars on every individual day up to the main results; the number of required parking spaces increases over the course of the simulation, while the extra traffic decreases. The red points are results of a modified simulation where the maximum number of available parking spaces is a fixed. For an explanation of these methodological differences, refer to the Supplementary Material.

3.3 Estimating induced extra miles traveled

Self-driving cars would allow parking farther away from the origin or destination of a trip. We have seen that this would further reduce the number of parking spaces required (Figs. 2 and 3). This benefit nevertheless comes at a price of increased traffic, which we quantify here as an increase in the total vehicle miles traveled (VMT). In this section, we present results for estimating this extra VMT to be able to find a good trade-off between less parking (and cars) and more traffic. To obtain this, during the course of the simulation, we recorded the distances between the origin or destination of a trip and the parking spot used; we sum these distances and compare them to the total distance that people have to travel between their home and work locations. We present the relative extra distance traveled as a function of the previously established reduction in parking demand and also in a slightly modified case where the maximum number of parking spots is capped at a number determined from previous simulation runs (see the Supplementary Material for more explanation on this). We see that using self-driving vehicles, achieving about 50% reduction in parking space requirement over scenario #1 will only add about 2% extra VMT, while further gains come at the cost of potentially significantly more vehicle travel. How this extra travel affects congestion will depend on how self-driving cars perform in real-world traffic, i.e., whether they can compensate increased traffic by being more efficient.

We note that allowing longer distances (and more traffic) can correspond to a scenario where instead of on-site parking garages, operators of self-driving fleets have depots placed in strategic locations in the city. Assuming a fleet of interchangeable vehicles (or a few vehicle types), these depots can be highly efficient, have a much smaller total area than traditional parking garages [27]. This would present further reductions in the footprint of parking in cities, introducing both opportunities and challenges in re-using existing parking facilities.

4 Discussion

In this paper, we evaluated the possible gains in parking demand if a significant number of commuters switched from private cars to shared or self-driving vehicles. We focused explicitely on home-work commuting as these trips contribute a large portion of traffic, are highly unbalanced, and reserved parking at home and work locations take up huge amount of space in cities. We used a large sample of commuters in Singapore, for whom we obtained home and work locations from a mobile phone dataset. We evaluated the effect of sharing parking, sharing cars, and using shared self-driving cars on the number of parking spaces required. We found that with self-driving cars, about 50% reduction of parking needs is possible with allowing only 2% more travel (VMT) due to cars traveling to and from parking spaces that now need not be placed on site for all home and work locations. We expect that further trips during the day could be served with only minimal extra cars and parking, potentially providing even higher benefits in efficiency as currently there could be as many as 3 parking spaces per car in a city.

We note that the main practical factor affecting the reported gains is the shared nature of vehicles. From a technical point of view, whether these vehicles are self-driving seems to have effect only on the reasonable values of the main parameter $r_{\max}$ in our model. On the other hand, there is a large conceptual difference between the two cases, where self-driving vehicles have further advantages. Since for conventional cars the $r_{\max}$ parameter represents walking distance, we expect people's expectations to be quite low, and also high dissatisfaction if this expectation is ever exceeded. This could also lead to an anxiety, which can deter potential users from relying on shared cars as their primary means of transportation. On the other hand, an operator of a fleet of self-driving cars has much more flexibility in choosing an $r_{\max}$ value and also can provide better worst-case guarantees on vehicle availability. As finding parking is no longer the users' responsibility, this can even present advantages over private vehicles. Furthermore, rebalancing is much simplified if no human employees are required.

Based on these factors, we find it reasonable that the adoption of conventional car-sharing has been relatively slow. On the other hand, we can expect the adoption of shared self-driving cars to take up much faster once the technology is deployed on commercial scales. Thus, we can expect that large areas which are currently dedicated to parking will be freed up in the near future. We note that repurposing existing infrastructure, especially underground parking facilities, can be challenging. On the other hand, repurposing of existing parking space can be especially attractive for logistics and light industrial use, which currently cannot afford such central locations.

