Estimating the potential for shared autonomous scooters

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February 4, 2020

Abstract

Recent technological developments have shown significant potential for transforming urban mobility. Considering first- and last-mile travel and short trips, the rapid adoption of dockless bike-share systems showed the possibility of disruptive change, while simultaneously presenting new challenges in fleet management and use of public spaces. At the same time, further advances are expected from adoption of electric vehicles and various forms of vehicle autonomy. In this paper, we evaluate the operational characteristics of a new class of shared vehicles that are being actively developed in the industry: scooters with self-repositioning capabilities, which we expect to become viable in the coming years and present an alternative to shared bicycles for short trips. We do this by adapting the methodology of shareability networks to a large-scale dataset of dockless bike-share usage, giving us estimates of ideal fleet size under varying assumptions of fleet operations. We show that the availability of self-repositioning capabilities can help achieve up to 10 times higher utilization of vehicles than possible in current bike-share systems. We show that actual benefits will highly depend on the availability of dedicated infrastructure, a key issue for scooter and bicycle use. Based on our results, we envision that technological advances can present an opportunity to rethink urban infrastructures and how transportation can be effectively organized in cities.

1 Introduction

The transportation landscape in cities is changing rapidly, with three important areas of technological advancement driving disruptive changes [1]. First, connected devices that enable real-time feedback, control, and optimization are becoming commonplace. The ubiquitous availability of smartphones allowed new operators providing on-demand transportation options to successfully compete with more traditional modes [2]. Many companies that fall under the "sharing economy" paradigm offer new options such as ride-hailing and ride-sharing [3], car-sharing [4] and bike-sharing [5, 6, 7]. Second, improvements in electric propulsion and battery technology are resulting in cleaner and lighter vehicles, reducing local emissions and opening up possibilities for new vehicle form factors [8, 9]. Lastly, rapid advances in autonomous driving can result in profound changes in urban mobility [10, 11, 12, 13]; indeed, several large companies are racing to be the first to deploy fully autonomous taxis in commercial service.

Despite the possibilities afforded by new technologies, it is still uncertain how the future of urban transportation will look like and what policies are needed for technological advances to result in net benefits. There is an unclear picture about the full benefits and drawbacks of ride-sourcing services, with concerns often raised about potential increase in total vehicle travel, congestion, and decreased public transit ridership [14, 15, 16]. Similarly, there are concerns that the benefits of autonomous cars will be mitigated by increased volume of trips and total energy use [11, 12]. Consequently, providing a core transportation infrastructure of high-capacity modes will remain important, with the question of keeping transit attractive in the age of on-demand autonomous mobility being crucial [17, 18, 19, 20, 21].

A central issue in transportation that has been elusive in the past over hundred years is providing first- and last-mile travel so that commuters can reach high-capacity modes in a convenient and efficient manner. Despite research suggesting that ride-hailing can serve this role [14, 22], there are concerns whether it could work in a scalable and affordable manner [22, 15]. In future-looking scenarios, shared autonomous vehicles (SAVs) are envisioned to provide first- and last-mile transportation in a more cost effective way [23, 17, 18, 19]. Nevertheless, other form factors beside full-size cars should be considered to further reduce costs, congestion and energy use. Recently, shared bicycles and scooters[1] have been deployed in many cities to provide a sustainable transportation mode for short trips [24, 25, 6, 7, 26]. While popular, these services face serious challenges since imbalances in demand result in vehicles accumulating in some locations while being unavailable in others; to avoid this, operators are required to spend significant cost and effort on rebalancing the fleet, i.e. employing people to move vehicles to areas with high demand [27, 5, 28, 29].

In this paper, we consider a new form of transportation, *self-repositioning shared personal mobility devices* (SRSPMD) as a potential way of providing efficient first- and last-mile transportation and serving short trips. An SRSPMD service would use small electric vehicles, e.g. scooters, that can move autonomously at slow speed to reposition themselves, but require to be driven by their user during trips. This would allow efficient fleet operations, while keeping the vehicles lightweight and simple. With recent interest in new vehicle technologies, there is significant ongoing research investigating the potential to create various small form-factor autonomous vehicles, e.g. personal mobility devices (PMDs), golf cars, wheelchairs, scooters or even bicycles [30, 31, 32, 33, 34, 35, 36]; thus we can expect such vehicles to be available in the near future. As of 2019, we know of at least one company that is pursuing commercial application of the SRSPMD concept [37].

We perform an evaluation of the benefits of SRSPMDs under the rigorous theoretical framework of shareability networks [3, 38] using real-world data of shared bicycle usage [6] and public bus use for short trips in Singapore as our basis. This results in a characterization of ideal SRSPMD fleet size and vehicle utilization required to serve trips currently taken by shared bikes. We compare these results to a simulated scenario of simple fleet management without proactive rebalancing. This way, we provide reasonable bounds of service efficiency for future operators under real-world conditions. These results allow us to characterize the main benefits and challenges for SRSPMDs in cities.

The main contribution of this paper is performing a first investigation into the fleet size requirements for an operator of shared scooters with self-repositioning capabilities based on real-world data about demand for short trips, with explicit focus on the benefits of autonomy. While a significant amount of work has focused on bikesharing, e.g. on understanding usage patterns [24, 6, 7, 26], optimizing fleet rebalancing [28, 5, 29] or determining optimal fleet size [39, 40], it is yet unclear how these results would apply to an SRSPMD operator, or how to quantify the benefits of self-relocation capabilities. An important difference is that while rebalancing for conventional shared bikes or scooters is usually performed in batches, under constraints on the available manpower and vehicles, SRSPMDs would allow operators to move vehicles individually, offering more flexibility. Furthermore, a crucial difference from any service utilizing full-size cars (either autonomous or chauffeur-driven) [38, 13] is the slow speed of SRSPMD vehicles that can be a serious limitation when estimating which trips can be served consecutively by the same vehicle.

[1] In this article, we use the term *scooter* to refer to a personal mobility device which is suitable to travel on pedestrian path, with the rider in a standing or sitting position, powered either by the rider (i.e. a kick-scooter) or by a small electric motor. We specifically limit the term to not include small motorcycles that are often referred to scooters in other contexts, but are significantly higher-powered, primarily designed to be used on roads.

2 Methods

2.1 Shared bike usage data

As the main data source for the current work, we use trips made by customers of a dockless bike-share operator over the one week period between 2017.09.11 and 2017.09.17. [6]. Data collection and preprocessing procedures were presented in more detail in Refs. [6, 7]. Notably, after identifying trips, we filter out excessively short and long trips; the former might be the result of inaccurate GPS measurements, while the latter can correspond to the operator removing the bike for maintenance. This way, we have a total of 284,100 trips over the course of the week. We show basic statistics of trips and bike usage in our dataset in Fig. S1 in the Supplementary Material.

As the location of the bikes during the trips are not reported, we first need to assign probable routes; we achieve this by obtaining a representation of possible paths from OpenStreetMap [41], finding the shortest path for each trip and assuming it is the route taken. Currently, the use of PMDs in Singapore on sidewalks and roads is forbidden; they are only allowed to be used on cycle paths, while previously, their use on sidewalks was allowed. Worldwide, with the increasing popularity of electric scooters and PMDs, cities are adopting different regulations, with use on sidewalks and cycling routes being prominent [42, 43]. It is uncertain what regulations will apply to SRSPMDs; in the current work, we use the assumption that they can use both sidewalks and cycling paths.

After assigning shortest paths to each trip, we calculate average travel speeds and filter out trips that have an average speed above 30km/h. One probable explanation for having such trips is that the path network obtained from OpenStreetMap is incomplete, thus for some trips, our estimated "shortest" path is still longer than the real route taken by the user. After these processing and filtering steps, we have a total of 278,826 trips left made by 32,782 unique bikes (identified by the 9 digit unique ID for each bike reported in the dataset).

This would mean that each bike makes on average 1.2151 trips per day. In reality however, the number of bikes used each day is much lower, between 13,000 and 18,000, thus the average number of trips per bike per day is between 2.3 and 2.75 (see Fig. 1 and SI Table S1) and on average, each bike is used for 26.2 minutes each day (see SI Fig. S1). We speculate that the large discrepancy between the total fleet size and daily active fleet is due to multiple factors, including intentional oversupply of bikes in a highly competitive market at the time of our data collection, and bikes being broken or left in hard-to-find locations by users for extended periods of time.

2.2 Random trips based on bus usage data

As a further data source, we downloaded bus usage data from the Singapore Land Transport Authority's DataMall interface for January 2019 [44]. The data includes the monthly total number of trips taken between any two bus stop pairs in Singapore, separated between weekdays and weekends and with a time resolution of one hour. We identify bus stops inside a limited study area based on the Toa Payoh neighborhood (mostly dense residential); we have a total of 94 bus stops (see Fig. S2 in the Supplementary Material for on overview of the study area). Between all bus stop pairs, we divide the total number of trips made on workdays by 22, the number of workdays in January 2019. We find that the average number of total daily trips in the study area is thus 68,499. Among these, we find that about 28% (approximately 19,364 trips per day) could be replaced by a PMD trip of less than 1 km, while 84% (approximately 57,508 trips per day) could be replaced by a PMD trip that is less than 2 km long. For comparison, in the original bike dataset, we have on average 710 trips within the Toa Payoh area per day. This shows that there is a large amount of additional short trips happening that could be served by SRSPMDs beside those that are already made by shared bicycles. Of course, not every bus passenger could switch to using PMDs, but even a small share of bus passengers switching will result in significant demand. Considering the whole of Singapore, we find that 13% of them, or approximately 512 thousand trips per day could be replaced by a PMD trip shorter than 1 km; 48%, or about 1.9 million trips per day could be replaced by a PMD trip under 2 km.

