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

Dániel Kondor\textsuperscript{1,2,*}, Hongmou Zhang\textsuperscript{1}, Remi Tachet\textsuperscript{1}, Paolo Santi\textsuperscript{1,3}, Carlo Ratti\textsuperscript{1}

\textsuperscript{1}Senseable City Laboratory, MIT, Cambridge MA 02139 USA
\textsuperscript{2}Singapore-MIT Alliance for Research and Technology, Singapore
\textsuperscript{3}Istituto di Informatica e Telematica del CNR, Pisa, Italy

\textsuperscript{*} E-mail: dkondor@mit.edu

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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 sub-urban communities, where planning is often centered around cars and parking spaces. E.g. 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]. Governments around the world respond with different strategies to the problems related with automobile usage; these range from spending high amounts on highways and parking garages and requiring developers provide off-street parking, to investing in public transportation and bicycling, to levyng congestion taxes on car users and to partnering with companies that aim to develop more modern transportation solutions such as those based on self-driving technologies [2, 3, 4]. There is an ongoing debate about possible solutions, with research showing that parking policies have substantial effects on urban areas in general [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]. Of course, this could be counterbalanced by more people switching to cars, similarly to how increasing road and parking capacity have been shown to draw increases in traffic, potentially mitigating its benefits; in the case of self-driving, a further increase in traffic is expected from people who currently are not able or prefer not to drive themselves [10, 13, 14, 15].

Further gains can be expected from using shared autonomous vehicles instead of private ones, with people buying mobility-as-a-service instead of cars [16]. One of the benefits is that vehicles could be optimized for the task at hand, instead of people owning a car which is supposed to fit all their potential transporta-
tion needs. Thus, most traffic can switch to smaller, more energy efficient cars. Furthermore, a shared car system can offer 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 on a much more granular level. Finally, 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, offering reductions in need for parking as well [17] [8] [15].

We note that the above described benefits of shared autonomous cars could already be achieved with conventional shared cars as well, at least to some degree; indeed, the idea of shared car ownership was originally proposed in the middle part of the 20th century, while successful commercial deployment of car-sharing systems only occurred on a large-scale in the past 15-20 years, made possible by the adoption of smart technologies [19]. Currently, the main target of companies providing such car-sharing service are still people who only need them occasionally, where the advantage in costs is more apparent. In accordance with this, most companies only allow cars to be returned to the pick-up location, although there is an increasing number of providers experimenting with one-way trips as a way to attract a larger user base due to the even higher flexibility offered (e.g. car2go, Zipcar). However, this presents the challenge of efficiently rebalancing the vehicle fleet, which is an active area of research from a theoretical viewpoint as well [20] [21]. Switching to autonomous vehicles could then drastically decrease rebalancing costs as no human drivers will be required, opening up a way for providers to target regular users and commuters as well with lower costs and less risks. Previous studies estimate costs for users to be significantly less than both taxi services and total ownership and operational costs of private cars [18] [22]. Thus, with shared self-driving cars, we can expect the distinction between taxi, ride-sharing, car-sharing services and even transit to blur and new, integrated solutions to become possible, providing services similar to personal rapid transit systems proposed but never implemented in the previous century [23] [22].

1.1 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 the effect on the behavior of users, traffic and emissions. Survey-based methods find that car ownership among car-sharing users decreases significantly, with about 5% – 22% of households participating in car-sharing reducing the number of vehicles they own, one shared vehicle substituting for 4 – 15 private vehicles and the total reduction of vehicles being around 40%, depending on the study and the parameters used to correct for sampling effects [24] [16]. We note that drawing conclusions for the more wide-spread adoption of shared vehicles is not straightforward, since the car-shared users who were the subjects of these studies might not form 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, 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]. A more recent study based on realistic 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 [20]. Concentrating on parking, a previous study based on travel survey data from Atlanta and assuming a low market penetration of 5% found that parking demand can be reduced by 90% for people switching to shared autonomous vehicle usage, with one vehicle freeing up about 20 parking spaces [27]. A few previous studies raise concerns about potential increases in travel due to the advantages provided by self-driving cars [15] [10], but we are not aware of any work which addressed this question in a detailed microscopic simulation.