Future work is necessary to assess the full impact on traffic congestion and total parking needs due to potentially changing habits and transportation mode choices as a result of the introduction of self-driving cars, which were not modeled in the current work. We finally note that our simulation methodology can be easily adapted to more detailed datasets, e.g., logs of individual trips; using these would provide even more accurate predictions on the effect that shared and self-driving cars can have on parking demand.

Acknowledgment

The authors thank all sponsors and partners of the MIT Senseable City Laboratory including Allianz, the Amsterdam Institute for Advanced Metropolitan Solutions, the Fraunhofer Institute, Kuwait-MIT Center for Natural Resources and the Environment, Singapore-MIT Alliance for Research and Technology (SMART) and all the members of the Consortium.

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Estimating savings in parking demand using shared vehicles for home-work commuting

Supplementary Material

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June 18, 2018

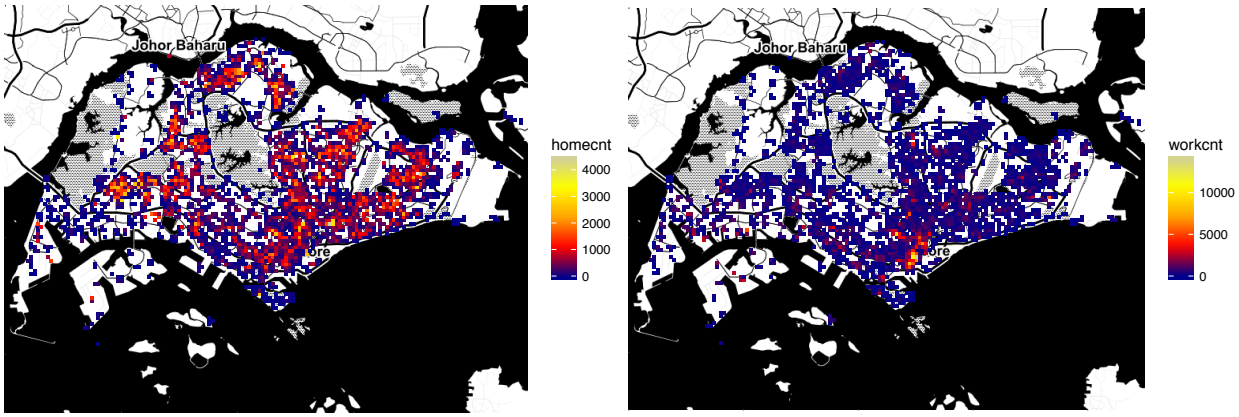

Figure S1: Spatial distribution of home (left) and work (right) locations in Singapore. Note that the distribution of home locations was verified using census data available in Singapore.

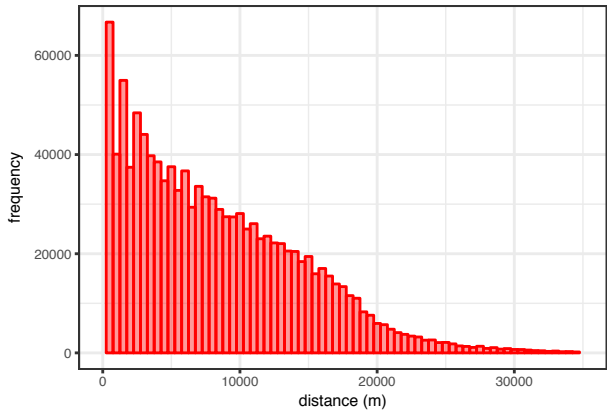

Figure S2: Distribution of travel distances between home and work locations (calculated as simple Euclidean distances). The mean distance is 8.4 km, the median distance is 7.2 km.