We created potential "trips" for SRSPMD users based on the bus trips. We generated trips of length up to $R = 2\,\mathrm{km}$ as candidates. We generated a subset of trips by a random selection of n_t trips from the bus trip dataset. Since the time resolution of the bus dataset is one hour, we assign a uniformly random trip start time within the one hour time window for each trip. Furthermore, for each trip, we assigned a building as the start and end location in a uniform random way from a set of buildings obtained from OpenStreetMap and matched to the start and end bus stops previously. We repeated the trip selection procedure for values of n_t between 100 and 40,000. We note that when generating trips, we assume users travel at a speed of $5\,\mathrm{km/h}$ when using SRSPMDs. For each value of n_t, we repeated the random trips generation process 100 times, and calculated minimum fleet sizes for each realization. In Fig. 3, we report the average and standard deviation of the results among the 100 random realizations.

2.3 Oracle model for estimating minimum fleet size

We use the methodology of shareability networks [38] to estimate a theoretical minimum for the fleet size. We use the list of trips as the input, and require all trips to be served by the fleet of SRSPMDs without any delay. For each day, we represent trips by nodes of a graph that are connected by a directed edge if the two trips can be served by the same vehicle (in the time order that corresponds to the direction of the edge). Calculating an ideal dispatching strategy is then equivalent to calculating a maximum matching on this graph [38]. In practice, we consider a weighted version of the problem, that also minimizes the total travel distance of the fleet as well.

Since this methodology require advance knowledge of all trips, we call this an *oracle* model, using the terminology of Santi. et al [3] and Vazifeh et al. [38]. The result of this estimation then shows the potential for efficient fleet management under ideal conditions. By comparing the case with and without self-repositioning, we can characterize the maximum potential benefit of autonomy.

2.4 Online model for estimating operational characteristics

In previous work applied to taxi data [38], Vazifeh et al. show that an online version of maximum matching can offer similar performance to the oracle model with only short delays. We note that a fundatmental difference in the case of SRSPMDs is the short relocation speed of vehicles that can hamper performance. It is thus important to investigate an online model, where the operator does not have advance knowledge of trip requests.

We use a combination of greedy heuristics [13] and batched maximum matching in short time windows [38] to simulate the performance of a fleet operator with a simple operating strategy that only includes response to user requests. In this case, requests are aggregated in $t_b = 1\,\mathrm{min}$ time windows; for each time window, the operator performs a maximum matching between available vehicles and unserved requests with the goal of serving the largest number of requests with the minimum amount of total waiting time. We explored different values of t_b and found that the value of one minute performs best when considering short maximum waiting times, i.e. $t_w = 5\,\mathrm{min}$, in line with the on-demand nature of our setting.

We note that the main limitation of the online model is that we are not considering strategic decisions made by the operators to rebalance the fleet of vehicles that can affect the performance drastically [5]. Notwithstanding the fact that bad decisions about fleet rebalancing can still result in worse performance than doing nothing, we expect that real operating conditions will present a middle ground between the two cases considered in our work. As commute patterns are highly regular [45, 46], operators will be able to make valuable predictions about expected future demand and thus make proactive rebalancing decisions. Even without actual predictions, an operator can make proactive rebalancing movements with the aim of balancing the spatial distribution of vehicles in the service area, ensuring maximum spatial coverage. This can drastically improve the performance of the system [28, 29], however, such strategic methods are demand and scenario dependent and thus not addressed in this work.

2.5 Estimating reachability for vehicles

Both methods for estimating fleet size rely on estimating when a vehicle can reach a trip request. Using the network of sidewalks and cycle paths extracted from OpenStreetMap [41] and use this as the path networks SRSPMDs can navigate on. Since we do not have estimates of vehicle travel speed in real-world conditions, we introduce the parameter v_R, the *average* speed that SRSPMDs are able to travel during relocation. We emphasize that in our analysis, v_R is not the actual *travel* speed of the vehicles, but the average speed, i.e. the total distance of the relocation trip divided by the total time taken; this includes any time spent stopping or slowing down due to traffic interactions, a main limitation while navigating in complex environments [47, 48, 49]. This way, we are able to incorporate different assumptions on the infrastructure available to SRSPMDs by varying this parameter. We use low values of $v_R = 1\,\mathrm{km/h}$ and $2.5\,\mathrm{km/h}$ as representative of a case where SRSPMDs will continue to use sidewalks, thus are required to carefully navigate among pedestrians, limiting both maximum and average speed for the sake of safety. We further perform our analysis with higher v_R values of $5\,\mathrm{km/h}$ and $10\,\mathrm{km/h}$ that represent scenarios where SRSPMDs can perform an increasing share of their relocation trips on a path infrastructure separated from pedestrians [50, 51].

3 Results

3.1 Oracle model

We display main results for lower and upper bounds on fleet size in Figs. 1A-1D. Further details are given in Tables S1–S5 in the Supplementary Material. Ideal fleet sizes in the oracle model range from around 4,000 vehicles for $v_R = 1\,\mathrm{km/h}$, to between 1,500 and 2,000 for $v_R = 10\,\mathrm{km/h}$. These present 4 to 10 times reductions compared to the number of active bicycles each day of the bikeshare operator which ranges between 13,500 and 18,000 and up to 17 times reduction compared to the total number of bikes seen in the fleet over the course of one week. At the same time, average daily travel per vehicle is still limited to below 40 km (see SI Table S5), well within the capabilities of commercial scooters, indicating that any extra costs due to charging infrastructure will be limited.

To better estimate the benefits and limits of self-relocation, we perform two comparisons in the oracle model. First, we estimate an ideal fleet size without autonomy. We do this by assuming stationary vehicles and the willingness to walk up to $d_{walk} = 100\,\mathrm{m}$ by users to reach a bicycle. This corresponds to a case where the operator assigns a bicycle to each user for their trip based on the results of an "oracle", instead of the user freely choosing any available bike. We see in Fig. 1 that this result offers only moderate improvements in fleet size over the base case, thus we can conclude that self-relocation capabilities are essential for making significant improvements in fleet size and vehicle utilization. We also calculate an absolute minimum on fleet size as the maximum number of bicycles in use simultaneously; this results in very low numbers, between 800 and 1,110.

3.2 Online model

Having estimated theoretical minimum fleet sizes in the oracle model, we compare these with the upper bounds obtained in the online model. We perform two variations to obtain (1) an estimation of "ideal" fleet size without knowledge of trips in advance; (2) a characterization of service quality in terms of waiting time for users. In the first case, we start the simulation with zero vehicles and allow the operators to "create" new vehicles when a trip request would go unserved for $t_w = 5\,\mathrm{min}$, similarly to the methodology used to estimated SAV fleet sizes previously [13, 52]. This results in significantly larger fleet sizes (Fig. 1C), comparable to the original fleet size of bicycles for low values of v_R and a more reasonable number of between 4,000 and 5,000 if vehicles can travel faster ($v_R = 10\,\mathrm{km/h}$). In the second case, we run the simulation with a predetermined number of vehicles distributed randomly in the city and record average waiting times and the ratio of trips served under $t_w = 5\,\mathrm{min}$. We can make similar conclusions as in the previous case: in Figs. 1E-1F, we again see that a fleet size between 4,000 and 5,000 vehicles and high v_R values are necessary for adequate service, e.g. considering a fleet size of 5,000 vehicles, for $v_R = 10\,\mathrm{km/h}$, we have an average waiting time of $2.2\,\mathrm{min}$ and 92.6% of trips are served within 5 minutes.

These results are easily understandable considering that in the online model, the operator needs to be ready to serve any trip request occurring in the service area with small delay; if trip requests are not known in advance, this requires an idle vehicle to be available at most t_w travel distance from any location in their service area. For an average relocation speed of $v_R = 1\,\mathrm{km/h}$ and $t_w = 5\,\mathrm{min}$, this would mean that a vehicle should be available no more than 83 meters away from any possible location. Obviously, this translates into having a large number of vehicles distributed in a regular fashion standing by to serve any request.

By drawing a $100\,\mathrm{m}$ circle around every trip start location in the dataset and merging the area of these, we obtain an estimate of $312\,\mathrm{km}^2$ as the service area of the dockless bike share operator in Singapore. For $v_R = 1\,\mathrm{km/h}$, we would need at least N_I =22,464 idle vehicles distributed evenly in the city to be able to serve any trip request within $t_w = 5\,\mathrm{min}$. Obviously, $N_I \sim v_R^{-2}$, thus larger relocation speeds allow much smaller number of vehicles to cover the service area: with $v_R = 2.5\,\mathrm{km/h}$ we already only need 3,594 such vehicles, for $v_R = 5\,\mathrm{km/h}$ we need 899 vehicles and for $v_R = 10\,\mathrm{km/h}$ we need 225 vehicles. In reality, available vehicles are not evenly distributed in the service