1.2 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 es-
mate 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. As commuting flows are highly regular and well-predictable, highly optimized solutions can be deployed with only small fluctuations to expect on the typical demand. Including additional mobility demand (e.g., usage of cars during the day, when they are not needed by commuters) can then further improve the benefits gained for commuters. 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 start and destination from 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. We note that an inherent limitation in our approach is that people’s behavior is expected to change in response to adoption of shared and self-driving vehicles, which we do not aim to model in our current work yet; we do however perform an analysis on subsamples of our data to determine whether the resulting gains stay significant if only partial adoption is considered.

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.

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 [28, 29, 30].

Clustering people’s locations and identifying the main nighttime and daytime clusters results 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 on 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.

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.
2.2 Travel times

In order to better estimate commute times, we calculate the time it takes to travel between their 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.

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 \( d_{\text{tot}} \). 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 \( N_P = 2N_C \). We note that this is the typical case for a large number of people, who commute with their car and a large number of cities, where there are separate residential and workplace parking facilities. Also, the total number of parking spaces in a city will be typically even larger, as other businesses (e.g. retail, entertainment, dining) also provide parking lots for their customers. E.g. in Los Angeles county, there are 3.3 parking spaces per vehicle, and about 0.57 cars per person. In this case, the total distance traveled is simply the sum of all distances between home and work locations, i.e. there is no extra travel due to finding a parking spot.

2. **Private cars, shared parking.** In this scenario, parking space can be shared between people who use them at night and during the day. In this case, when a commuter leaves their home location in the morning, their parking spot becomes available for others to use during the day. This could be curb parking, or parking garages which are available to anyone (i.e. their usage is not restricted to only people who work or live in a certain building). In this case, \( N_C = N_U \), \( N_C \leq N_P \leq 2N_C \), while the total distance traveled can increase due to people having to find a parking space close to their destination. Of course, the actual number of parking spaces that can be shared is limited due to the imbalances in commuting flows and to the need that parking requirements of people sharing a spot are temporally compatible. In this case, we simulate commuters’ trips and the result is the actual number of parking spaces needed so that each person in the simulation can park their car within a given \( r_{\text{max}} \) radius of their home and work locations. This radius is a parameter of the model, and the result will depend on its value.

3. **Shared vehicles.** In this case, we assume that everyone is using shared cars to commute to work. This means that people take any available car closer than \( r_{\text{max}} \) to the starting location of their trip (i.e. either their home or work location) and park it at any available parking spot closer than \( r_{\text{max}} \) to their destination. 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 workplace locations and then find an available parking spot in the neighborhood. Compared to the previous cases, this guarantees that people will not have to walk excess distances, while the \( r_{\text{max}} \) parameter will be the radius in which self-driving cars are allowed to travel without a passenger. Computationally, this scenario is very similar to the previous one, thus we will have \( N_C \leq N_U \) and \( N_C \leq N_P \leq 2N_C \).

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\(^1\)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).
again. The main difference is that $r_{\text{max}}$ in this scenario represents the range autonomous vehicles are allowed to drive empty to reach a parking spot. Thus, much larger values of $r_{\text{max}}$ than in scenario 2 and 3 can be used. However, this happens at the price of potentially further increasing $d_{\text{tot}}$, resulting in increased traffic.

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. In contrast to this, shared parking and conventional shared vehicles present an anxiety whether a vehicle or parking will be available at a convenient location. On the other hand, a system with shared self-driving vehicles could guarantee pickup and drop-off at exact locations, thus providing a much more attractive option for passengers.

2.4 Computational implementation

We run a simulation 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. The main loop in both cases models one day, moving everyone from their home locations to work, and then back home, with the trips happening at random times. This is repeated for several days in a row so that the result will not depend on the exact order in which people time their commute.