Commute timings

Transit-based commute times model: For every user in the dataset, a random time for going to work is selected from the distribution of transit usage data displayed in Fig. S4. Similarly, a random time is selected for going home after work. These random times are constrained between a realistic "commute window" in this case as well, which we select to include the distinctive main peaks of commuting behavior in the data: these are between 6am and 9am for the morning commute and between 5pm and 8pm for the afternoon commute. These are represented by the shaded areas in Fig. S4.

A realistic estimate on when people travel to work or home can have a significant impact on the shareability. While there was a lot of previous work on estimating commutes from mobile phone data as well, we now use a separate, one

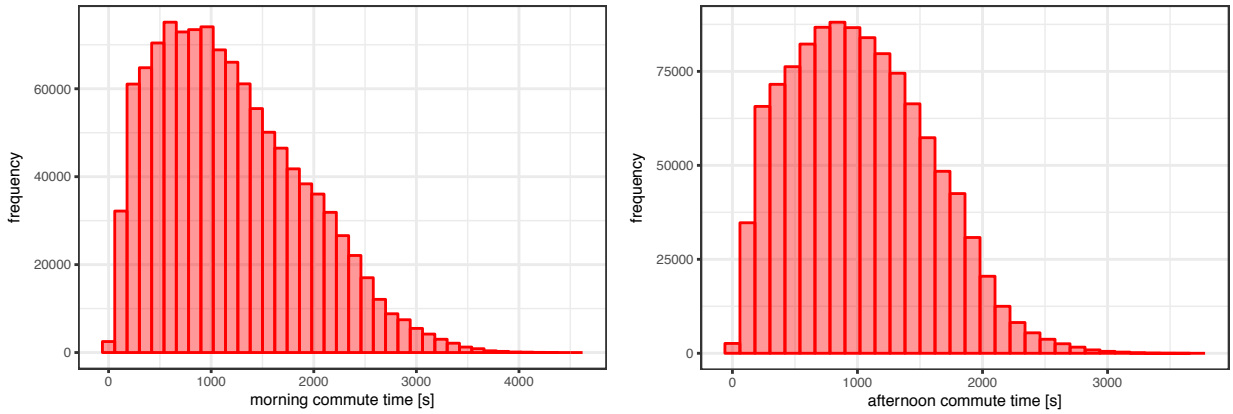

Figure S3: **Distribution of travel times for commuters.** On the left, the distribution of travel times from work to home is displayed; on the right, the distribution of travel times from work to home. The mean of the distributions is 1199 s and 1027 s respectively, while the median is 1090 s and 983 s.

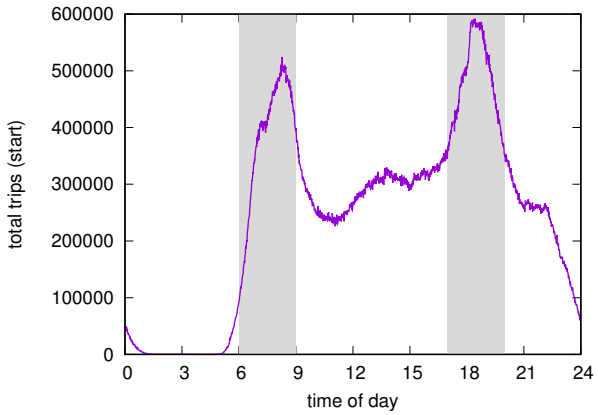

Figure S4: **Temporal distribution of transit usage.** Transit trip start times on an average weekday are displayed. The shaded regions are used in estimating commute start times when validating some of our findings later.

week dataset of public transportation records supplied by Singapore's Land Transportation Authority (LTA) to estimate the typical times of day people travel to work and back home. While having the obvious drawback that it requires the assumption that the habits of people using transit and commuting by cars are similar, this method presents an easier and possibly more reliable picture than trying to find individual trips in the mobile phone data. On the other hand, using average commuting times also neglects any possible systematic variation in commute times which might further affect the results. The distribution of trip start times is displayed in Fig. S4.