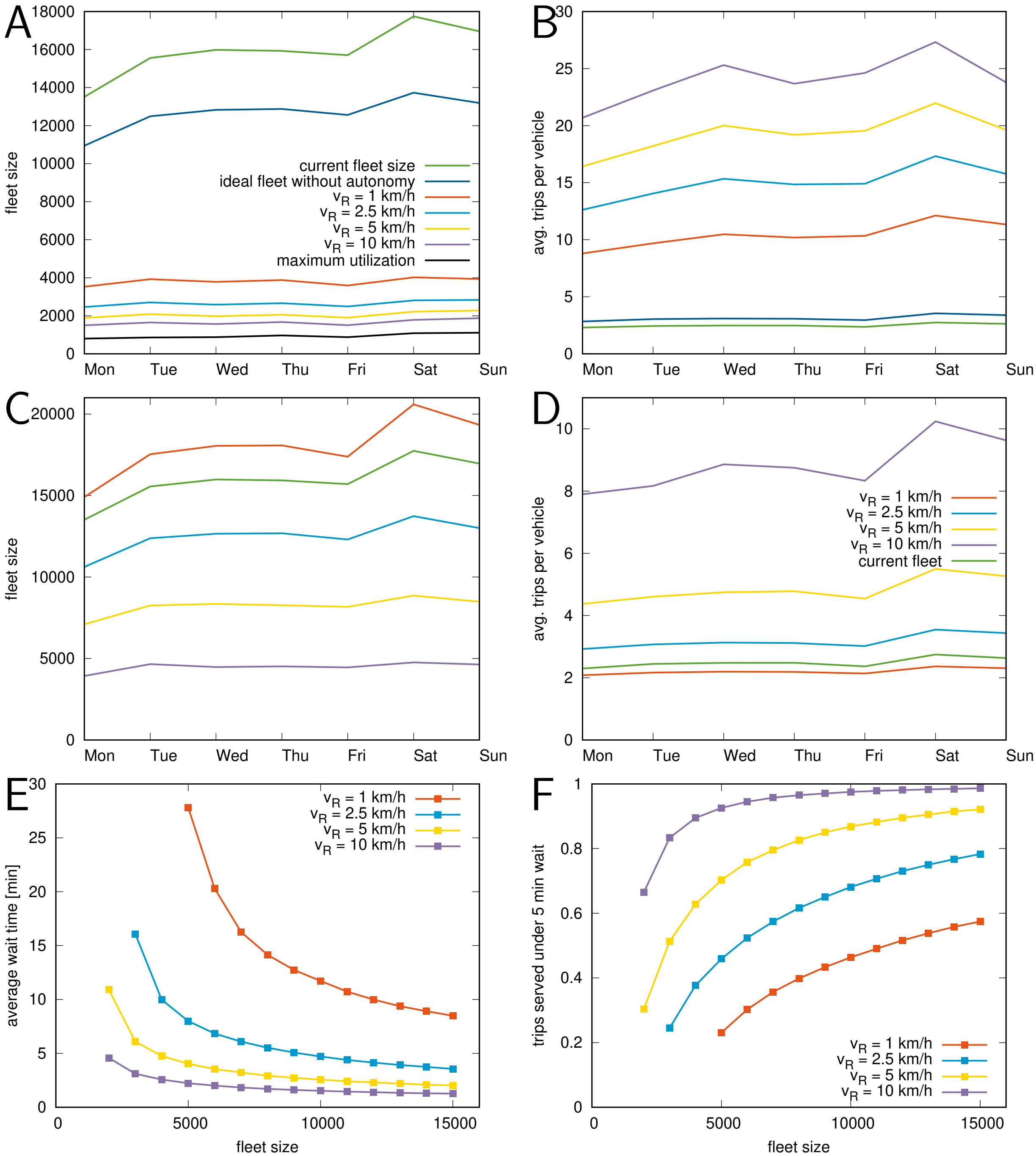

Figure 1: Main results for fleet size, vehicle utilization and passenger waiting times. Top row: fleet sizes (A) and average number of trips per vehicle per day (B) are compared over the course of seven days for different average relocation speed of SRSPMDs (v_R). For comparison, we further show the current fleet size and average utilization of the bike-share operator serving the same trips (green line; only bikes that are used at least once that day are counted), and the result of an optimal allocation of bikes without autonomy (dark blue line). Middle row: (C,D) the same measures are displayed for the online model. Note that fleet size can be larger than current bikeshare fleet as a result of uncertainties in GPS data and filtering procedure we carried out for the raw data as described in the Materials and Methods section. Bottom row: average waiting times (E) and ratio of trips served under $t_w = 5\,\text{min}$ waiting time (F) in the online model.

area, nor is the demand. Furthermore, we have to account for the vehicles engaged in serving trips or relocating beside N_I. Empirically, we find a lower exponent of about 0.87 when we consider fleet sizes necessary to serve at least 50% of trips with a maximum of 5 min waiting time (see Figure S3 in the Supplementary Material). We note that this relationship will likely be influenced by the overall density of trips, since as total demand grows, the size of the "stand-by" fleet, N_I will constitute a decreasing fraction of total fleet size.

3.3 Effects of upgrading infrastructure

Our analysis so far outlines that the v_R average relocation speed plays a crucial role in the viability of an SRSPMD service, especially in the online model. To further characterize the benefits from upgrading path infrastructure, we repeat our previous analyses in a presumed "two-tiered" infrastructure system: in this case, we have separate paths upgraded specifically for PMD, SRSPMD and potentially bicycle use, allowing high average relocation speed of $v_R^* = 15\,\mathrm{km/h}$. The ratio of such paths among all is controlled by the parameter $r \in \{0.05, 0.1, 0.2, 0.25, 0.5\}$. On the rest of the path network, we assume the same travel speeds as previously, namely, $v_R = 1\,\mathrm{km/h}$, $2.5\,\mathrm{km/h}$, $5\,\mathrm{km/h}$ or $10\,\mathrm{km/h}$. We exploit the fact that usage of paths in the system is not uniform: some path segments see significantly higher usage than others (see SI Fig. S4), similarly to what was observed regarding taxi trips previously [53]. Thus, we envision path upgrades starting with the most used segments, continuing by decreasing usage rank until a total of r fraction of path length is reached. While a more complex approach would naturally consider other constraints as well [50, 51], we perform a simpler choice of path segments to upgrade based only on activity to gain a better understanding of the underlying fundamental relationship between path infrastructure and fleet utilization.

We display results for average vehicle utilization using the two-tier infrastructure in Fig. 2. We see that significant improvements in utilization are possible for relatively minor upgrades in infrastructure. These increases in average vehicle utilization correspond to decrease in total fleet size; more detailed results are displayed in Figs. S5–S10 in the Supplementary Material.

3.4 Scaling of utilization with demand

Our main analysis was carried out using data from a bikeshare operator as an estimate of the demand for short trips, but is in itself limited by the usage patterns and market share of the operator. To overcome this limitation, we performed an additional analysis in which we sampled trips made by bus passengers in Toa Payoh, a dense residential neighborhood of Singapore (see map of study area in Fig. S2 in the Supplementary Material).

We display results in Fig. 3 as average daily vehicle utilization as a function of the number of daily trips. We see that initially there is a strong dependence between these. However, as the number of daily trips grows, vehicle utilization seems to saturate: above 5,000 trips per day, there are only marginal benefits of more trips. In Fig. S2 in the Supplementary Material, we show that below this saturation, average utilization of vehicles can be well modeled to grow logarithmically with the number of daily trips. Comparing these results with our results for the bikeshare data shown in Fig. 1, we see that there is a moderate room for improvement if higher usage rates are achieved; e.g. in our "best case" scenario (with $v_R = 10\,\mathrm{km/h}$), the average utilization of vehicles can be increased from between 20 to 25 to slightly above 30 trips per day.

We see in Fig. 3 that in the case of the oracle model, results based on the bikeshare data (constrained to trips happening in the Toa Payoh region in this case, between 600 and 800 trips per day in total) and the bus usage data fit together well, thus we can regard the results from the bus trip data as a meaningful extrapolation. Conversely, we find that there is no such correspondence in the case of the online model; there, results based on bikeshare data show much higher vehicle utilization than results based on bus trips. One possible explanation for this is that the bikeshare trips are already biased by the availability of vehicles, since we have no data on lost demand. This highlights the difficulties likely encountered by an operator that aims to provide reliable service, i.e. with a low level of lost demand.

4 Discussion

We note that there is a clear cost component of SRSPMDs, i.e. the extra hardware and software needed to enable autonomy. We estimate the average cost of conventional electric scooters approved by the Land Transport Authority of Singapore as 566 SGD [54] and the cost of an autonomous version to be about thrice as much, i.e. around 1,500 SGD (including the cost for a short range LIDAR and an on-board computer). This implies that considering the static cost of deploying a fleet, using SRSPMDs instead of conventional scooters will be financially reasonable if self-relocation capabilities allow the fleet size to be reduced to one third or less. While this is clearly the case for the solutions of the oracle model, focusing on the online model, we see that a fleet size of 5,000 could potentially provide reasonable service if an average relocation speed of $v_R = 5\,\mathrm{km/h}$ or higher is achieved, at a comparable cost of deploying a fleet of over 15,000 conventional scooters, or the equivalent of the active fleet size in the bikesharing system studied (see Fig. S11 in the Supplementary Material for a more detailed analysis of capital costs). We note that beyond capital costs, further factors will include extra liability insurance and maintenance requirements for the SRSPMDs, while at the same time, significant savings can be realized due to eliminating the manpower needs for fleet rebalancing. Both conventional and autonomous scooters are expected to incur similar costs for battery charging or swapping; at the same time, automated solutions for charging could realize further savings for operators.

While our results show that self-repositioning shared per-

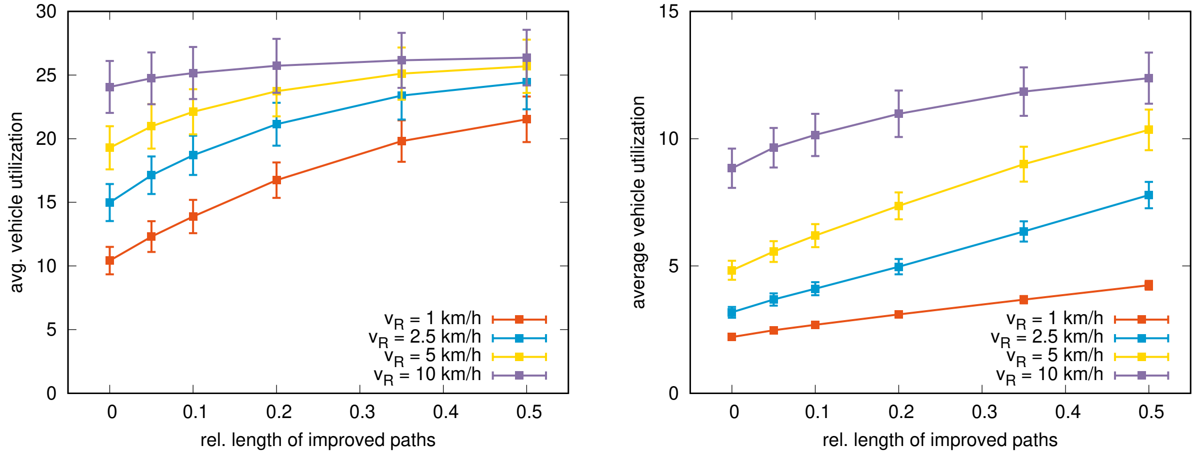

Figure 2: Average utilization of SRSPMD fleet in the oracle model (left) and online model (right) after improving a given relative length of paths, compared to the original utilization at a given relocation speed v_R. It is assumed that vehicles can travel at an average speed of $v_R^* = 15\,\text{km/h}$ on upgraded path segment and with v_R on original path segments. Results are averaged over the 7 days of data; separate results for each day are shown in the Supplementary Material.

