Estimating the potential for shared autonomous scooters

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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, 4], car-sharing [5, 6] and bike-sharing [7, 8, 9]. 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 [10, 11]. Lastly, rapid advances in autonomous driving can result in profound changes in urban mobility [12, 13, 14, 15, 16, 17]; 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 [18, 19, 20]. Similarly, there are concerns that the benefits of autonomous cars will be mitigated by increased volume of trips [21, 22]. 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 [23, 24, 25, 26, 27].

A central issue in transportation that has been elusive in the past over hundred years is providing first- and last-mile transportation so that commuters can reach high-capacity core transit nodes in a convenient and efficient manner. Despite research suggesting that ride-hailing can serve this role [18, 28], there are concerns whether this function can work in a scalable and affordable manner [28, 19]. In future-looking scenarios, shared autonomous vehicles (SAVs) are envisioned to provide first- and last-mile transportation in a more cost effective way [29, 23, 24, 25]. Nevertheless, other form factors beside full-size cars should be considered to further reduce costs, congestion and energy use. Recently, shared bicycles and scooters¹ have been de-

¹In 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.
ployed in many cities to provide a sustainable transportation mode for short trips [30, 31, 32, 8, 9, 33]. 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 [7, 34, 35, 36].

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, but allows to keep 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 [37, 38, 39, 40, 41, 42]: 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 [43]. With the recent popularity of bikeshare operations, there has been a significant amount of research on understanding usage patterns [30, 31, 8, 9, 33], optimizing fleet rebalancing [34, 7, 35] or determining optimal fleet size [44, 45, 46, 47]. It is yet unclear how these results would apply to an SRSPMD operator, or how to quantify the benefits of self-relocation capabilities.

In this paper, we perform an evaluation of the benefits of SRSPMDs under the rigorous theoretical framework of shareability networks [3, 48] using real-world data of shared bicycle usage in Singapore as our basis [8]. 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 worst case scenario obtained under a simple simulation of fleet management without proactive rebalancing. This way, we provide upper and lower 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.

We use data collected from the public interface of an operator over the course of one week in September 2017 [8]; after preprocessing and filtering out inconsistent and erroneous records, we have a total of 278,826 trips made by 32,782 unique bikes over the course of the week. In the following, we require all of the trips in this dataset to be served by SRSPMDs.

To calculate lower and upper bounds on fleet size, we use two approaches that differ in the amount of information available to the operator about trip requests in advance. We calculate a lower bound in an oracle model, where we assume that all trips in a day are known in advance. In this case, we can calculate a theoretically established minimum fleet size along with an ideal dispatching strategy by adopting the shareability network methodology of Vazifeh et al. [48] (see Methods section). We also calculate an upper bound on fleet size in an online model, where we assume that the operator has no advance knowledge or intelligence on the trip requests and performs only reactive repositioning movement of vehicles. In this case, trips are processed in $t_b = 1\text{ min}$ batches, and vehicles are assigned to trips in each batch based on a maximum weighted matching that minimizes total waiting times for passengers.

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 [7]. 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 [49, 50], 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 [34, 35], however, such strategic methods are demand and scenario dependent and thus not addressed in this work.

Both methods for estimating fleet size rely on estimating when a vehicle can reach a trip request. We extracted the network of sidewalks and cycle paths in Singapore from OpenStreetMap [51] 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 [52]. This way, we are able to incorporate different assumptions on the infrastructure available to SRSPMDs by varying this parameter. We use low values of $v_R = 1\text{ km/h}$ and $2.5\text{ km/h}$ 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 [52]. We further perform our analysis with higher $v_R$ values of $5\text{ km/h}$ and $10\text{ km/h}$ that represent scenarios where SRSPMDs can perform an increasing share of their relocation trips on a path infrastructure separated from pedestrians [53].

## 2 Results

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 vehi-
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 bike-share 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 $t_w = 5$ min waiting time (F) in the online model.
cycles for $v_R = 1 \text{ km/h}$, to between 1,500 and 2,000 for $v_R = 10 \text{ km/h}$. These present 4 to 10 times reduction 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.