Varying simulation length, imposing a strict maximum limit on parking

So far, the results we presented were obtained after running the simulation for 30 days in a row to account for daily stochastic differences in commute patterns. Now, in Fig. S5, we present a case when we run the simulation for longer time intervals. We present results for the cumulative number of parking spots required as a function of time the simulation is run. We see that there is a small but steady increase in the shared or self-driving scenario (#3 and #4), showing resulting configurations after a day are typically inadequate for satisfying the mobility demand on the next day. This raises the question about what is a realistic number of vehicles that we can expect to cope with the long-term mobility demand. We can consider two possible ways to solve the problem of apparent increasing demand in parking as simulation time progresses. One is the obvious possibility of implementing some rebalancing; while this can present a significant cost for operators of car-sharing systems (i.e. scenario #3), in the case of self-driving cars (scenario #4), rebalancing will require only minimal costs; we emphasize that all our results were obtained without including rebalancing.

On the other hand, in the case of self-driving, we can simply further relax the strict requirement that cars should not travel more than $r_{\max}$ without a passenger. We note that the $r_{\max}$ limit is actually a technical part in our simulation which allows us to evaluate how many parking spots to "add" to the city. In a realistic scenario however, any request by a user would be serviced by the closest car, regardless of the actual distance. While in the case of car-sharing, not having a

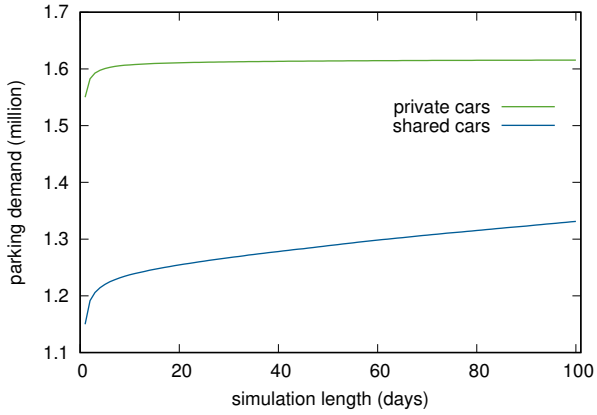

Figure S5: Parking spaces needed to meet the mobility demand as a function of the number of days we run the simulation. We see that the number of parking spaces quickly saturates in the case of private cars, meaning that we can easily account for the stochastic nature of our simulation. In the case of shared vehicles, the number of parking spaces keeps growing, albeit at a slow rate; this implies that we do not reach a stable configuration of cars and in a real system some rebalancing might be necessary.