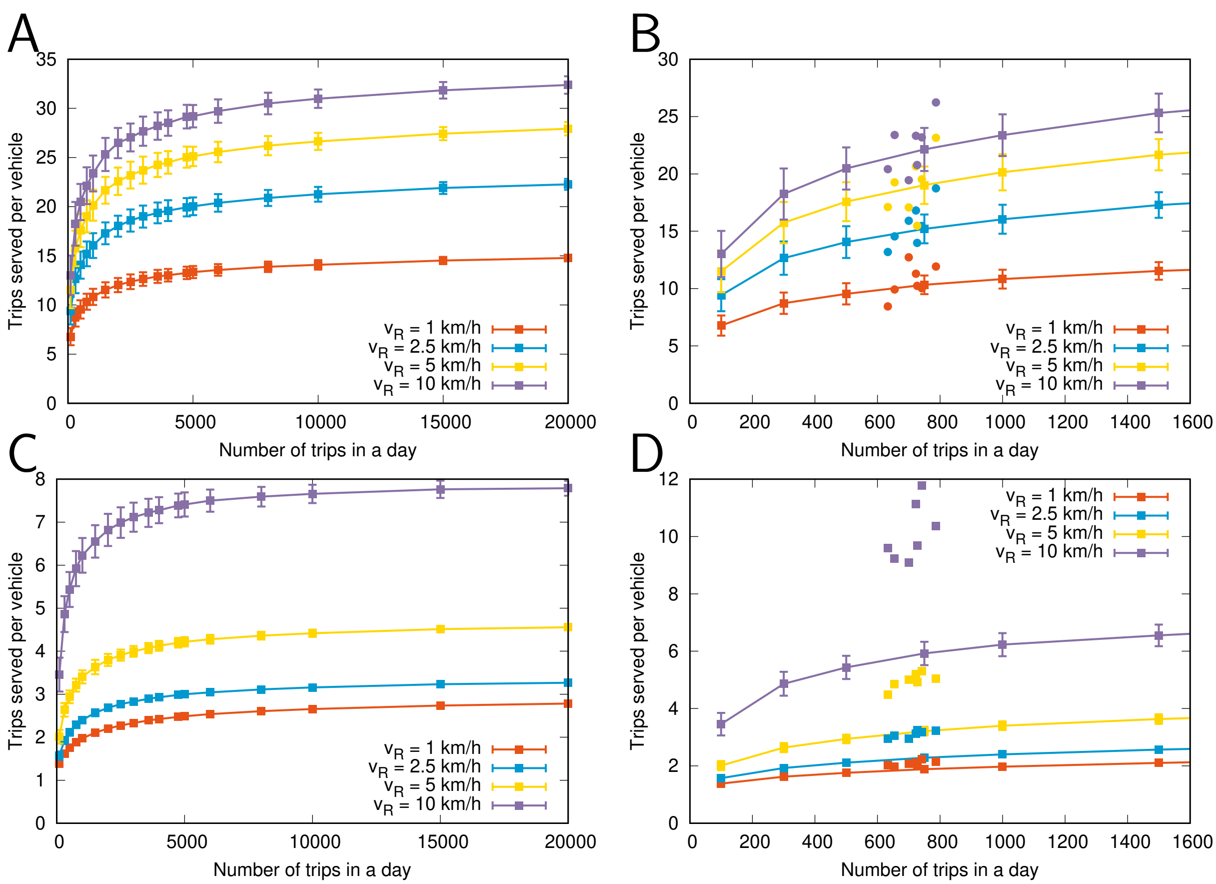

Figure 3: Average fleet utilization as the function of the number of daily trips in Toa Payoh, with trips generated based on bus usage data. Top row shows results in the oracle model, while bottom row shows results for the online model, with $t_w = 5\,\text{min}$ maximum wait time. Left panels (A and C) show results for a wide range of daily activity values. Right panel (B and D) show results for relatively small number of daily trips. In these figures, dots show results calculated based on the bikeshare dataset, limited to trips happening in the Toa Payoh area. These show good agreement with results based on bus trips data in the oracle model (B), while there is a significant difference in for the online model (D).

sonal mobility devices (SRSPMDs) offer a promising transportation concept for short trips and first- and last-mile segments of longer trips, there are several challenges for adoption. We have seen that a crucial parameter is v_R, the average speed SRSPMDs are able to achieve when repositioning themselves. While we used v_R as a parameter in our models, in reality it will be determined by the ability of the vehicles to navigate in a complex environment. This way, operations can be severely affected if SRSPMDs have to share narrow sidewalks with pedestrians [47, 48, 51, 49].

In the current work, we mainly focused on the operational efficiency aspects of the average relocation speed and the main reason for the need for upgraded paths was to allow vehicles to travel faster. At the same time, more infrastructure will be also needed to avoid conflicts among pedestrians, SRSPMDs, and cyclists. An important future direction needs to assess interactions between SRSPMDs, pedestrians, other PMD users, cyclists and even traditional and autonomous cars to determine the best road, sidewalk and path design to achieve this goal, while allowing ideal flow of people and efficient relocation of SRSPMDs. This will require extending the limited research on cyclist behavior and maneuvering [55, 56] for the case of human-driven and self-repositioning scooters. Well-designed sidewalks and PMD paths will be essential for for SRSPMDs to gain acceptance.

Further research should consider the full sustainability benefits of SRSPMDs, including lifecycyle energy use under different scenarios of usage patterns and integration with public transit services [19]. We believe the main potential for positive change is solving the first- and last-mile transportation problem. SRSPMDs can effectively increase the catchment area of rapid transit stations [57], and relieve buses and road capacity from short trips. Increased convenience can help transit remain a competitive choice for travel; this is especially important when autonomous cars are expected to offer cheap point-to-point transportation to captive transit users as well [17, 20]. At the same time, SRSPMDs pose an attractive alternative to short trips that are currently made by active modes (i.e. walking or cycling) or transit, implying a potentially disruptive change for local bus service operations and highlighting the need a for a more rigorous study considering the net sustainability effects of SRSPMDs.

Looking beyond, we believe that deployment of SRSPMDs and the implied infrastructure needs should be studied together with the opportunities offered by the three main technological advances in transportation, i.e. connected devices, electric mobility, and autonomy. The combination of these offers us the opportunity to rethink the design of transportation infrastructure in cities, a change that can be compared to the effect that the internal combustion engine and electric rail transit had on cities more than a hundred years ago. Competition between private cars and mass transit could be transformed into the management of a more fluid landscape of shared, connected, electric and autonomous transportation solutions of various form factors and operational models. The transportation network infrastructure shall evolve to support the above landscape to provide convenient, accessible and green transportation in dense new megacities as well as in sprawling suburban areas inherited from the 20th century.

Acknowledgements

This research is supported by the Singapore Ministry of National Development and the National Research Foundation, Prime Minister's Office, under the Singapore-MIT Alliance for Research and Technology (SMART) programme.

We thank Allianz, Amsterdam Institute for Advanced Metropolitan Solutions, Brose, Cisco, Ericsson, Fraunhofer Institute, Liberty Mutual Institute, Kuwait–MIT Center for Natural Resources and the Environment, Shenzhen, UBER, Victoria State Government, Volkswagen Group America, and all of the members of the MIT Senseable City Laboratory Consortium for supporting this research.

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Supplementary Material

day	avg. trips / vehicle					
	shared bikes		SRSPMDs			
	current	ideal	1 km/h	2.5 km/h	5 km/h	10 km/h
Monday	2.30	2.84	8.80	12.62	16.43	20.69
Tuesday	2.44	3.05	9.69	14.05	18.21	23.08
Wednesday	2.48	3.09	10.48	15.34	20.00	25.30
Thursday	2.48	3.07	10.20	14.85	19.19	23.67
Friday	2.37	2.96	10.34	14.90	19.54	24.61
Saturday	2.75	3.55	12.12	17.32	21.98	27.32
Sunday	2.63	3.39	11.34	15.77	19.62	23.80

Table S1: Main results for average vehicle utilization (trips / vehicle).

day	trips	fleet size							
		shared bikes			SRSPMDs				maximum
		available	used	ideal	1 km/h	2.5 km/h	5 km/h	10 km/h	utilization
Monday	31058	35350	13512	10944	3531	2461	1890	1501	800
Tuesday	38030	35535	15556	12488	3926	2706	2088	1648	859
Wednesday	39645	37642	15984	12828	3784	2584	1982	1567	876
Thursday	39537	37885	15929	12878	3878	2663	2060	1670	966
Friday	37143	38229	15702	12560	3592	2492	1901	1509	878
Saturday	48747	38128	17743	13729	4021	2814	2218	1784	1083
Sunday	44666	38150	16956	13192	3938	2832	2277	1877	1110

Table S2: Main results for fleet size. Fleet sizes for SRSPMDs with different assumed average relocation speed are compared to current fleet size of shared bikes, minimum achievable fleet size of shared bikes with users willing to walk up to 100 m, and to the fleet size corresponding to the maximum number of bikes simultaneously in use each day.

day	avg. time used / vehicle [min]					
	shared bikes		SRSPMDs			
	current	ideal	1 km/h	2.5 km/h	5 km/h	10 km/h
Monday	23.21	28.66	88.83	127.45	165.95	208.96
Tuesday	24.09	30.01	95.47	138.51	179.50	227.43
Wednesday	24.37	30.36	102.92	150.72	196.49	248.53
Thursday	24.80	30.68	101.88	148.36	191.79	236.58
Friday	23.76	29.71	103.88	149.73	196.28	247.27
Saturday	32.40	41.88	142.98	204.31	259.21	322.27
Sunday	29.40	37.78	126.58	176.01	218.91	265.56

Table S3: Main results for average vehicle utilization (time used / vehicle).

day	total distance traveled [km]				
	original	connecting trips			
	trips	1 km/h	2.5 km/h	5 km/h	10 km/h
Monday	26171	7527	10064	12524	15270
Tuesday	31971	9653	13057	15718	18759
Wednesday	33219	10111	13683	16739	20281
Thursday	32780	9846	13207	16176	19188
Friday	31473	10318	13491	16617	19962
Saturday	42806	12225	16110	19522	23555
Sunday	38530	11123	14175	16477	19231

Table S4: Total distance traveled by users during the original trips and by SRSPMDs during connecting trips with different assumed relocation speed. We see that the distance traveled by the vehicles without a user (in connecting trips) can exceed 50% of the distance traveled with a user.

day	avg. distance traveled / vehicle [km]				
	original fleet	SRSPMD fleet			
		1 km/h	2.5 km/h	5 km/h	10 km/h
Monday	1.94	9.54	14.72	20.47	27.61
Tuesday	2.06	10.60	16.64	22.84	30.78
Wednesday	2.08	11.45	18.15	25.21	34.14
Thursday	2.06	10.99	17.27	23.77	31.12
Friday	2.00	11.63	18.04	25.30	34.09
Saturday	2.41	13.69	20.94	28.10	37.20
Sunday	2.27	12.61	18.61	24.16	30.77

Table S5: Average distance traveled by each vehicle in the fleet.