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), so we set the total number of parking spots in the city to be $N_P = N_C = N_U$. 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). When someone arrives at their work location, they search for free parking spots in $L_P$ within a $r_{\text{max}}$ radius. If such a parking spot is found (i.e. someone's home spot that they left), it can be occupied. If there are no free parking spots close to an arriving person's work location, we add one more parking spot to the system which they can now occupy. Thus, we increase the number of parking spots, $N_P$ by

### Algorithm 1 Main algorithm to calculate parking demand for private vehicles with shared parking (scenario #2 above).

$$U = \{$list of user home and work locations and travel times\}$$

$n_d = \text{number of days to run the simulation for}$

$r_{\text{max}} = \text{maximum distance people are willing to walk}$

$N_P = |U| \text{ parking spaces required}$

$L_P = \{$empty list for free parking spaces\}$

repeat

$E = \{$empty event list\}$

for all $u \in U$ do

generate random timestamps:

$t_{u1}: u$ goes to work

$t_{u2}: u$ goes back home

generate events (points with timestamps):

$e_1: u$ leaves home (trip start)

$e_2: u$ arrives at work (trip end)

$e_3: u$ leaves work (trip start)

$e_4: u$ arrives at home (trip end)

add $\{e_1, e_2, e_3, e_4\}$ to $E$

end for

process all events in $E$ in time order:

for all $e \in E$ 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 a free parking space $p \in L_P$

s.t. $\text{dist}(e, p) < r_{\text{max}}$

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

until $n_d$ days

Result: $N_P$ total number of parking spaces needed to satisfy mobility demand for $n_d$ days
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 \(LP\)), 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 any available alternative spot, or if none is found within an \(r_{\text{max}}\) radius, we again add a further parking space to the city, again increasing \(NP\). When we repeat this process for several days, again people in the morning take their car from the spot they left it in the evening, and we keep the existing list of free parking spots \((LP)\). Since on a different day, people will possibly leave and arrive at home and work in a different order, the same configuration of parking spaces might not be sufficient, we will need to add somewhat more to account for these differences. Running the simulation for several days then allows us to account for possible stochastic variation in people’s commuting habits; we used \(n_d = 30\) in practice to obtain the main results in this work.

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 \((LP)\), but also of available vehicles, again including the coordinates where they are parked \((LC)\). When someone starts a trip, we first search in the list of available cars \((LC)\), and if a suitable car \(c\) is found within \(r_{\text{max}}\) distance of the start of the trip, we remove \(c\) from \(LC\) and add its location to \(LP\) 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 start location, increasing the total number of cars \(NC\). We also increase the number of parking spaces \(NP\) 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 \(LP\). 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 \(NP = NC = 0\) and the \(LP\) and \(LC\) 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 start or destination of a trip and the parking location. This can become significant for self-driving vehicles, if we consider a larger \(r_{\text{max}}\) radius.

For all scenarios #2–#4, the main parameter that will affect the results is the \(r_{\text{max}}\) distance that people are willing to walk between a parking spot and their destination (in the case of #2 and #3), or the distance that self-driving cars are allowed to travel without a passanger to reach a parking spot. Realistic values of \(r_{\text{max}}\) are between 300 m and 500 m for walking, while we explore a larger range of options for self-driving

**Algorithm 2** Main algorithm to calculate parking demand for shared or self-driving vehicles with shared parking (scenarios #3 and #4 above).