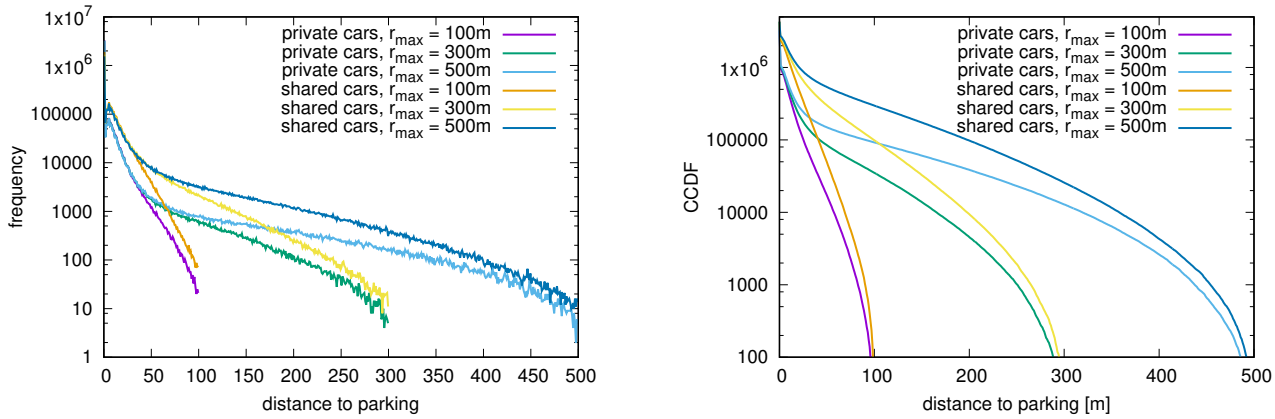

Figure S6: Distribution of distances between trip start and end locations and parking locations. For conventional vehicles, this corresponds to the distance users need to walk, while for AVs, this is the extra distance the vehicle has to travel without a passenger. The left panel displays individual frequencies (binned in 1 m intervals), while the right panel displays the complementer cumulative distribution, i.e. the number of cases where a passenger has to walk *at least* the distance shown on the x-axis. Note that the y-axis is logarithmic in both panels. The large majority of trips only requires very short extra distances, while there is a small share requiring walking / extra travel up to the limit $r_{\max}$.

car or parking spot available under $r_{\max}$ will result in a user having to walk an excess distance and thus will lead to a high level of user dissatisfaction, in the case of self-driving cars, having a car further than $r_{\max}$ will only result in a slightly increased waiting time for the user in question, which will have a much less effect on user satisfaction with the service (given that it happens rarely). With this in mind, we also implemented a modified version of our simulation algorithm (Algorithm 2 in the main text). In this case, we limit the maximum number of parking spaces to a predetermined amount. After this limit has been reached, the closest car or parking space is selected regardless of the distance to the destination and thus no new parking is added to the system. In this case, the $r_{\max}$ parameter is not a direct determinant of the functioning of the system but a parameter which affects the process of how we distribute the available parking spaces in the city. To accommodate this change, we run the simulation with different $r_{\max}$ values for each limit value we select for parking spaces and select the $r_{\max}$ which minimizes the extra distance traveled in practice. As seen in Fig. 6 in the main text, results obtained this way show a good agreement with the results of the original simulation methodology. This allows us to accept the results presented in Fig. 6 as a good approximation for the trade-off between reduced parking and extra traffic.

Walking distances

While the $r_{\max}$ distance acts as an upper bound for the distance passengers have to walk (in scenarios #2 and #3) or AVs have to travel without a passenger before the start or after the end of the trip, actual distances will be typically lower as we always select the closest available vehicles or parking. In Fig. S6, we present the distribution of actual distances of the vehicles used to the trip origin and parking spot to trip destination for several different values of $r_{\max}$ in the case of private vehicles (scenario #2) and shared vehicles (either scenario #3 or #4). We see that a large share of trips involves significantly less walking / extra travel than the $r_{\max}$ upper bound. Nevertheless, a non-negligible amount of trips has extra travel close to $r_{\max}$. In the case of conventional vehicles (either scenario #2 or #3) where this is a walking distance, this makes it reasonable to limit $r_{\max}$ to small values.

Statistical variation in results

All simulations in the current work involve randomness as the timing of trips are randomly generated. To characterize the extent this affects the results, we repeated all simulation runs 100 times and calculated relevant statistics on the results. Generally we find that variations can be well characterized by a normal distribution and the standard deviations are very small compared to the mean values (less than 1% in all cases). We further carried out a Shapiro-Wilk test for normally distributed values and found that a null hypothesis for normal distribution cannot be rejected in almost all cases; the number of cases having low p-values is consistent with the large number of total parameter tests, meaning that these could occur randomly. This way, we conclude that an assumption of normally distributed results is reasonable. In Table S1 (available as separate download), we display results for all parameter combinations tested together with standard deviations, Shapiro-Wilk test statistics and p-values. In Fig. S7 we display the distribution of result values for the case of shared cars, $t_W = 1\,\text{hour}$ and $r_{\max} = 500\,\text{m}$ as an example of typical cases. Furthermore, to visually assess difference from a normal distribution in some of the worst cases, in Fig. S8, we display the distributions with the two lowest p-values. We see that the difference is not systematic and there are no significant outliers in these cases as well. This way, we believe that using the mean and the standard deviation to characterize the results is reasonable. In Fig. S9, we display the cumulative distribution of the p-values obtained in the different test cases. We see that these are relatively evenly distributed in the $[0, 1]$ interval, supporting that these are obtained with a random process. We note that in total we had results for 196 different parameter combinations for N_C, in 316 parameter combinations for N_P and in 321 different parameter combinations for d_{tot}. This is the number of Shapiro-Wilk tests carried out and the number of different p-values obtained as well. In this case, finding the low p-values can be attributed to randomness as well, thus we believe our choice of modeling the results with normal distributions is reasonable.