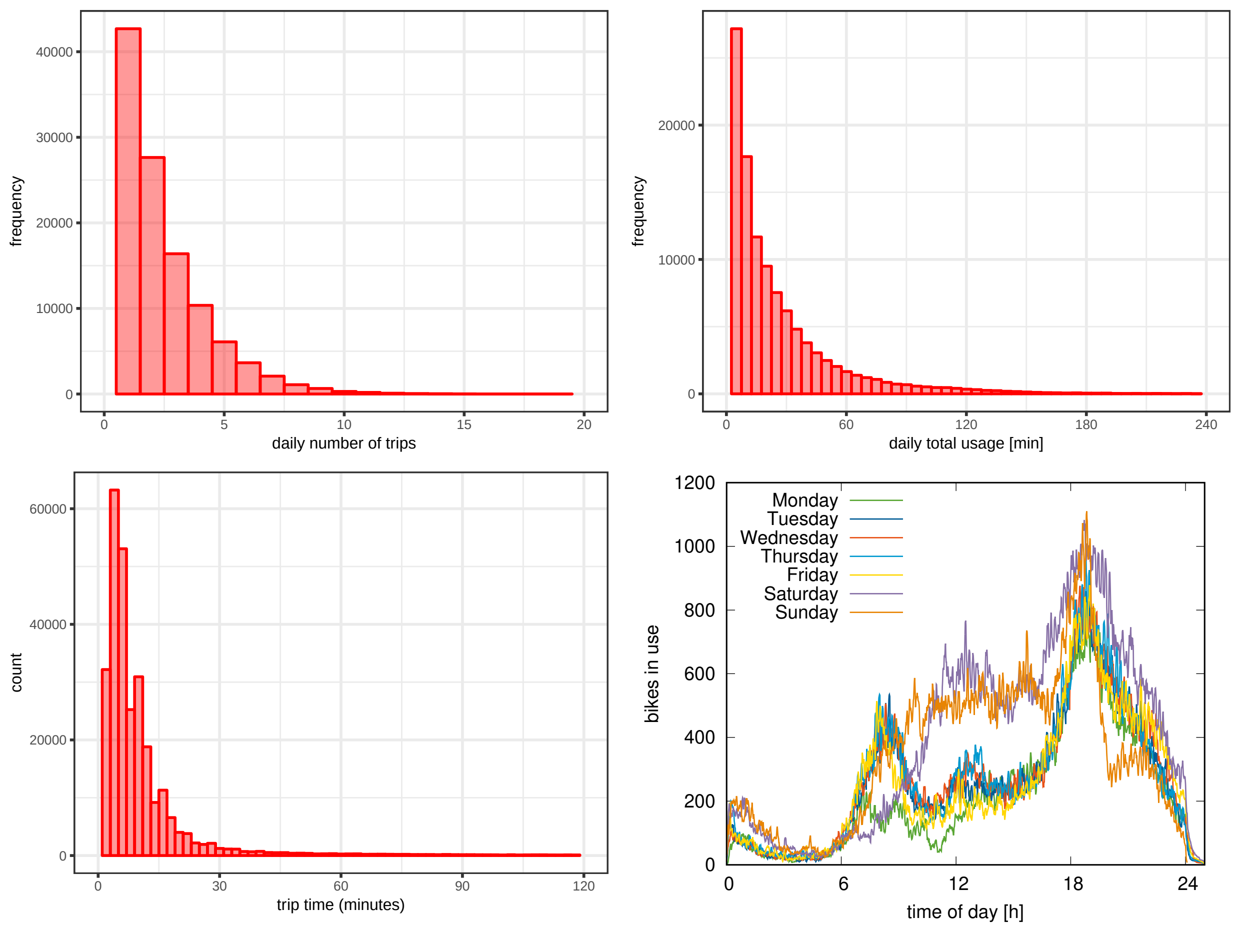

Figure S1: Basic statistics of bike usage. Top left: distribution of the number of daily trips per bike. Only active bikes (i.e. having at least one trip that day) are considered. Most bikes are used only a few times. Top right: distribution of total time bikes are used during the day. Bottom left: distribution of trip durations. We see that most trips are shorter than 30 minutes. Bottom right: number of bikes simultaneously in use during the day (i.e. number of trips happening simultaneously). We see that usage is highest during the evening. Also, weekdays and weekend have a distinctive pattern, with morning and evening peaks being dominant for weekdays, and a more even usage during the day for weekends.

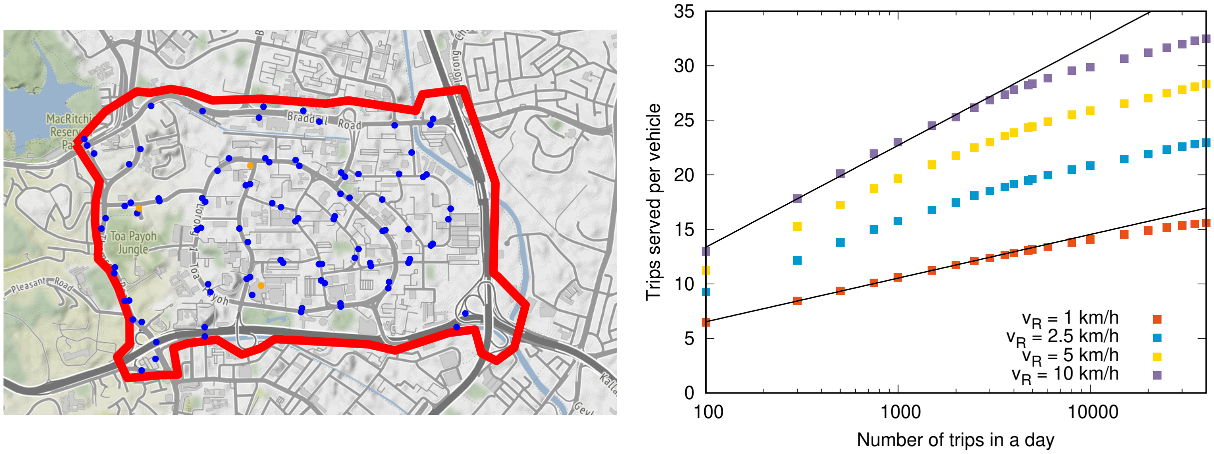

Figure S2: Left: Study area for bustrip data. Bus trips within the area marked by the red border are used in our analysis. Blue dots represent bus stops considered in this study, while the orange dots are the three MRT stations in this area (Toa Payoh and Braddel on the North-South Line and Caldecott on the Circle Line). Note thtat we excluded three bus stops on the north side of Braddel Road (the northern border of the study area) as it is unclear if crossing the road from there would be possible for SRSPMDs. Right: daily average utilization of SRSPMDs as a function of daily number of trips with a logarithmic x-axis. We see that vehicle utilization can be well modeled to grow logarithmically as a function of the daily number of trips until about 5000 trips / day, when a saturation effect becomes significant. The black lines are fits of logarithmic growth for the $v_R = 1\,\mathrm{km/h}$ and $v_R = 10\,\mathrm{km/h}$ cases.

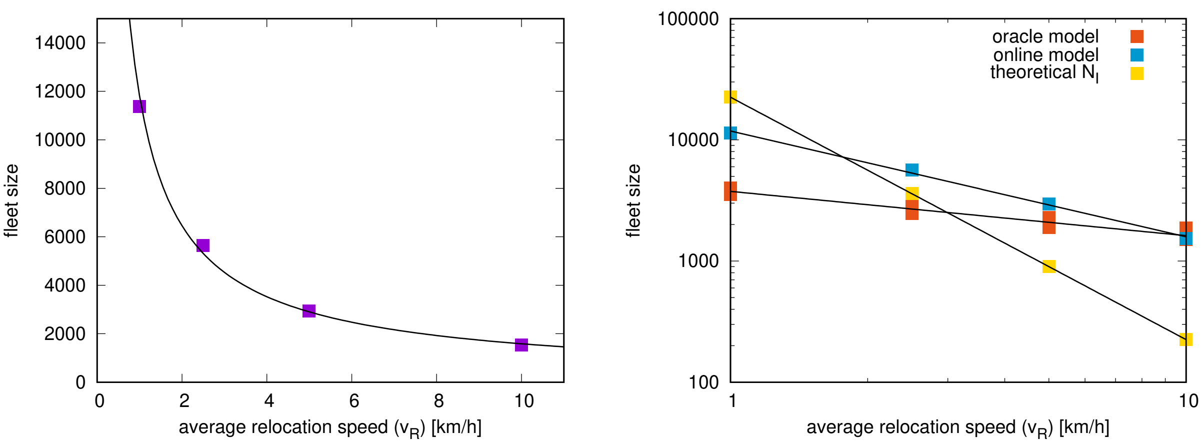

Figure S3: Estimating the relationship between average relocation speed and fleet size. Left: number of vehicles needed to serve at least 50% of trips with up to 5 min waiting time in the online model. The 50% threshold was chosen to obtain a robust estimation of fleet size scaling with vehicle speed. The fitted power-law function has an exponent of -0.872. Right: comparison of scaling in the online model with the oracle model and the simple estimate of N_I vehicles covering all of the service area. The exponents are -0.365 (oracle model), -0.872 (online model) and -2 (N_I estimate). For low relocation speeds, the concern for availability of vehicles (represented by N_I) is dominant. Real fleet sizes are smaller: in the oracle model, relocation decisions are made in advance, thus positioning vehicles close to demand is less important; in the case of the online model, we only require 50% of trips to be served within 5 min waiting time, thus a smaller fleet is effective. For larger relocation speeds ($v_R \geq 5\,\mathrm{km/h}$), N_I quickly becomes very small compared to the fleet size determined by the vehicles performing trips or engaged in relocation movements.