\[
U = \{ \text{list of user home and work locations and travel times} \} \\
n_d = \text{number of days to run the simulation for} \\
r_{\text{max}} = \text{maximum distance that} \\
\text{people are willing to walk (} #3 \text{ case) or} \\
\text{self-driving cars travel empty (} #4 \text{ case)} \\
NP = 0 \text{ parking spaces required} \\
NC = 0 \text{ number of cars required} \\
LP = \{ \text{empty list for free parking spaces} \} \\
LC = \{ \text{empty list for available cars (with current locations)} \} \\
\text{repeat} \\
\quad E = \{ \text{empty event list} \} \\
\quad \text{for all } u \in U \text{ do} \\
\quad \quad \text{generate random timestamps:} \\
\quad \quad \quad t_{u1}: u \text{ goes to work} \\
\quad \quad \quad t_{u2}: u \text{ goes back home} \\
\quad \quad \text{generate events (points with timestamps):} \\
\quad \quad \quad e_1: u \text{ leaves home (trip start)} \\
\quad \quad \quad e_2: u \text{ arrives at work (trip end)} \\
\quad \quad \quad e_3: u \text{ leaves work (trip start)} \\
\quad \quad \quad e_4: u \text{ arrives at home (trip end)} \\
\quad \quad \quad \quad \text{add } \{e_1, e_2, e_3, e_4\} \text{ to } E \\
\quad \text{end for} \\
\quad \text{process all events in } E \text{ in time order:} \\
\quad \quad \text{for all } e \in E \text{ do} \\
\quad \quad \quad \text{if } e \text{ is the start of a trip} \text{ then} \\
\quad \quad \quad \quad \text{find } c \in LC \text{ s.t. } \text{dist}(e, c) < r_{\text{max}} \\
\quad \quad \quad \quad \text{if found then} \\
\quad \quad \quad \quad \quad \text{remove } c \text{ from } LC \\
\quad \quad \quad \quad \quad \text{add } c\text{'s location to } LP \\
\quad \quad \quad \quad \quad \text{add travel time between } c \\
\quad \quad \quad \quad \quad \text{and } e \text{ to the total trip time} \\
\quad \quad \quad \quad \text{else} \\
\quad \quad \quad \quad \quad \text{assume there is a free car at } e \\
\quad \quad \quad \quad \quad \text{increase both } NP \text{ and } NC \text{ by one} \\
\quad \quad \quad \quad \quad \text{add } e\text{'s location to } LP \\
\quad \quad \quad \quad \text{end if} \\
\quad \quad \quad \text{else } e \text{ is the end of a trip} \\
\quad \quad \quad \quad \text{find } p \in LP \text{ s.t. } \text{dist}(e, p) < r_{\text{max}} \\
\quad \quad \quad \quad \text{if found then} \\
\quad \quad \quad \quad \quad \text{remove } p \text{ from } LP \\
\quad \quad \quad \quad \quad \text{add travel time between } e \\
\quad \quad \quad \quad \quad \text{and } p \text{ to the total trip time} \\
\quad \quad \quad \quad \quad \text{add } p\text{'s location to } LC \\
\quad \quad \quad \quad \text{else} \\
\quad \quad \quad \quad \quad \text{assume there is a more parking} \\
\quad \quad \quad \quad \quad \text{increase } NP \text{ by one} \\
\quad \quad \quad \quad \quad \text{add } e\text{'s location to } LC \\
\quad \quad \quad \quad \text{end if} \\
\quad \quad \text{end if} \\
\quad \text{end for} \\
\text{until } n_d \text{ days} \\
\text{Result: } NP \text{ total number of parking spaces and } NC \text{ total number of cars needed to satisfy mobility demand for } n_d \text{ days}
cars. We note that the simulation methodology is exactly the same in scenarios #3 and #4 (regular and autonomous shared cars), the main difference is only the reasonable range of the $r_{\text{max}}$ parameter. On the other hand, there are important conceptual differences between these two cases, which we will discuss in more detail later.

Furthermore, 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 uniformly random from a time window of length $t_W$, which is a secondary parameter of our model. For the main simulations, we use $t_W = 1$ hour. We perform further analysis with varying $t_W$ to assess the robustness of the results obtained. Furthermore, we repeat the same analysis with commute start times generated randomly, but based on transit usage data in Singapore: this is explained in more detail in the Supplementary Material.

3 Results

3.1 Reduction in parking spaces and cars required

The main result of this estimation then 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 cases of private and shared vehicles (scenarios #1 – #3) and a further comparison between scenarios #2 and #3 as a function of the $r_{\text{max}}$ maximum distance between parking spots and people’s destinations in Fig. 2. We note that these results were obtained by simulating 30 consecutive days with different randomly generated trip start times each day. This allows us to account for variations in individual daily routines. Also, to account for the stochastic nature of the simulation, we repeated the simulation for each combination of parameters one hundred times and display the averages here. All hundred runs gave very similar results, with standard deviations under 1% in all cases. We display the exact values in Table S1, part of the Supplementary Material.

Looking at the results in Fig. 2, we see that for reasonably small values of $r_{\text{max}}$ (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. Furthermore, about 30% less cars are needed.

For private or shared cars driven by their users, the $r_{\text{max}}$ distance is essentially the maximum distance people are willing to walk from their parking spot to their final destination. In the case of a city with humid climate like Singapore, we expect that the usual value of 500 m used e.g. when planning access to public transit in many cities [31, 32] is already an optimistic estimate. On the other hand, in the case of self-driving vehicles, $r_{\text{max}}$ denotes the radius the car has to travel without a passenger to find a parking spot, which can be much longer, at the expense of additional road traffic. Results for this case are displayed in Fig. 3. These show that allowing self-driving cars to travel about 2 km without a passenger to a parking spot will result in a demand of 52% less parking spaces compared to everyone having their private spot at home and work (case #1). This also presents an about 37% saving to a typical case of private vehicles and highly efficient shared parking (scenario #2 with $r_{\text{max}} = 500$ m, a realistic upper bound for this parameter in Singapore). Furthermore, over 40% less vehicles are required as well.