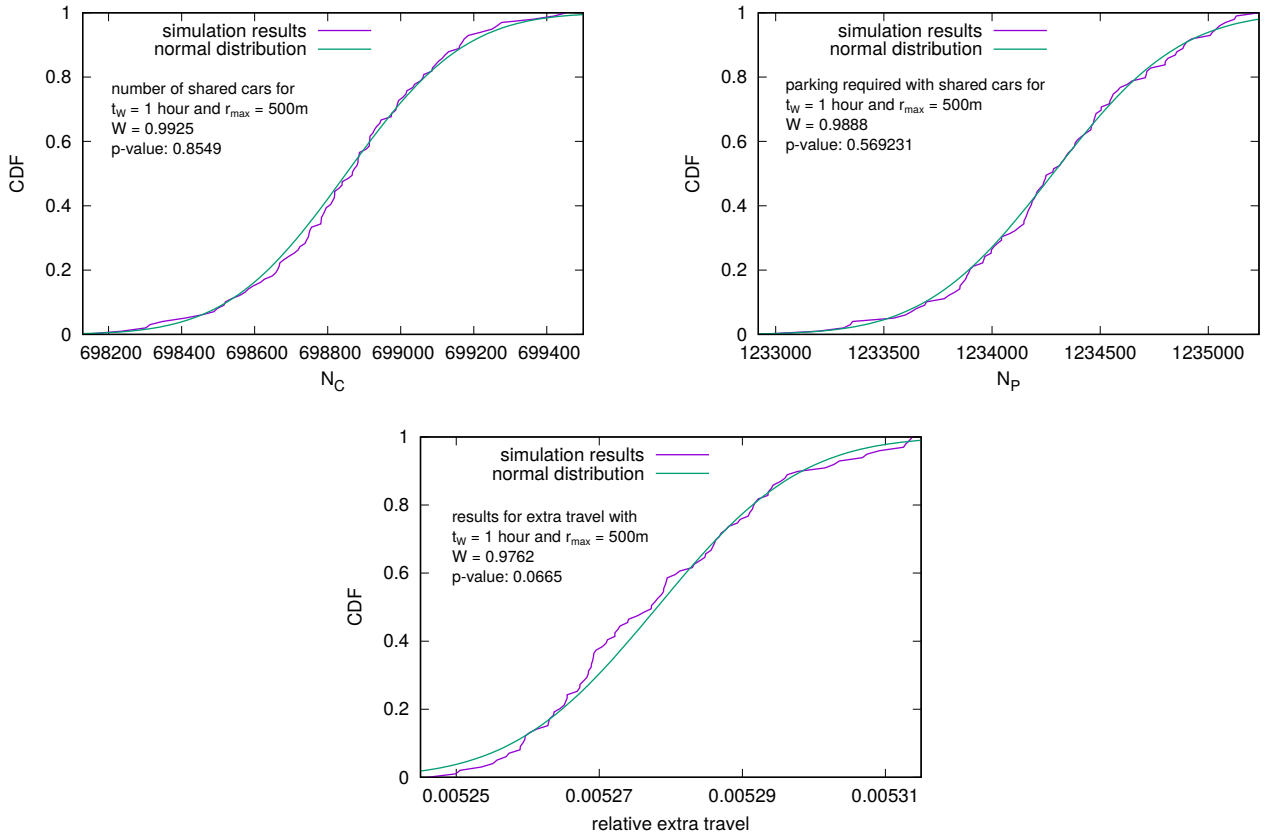

Figure S7: Distribution of results obtained from individual runs with different random trip start times. Example empirical cumulative distribution for shared vehicles (scenario #3 / #4) and parameters $t_W = 1\,\text{hour}$ and $r_{\max} = 500\,\text{m}$ is displayed for the number of cars (N_C, top left panel), number of parking spaces (N_P, top right panel) and extra travel distance (bottom panel). In all cases, all 100 simulation result values in the empirical distribution fall close to the mean (standard deviations are $< 0.04\%$ for the number of cars and parking and $\sim 0.3\%$ for the extra travel distance). The empirical distribution is well approximated with a normal distribution in all cases. The respective normal distributions (i.e. distributions with the same mean and standard deviation as the empirical ones) are shown for comparison as well.