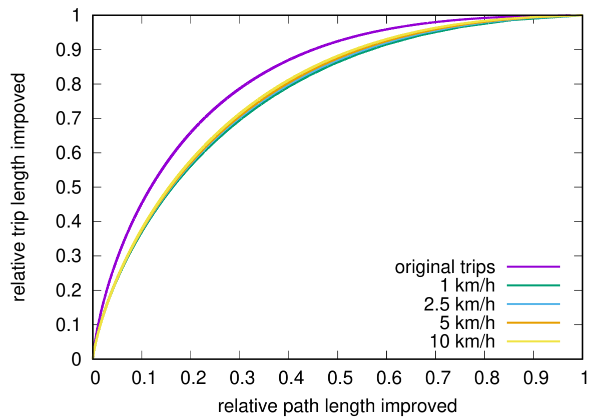

Figure S4: Quantifying the benefits of improving paths. We display the ratio of cumulative travel on improved paths as a function of the ratio of total path length upgraded. We see that small improvements in the path network will affect relatively large share of total distance traveled, e.g. upgrading 26.2% of total length of the path network (approximately 1,500 km of paths) will improve 73.8% of all trips by distance (approximately 175,000 km travel by bike users in one week). Results are shown separately for the original and relocation trips.

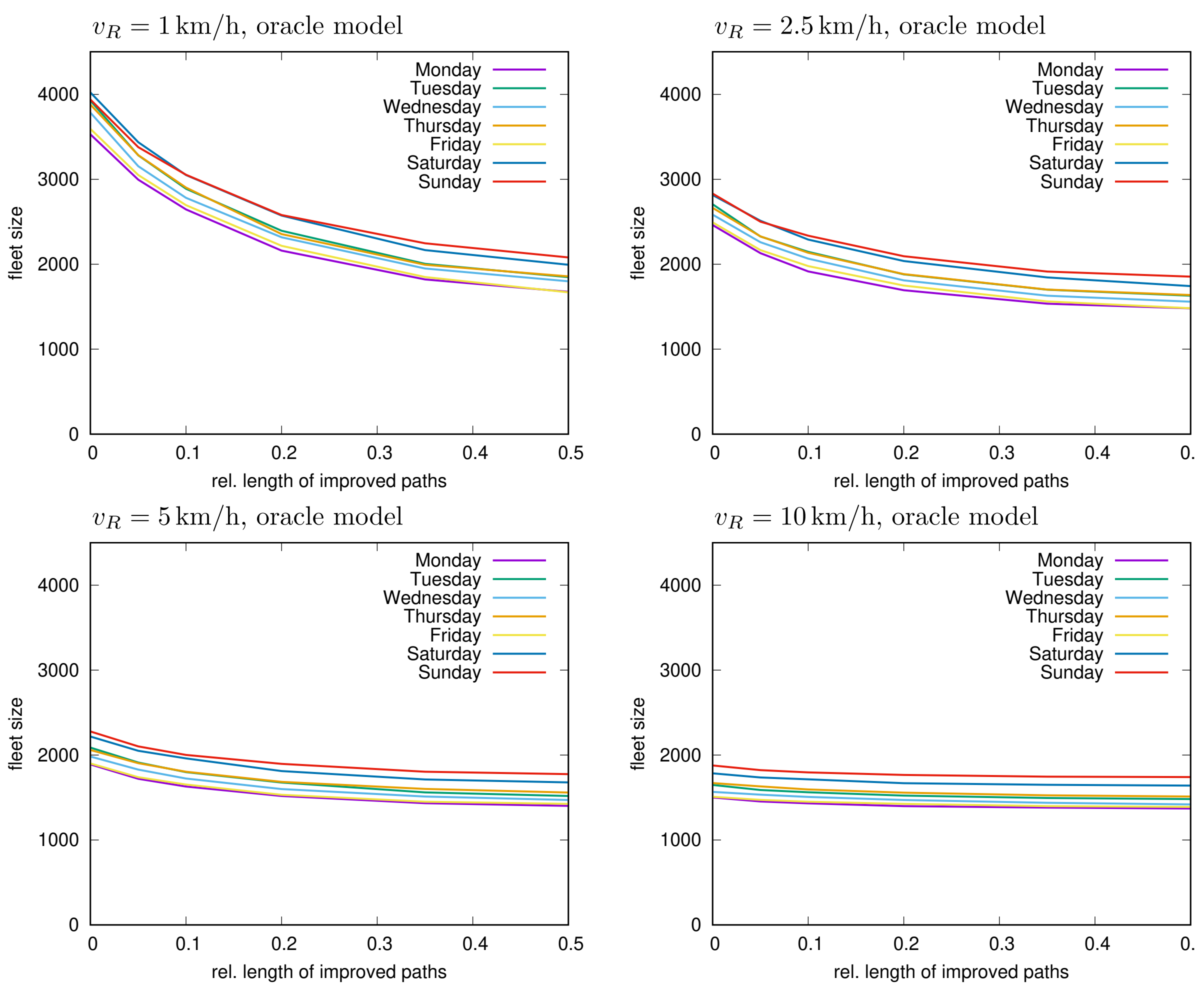

Figure S5: Reductions in fleet size in the oracle model due to upgrading parts of the path network with original $v_R = 1$ km/h (top left), $v_R = 2.5$ km/h (top right), $v_R = 5$ km/h (bottom left) and $v_R = 10$ km/h (bottom right).

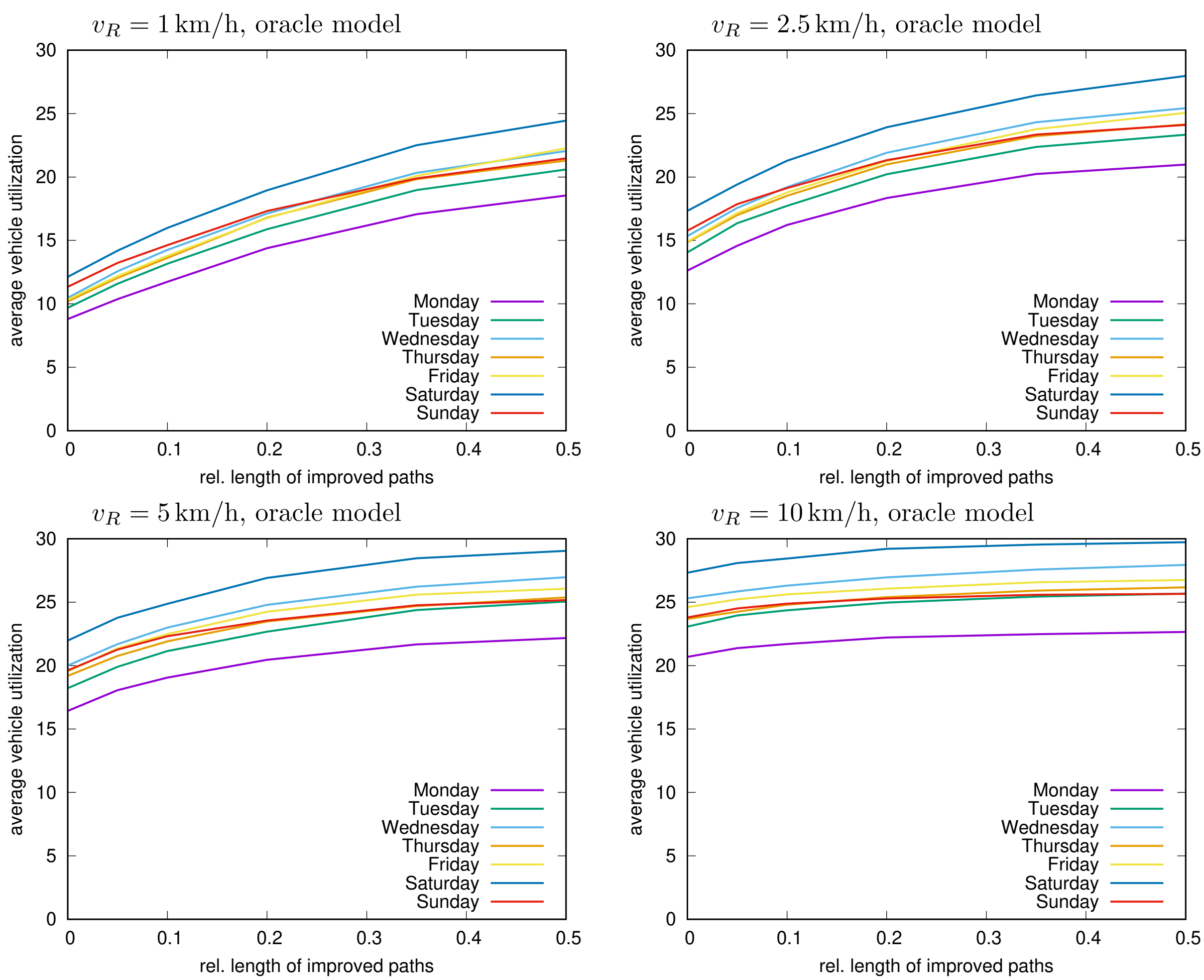

Figure S6: Increase in average fleet utilization in the oracle model due to upgrading parts of the path network with original $v_R = 1\,\mathrm{km/h}$ (top left), $v_R = 2.5\,\mathrm{km/h}$ (top right), $v_R = 5\,\mathrm{km/h}$ (bottom left) and $v_R = 10\,\mathrm{km/h}$ (bottom right).