3.2 Robustness analysis

So far, we have presented results for a reasonable set of parameters modeling commuting in Singapore. In this section we present further results obtained when varying these parameters to assess the robustness of our methodology. This includes subsampling the set of users to account for possible differences in the actual number of commuters using private vehicles and a possible partial adoption of shared or self-driving cars. Furthermore, we evaluate the effect of using different strategies to select trip start times which is a major determining factor in shareability and is only approximated in our analysis. We also evaluate how the length of the simulation run (i.e. different realizations on different days) affect the results and how an external limit on the maximum number of parking spaces and shared cars will have an effect on the results.

3.2.1 Trip start times

Since the timing of commutes is a major determining factor in how shared cars can be utilized, we repeat our simulation with different commute start window sizes. Results obtained for Scenario #3 (also applicable to Scenario #4) are displayed in Fig. 3. We see that this is indeed a very important parameter: commute windows below one hour significantly decrease sharing opportunities. Higher commute windows will only add moderate gains in shareability. We note that the one
Figure 2: Left: Parking demand in scenarios #1-#3. The number of parking spaces required is displayed for the 3 cases. Relative numbers (compared to case #1, i.e. private parking spaces) are displayed on the right axis. Right: relative demand for parking spaces and cars when comparing scenario #3 (shared cars) to #2 (private cars). Displayed here are the number of parking spaces (green) and cars (blue) required in case #3, divided by the same number in case #2. Number of parking spaces corresponds to the absolute numbers displayed in Fig. 2, while the number of cars is a constant value of \( N_C = N_U = 1,066,504 \) in case #2, and is a decreasing function of \( r_{\text{max}} \) in case #3.

Figure 3: Left: Parking demand with self-driving cars (scenario #4) with allowing cars to travel higher distance without a passenger. The number of parking spaces required is displayed on the left axis. Relative numbers (compared to case #1, i.e. private parking spaces) are displayed on the right axis. Right: Relative demand for parking spaces and cars when comparing scenario #4 (self-driving vehicles) to #2 (private cars), with a fixed parameter of \( r_{\text{max}} = 500 \text{ m} \) in the latter case. Displayed here are the number of parking spaces (green) and cars (blue) required in case #3, divided by the previous result in case #2. Absolute number of required cars is displayed on the right axis as well.
hour commute window we applied 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). Future work using real trip data from a denser dataset to run our model would allow to test this estimate in more detail.

We compute a further measure to characterize the inherent inefficiency due to unbalanced commute flows. We obtain this by running the same model with assuming instantenous travel (i.e. all trip times are set to zero, but trips are processed in a random order). The result of this process is a measure where the only inefficiency comes from the way trip origins and destinations are distributed. We see that there is about 20% – 30% difference between the main results (considering \(t_W = 1 \text{ hour}\)) and this limit value.

### 3.2.2 Subsampling users

Another parameter which determines the possible gains when using shared vehicles is that actually how many people use cars as their primary means for commuting to work and what percentage of them would adopt such a service. Since our dataset is drawn from the general population, we don’t know who actually uses private cars for commuting. Our main argument is that the commuting patterns obtained from the CDR dataset are statistically representative, but the numbers might need to be scaled to accomodate the real number of commuters using cars and willing to switch to shared vehicles. To account for this, we repeated the simulations for varying subsets of the data and display these results in Fig. 5. We see that the possible relative gains (in terms of parking spaces) barely change when limiting the analysis to subsets of people down to 25% (i.e. about 267,000); a smaller sample of only 10% of people in our dataset (107,000 people) will result in noticeably less gains (about 5% difference) when using a radius of \(r_{\text{max}} = 300 \text{ m}\), which we consider a reasonable value for walking. On the other hand, for radii of at least 500 m, the gains in parking efficiency are only slightly worse even in this case, suggesting that for self-driving cars, a relative small adoption ratio could 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, performing taxi-like service as well.