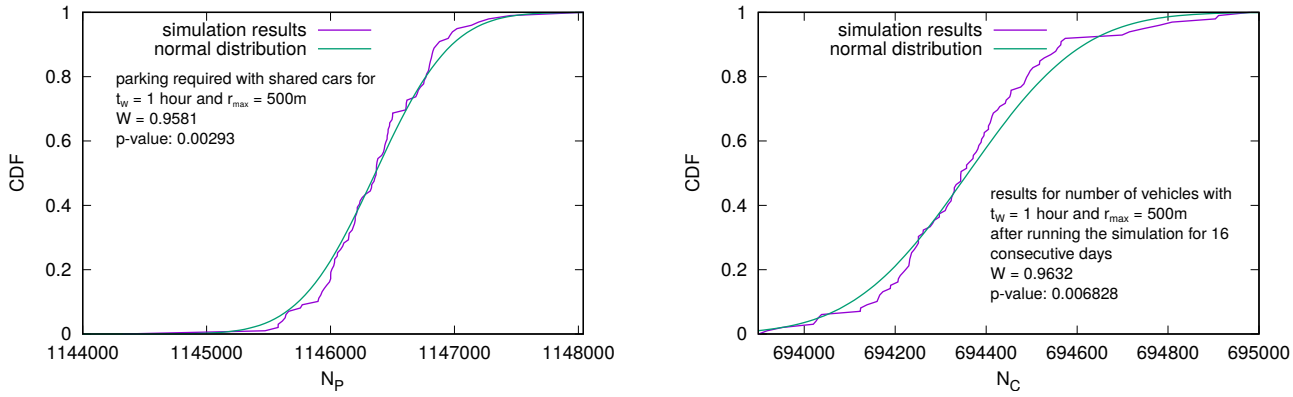

Figure S8: Illustration of the distribution of result values for the two "worst" cases, i.e. where the resulting p-values would indicate rejecting a normal distribution. Note that distributions are still relatively close to a normal distribution and the differences are mainly in the shape, without significant outliers. This way, using the mean value as an estimate of result is still justified.

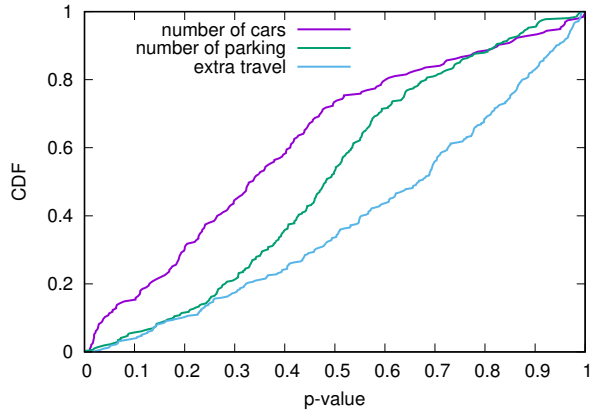

Figure S9: Distribution of p-values resulting from all Shapiro-Wilk tests carried out for all different combinations of parameter values. We note that these are quite evenly distributed, thus the lower p-values are likely the result of random variation as well.