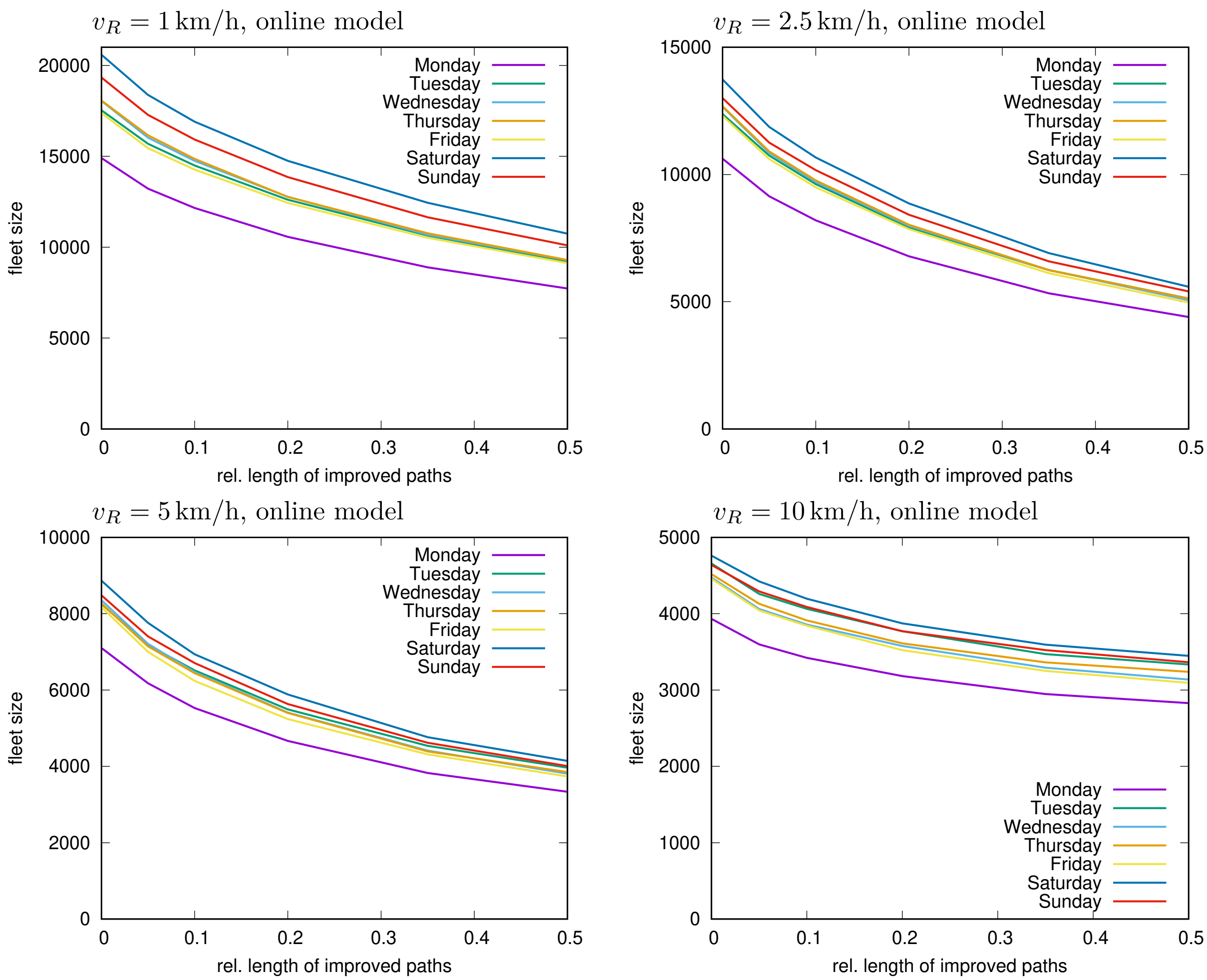

Figure S7: Reductions in fleet size in the online model due to upgrading parts of the path network with original $v_R = 1\,\mathrm{km/h}$ (top left), $v_R = 2.5\,\mathrm{km/h}$ (top right), $v_R = 5\,\mathrm{km/h}$ (bottom left) and $v_R = 10\,\mathrm{km/h}$ (bottom right).

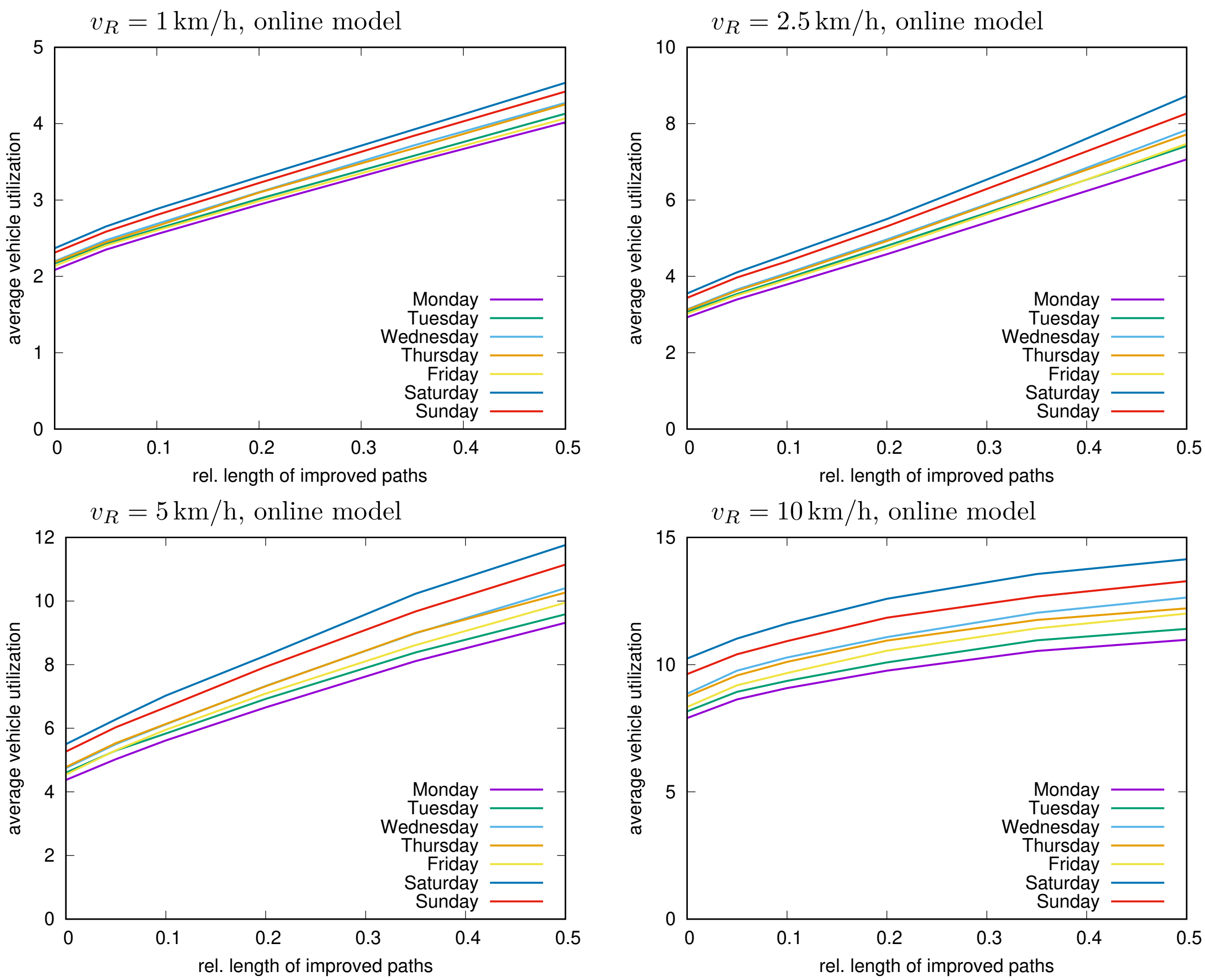

Figure S8: Increase in average fleet utilization in the online model due to upgrading parts of the path network with original $v_R = 1\,\mathrm{km/h}$ (top left), $v_R = 2.5\,\mathrm{km/h}$ (top right), $v_R = 5\,\mathrm{km/h}$ (bottom left) and $v_R = 10\,\mathrm{km/h}$ (bottom right).