### 3.2.3 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. 6 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 $r_{\text{max}}$ without a passenger. We note that the $r_{\text{max}}$ 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 car or parking spot available under $r_{\text{max}}$ 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 $r_{\text{max}}$ 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 this case, we limit the maximum number of parking spots 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 $r_{\text{max}}$ 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 $r_{\text{max}}$ values for each limit value we select for parking spaces and select the $r_{\text{max}}$ which minimizes the extra distance traveled in practice. As seen in Fig. 6, 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.

Figure 6: 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 7: 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 the private cars (#2) and shared or self-driving cars (#3 or #4) cases 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 (refer to Section 3.2 for more discussion); 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 parameter as explained in Section 3.2.
3.3 Estimating induced extra traffic

Self-driving cars would allow for the possibility of parking farther away from the start or destination of a trip, which will allow to further reduce the number of parking spaces required. This benefit will nevertheless come 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. During the course of the simulation, we recorded the distances between the start 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 in Fig.[1] 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 this can be a significant number when estimating traffic with human drivers, we expect that efficiency gains in traffic due to self driving can offset this.

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, i.e. with a much smaller footprint than traditional parking garages. This would present further reduction in the footprint of parking in cities, with potentially higher benefits in efficiency (note that currently, there could be as many as 3 parking spaces per car in a city). An inherent inefficiency which we did not consider explicitly is the need for vehicles to search for a free parking spot once they arrived at their destination. It was estimated that in busy downtown areas, up to 10% – 30% of traffic is people searching for parking.[33, 34] With the advent of smart technologies, these processes can be greatly improved. Concentrating on human drivers, it can still be a challenge to develop a user interface which allows the driver to search for and get directions to available parking without being a potentially dangerous distraction from driving; on the other hand, self-driving vehicles can naturally and seamlessly integrate their navigation systems with data providers about available parking in real time. A further mitigating factor is the higher efficiency of traffic with self-driving than with manually driven cars. We note that our models do not explicitly deal with how drivers or self-driving cars find available parking; with the main focus of our attention on self-driving cars, we assumed that this problem can be solved efficiently in the future.

We note that the main practical factor potentially 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 parameter ranges of our model (i.e. both scenarios #3 and #4 above can be modeled with the same algorithm, but in the latter case, higher \( r_{\text{max}} \) values are feasible, giving rise to more gains in efficiency). On the other hand, there is a large conceptual difference between the two cases, with shared regular vehicles presenting serious practical problems which we expect to be efficiently solved with self-driving. These problems can be summarized as the following:

- **Maximum walking distance.** The \( r_{\text{max}} \) parameter has a different meaning in the two cases. For scenario #3, it is a distance people need to walk, thus we need to set a conservative, “hard” limit on it, as long walking distances would result in highly dissatisfied users. On the other hand, for scenario #4, varying this parameter only affects the trade-off between less cars and more traffic, thus allowing more flexibility for designers and operators of such transportation systems.

- **Cost of rebalancing.** For scenario #3, the cost of fleet rebalancing is especially high (i.e. it involves a human employee traveling to the parked car with
alternate methods and driving it to an other location), thus high rebalancing requirements might make the service operation prohibitively expensive. Also, variation in rebalancing demand can amplify this problem, as the operator would need to size the number of rebalancers employed according to peak demands, while under-estimating rebalancing demands can lead to service outages in certain parts of the city and thus again to high user dissatisfaction.

- **User anxiety.** If people are to adopt a shared car platform as their primary means of transportation (i.e. giving up their private vehicle), they need to be convinced that a car will be available whenever they need it. Even if rebalancing works perfectly, potential users might have concerns about availability. A service based on autonomous vehicles has an advantage at giving guarantees for its users about vehicle (and parking) availability, e.g. based on the maximum time needed for a car to travel from their depots to any location and also building on the fact that finding a free parking spot is not the passenger’s concern.

- **Motivation for adoption.** Convincing people who are interested in switching to self-driving cars to switch to a shared service provider rather than a privately owned one can be easier than convincing someone who already has a private car to switch to using conventional shared cars. This can be supported by the projected low costs of using shared autonomous cars.

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 happen 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. With the possibility to utilize more efficient parking depots for self-driving vehicles, the area that can be saved can be even higher, having a transformative effect on urban environments currently shaped by the needs of car traffic and parking to a high degree. On the other hand, we believe that 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 was 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.

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