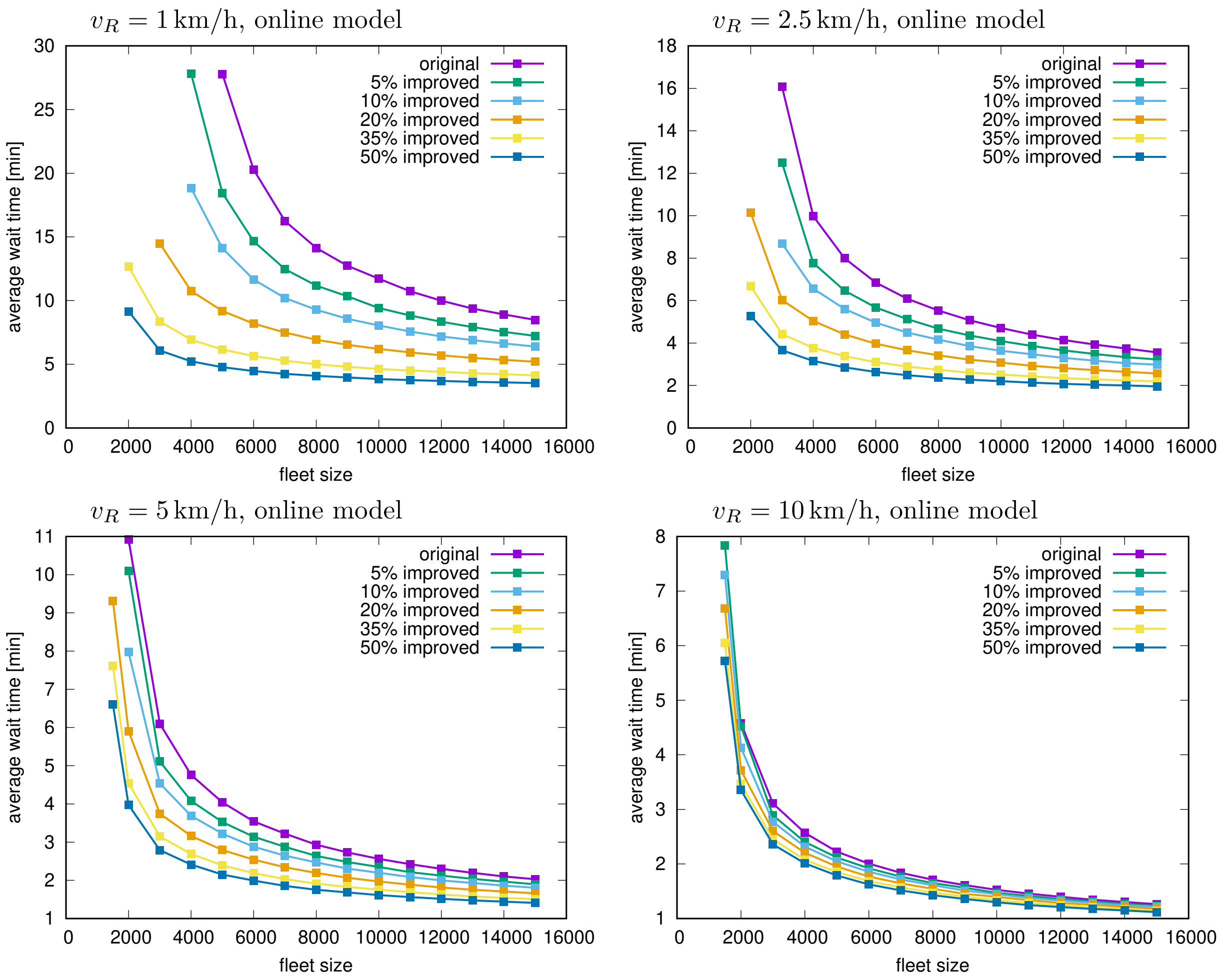

Figure S9: Average waiting times in the online model and improvements due to infrastructure upgrades for original travel speed $v_R = 1\,\mathrm{km/h}$ (top left), $v_R = 2.5\,\mathrm{km/h}$ (top right), $v_R = 5\,\mathrm{km/h}$ (bottom left) and $v_R = 10\,\mathrm{km/h}$ (bottom right).

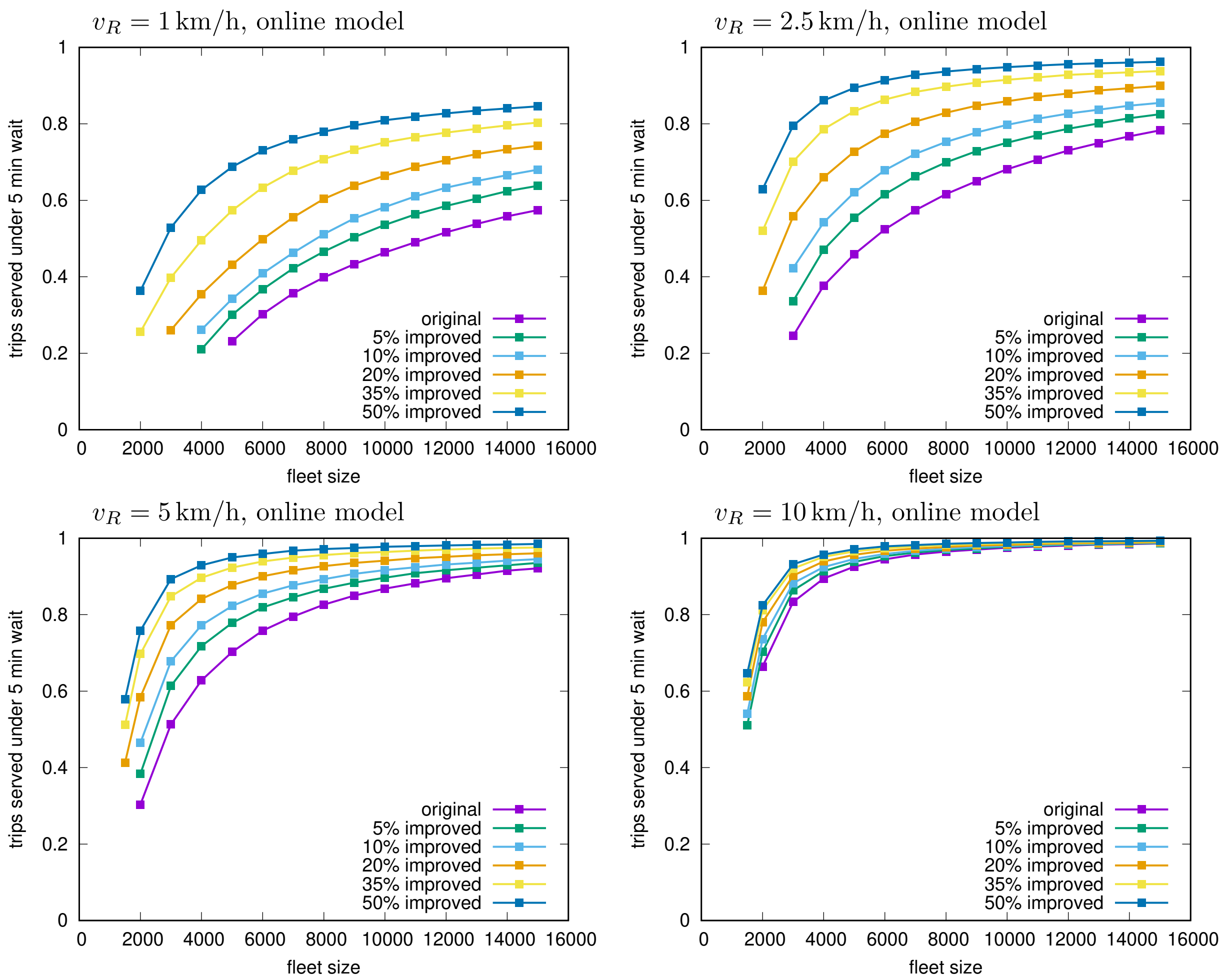

Figure S10: Ratio of trips served within $t_w = 5\,$minutes waiting time in the online model and improvements due to infrastructure upgrades as a function of fleet size for $v_R = 1\,\text{km/h}$ (top left), $v_R = 2.5\,\text{km/h}$ (top right), $v_R = 5\,\text{km/h}$ (bottom left) and $v_R = 10\,\text{km/h}$ (bottom right).

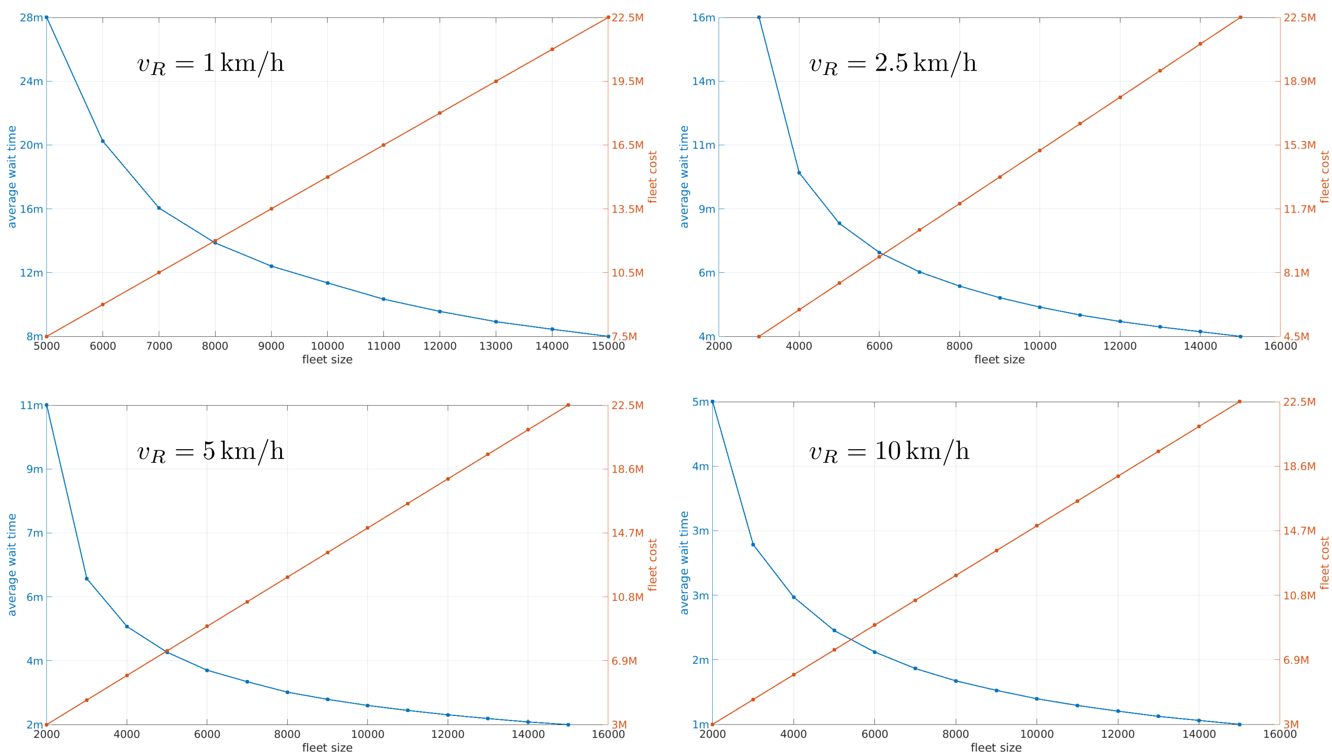

Figure S11: Comparison of user waiting times (blue, left y-axis) and fleet deployment cost (red, right y-axis, in SGD) in the online model for the four values of v_R considered in our analysis. We note that the estimated cost of deploying non-autonomous vehicles corresponding to the average number of bikes in use (15,912 over one week) is approximately 9M SGD.