To better estimate the benefits and limits of self-relocation, we perform two comparisons in the oracle model. Firstly, we estimate an ideal fleet size without autonomy. We do this by assuming stationary vehicles and the willingness to walk up to $d_{walk} = 100 \text{ m}$ 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.

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 $t_w = 5 \text{ min}$, similarly to the methodology used to estimated SAV fleet sizes previously [16, 17, 54]. 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 ($v_R = 10 \text{ km/h}$). 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 $t_w = 5 \text{ min}$. 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 $v_R = 10 \text{ km/h}$, we have average waiting time of 2.2 min and 92.6% of trips 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 $v_R = 1 \text{ km/h}$ and $t_w = 5 \text{ min}$, 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 m circle around every trip start location in the dataset and merging the area of these, we obtain an estimate of 312 km$^2$ as the service area of the dockless bike share operator in Singapore. For $v_R = 1 \text{ km/h}$, 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 $t_w = 5 \text{ min}$. Obviously, $N_I \sim v_R^2$, thus larger relocation speeds allow much smaller number of vehicles to cover the service area: with $v_R = 2.5 \text{ km/h}$ we already only need 3,594 such vehicles, for $v_R = 5 \text{ km/h}$ we need 809 vehicles and for $v_R = 10 \text{ km/h}$ we need 225 vehicles. In reality, available vehicles are not evenly distributed in the service 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 S1 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.

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 $v_R = 15 \text{ km/h}$. 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, $v_R = 1 \text{ km/h}$, $2.5 \text{ km/h}$, $5 \text{ km/h}$ or $10 \text{ km/h}$. We exploit the fact that usage of paths in the system is not uniform: some path segments see significantly higher usage than others, similarly to what was observed regarding taxi trips previously [55]. 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. We display this non-uniform behavior in Fig. 2, by showing 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).

We then display results for average vehicle utilization using the two-tier infrastructure in Fig. 3. 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. S2–S7 in the Supplementary Material.

Finally, we note that there is clear cost of SRSPMDs, i.e. the extra components needed to enable autonomy. We
estimate the average cost of electric scooters approved by the Land Transport Authority of Singapore as 566 SGD [56]. For automating the platform, we consider an additional cost for a short range LIDAR sensor and an on-board computer which together levels up the cost of autonomous scooter to approximately 1,500 SGD, i.e. thrice the cost of a conventional scooter. This implies that deploying SRSPMDs instead of conventional electric scooters will become financially reasonable if self-relocation capabilities allow the fleet size to be reduced to one third or less. 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 \( v_R = 5 \text{ km/h} \) or higher is achieved; in this case, the investment cost for deploying the fleet would be 7.5M SGD, already below the cost of approximately 9M SGD of deploying 15,912 conventional scooters, a number corresponding to the average number of bikes in use in our dataset per day. Notice that operational costs will favor SRSPMDs more since fleet rebalancing can be achieved without additional expenses on manpower and vehicles used, while we expect that charging infrastructure requirements will be similar, thus we do not consider this as a separate factor. We display a more detailed analysis of the trade-off between average wait time for users and capital costs of fleet deployment in Fig. S8 in the Supplementary Material.

3 Discussion

While our results show that self-repositioning shared personal 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 [52].

While an SRSPMD service can potentially be financially viable by concentrating in areas of high demand, we believe to help positively transform cities, it needs to offer highly reliable service, providing strong guarantees that a vehicle will be available anywhere in a broad service area within a short wait time whenever a user requests it. This way, SRSPMDs could become a primary choice of transportation for first- and last-mile travel and short trips instead of being only considered as an auxiliary mode. This could imply effectively increasing the catchment area of rapid transit stations [57], relieving buses and road capacity from short trips, facilitating a more efficient transportation system, and transforming neighborhoods away from being centered on the necessities of car traffic. To achieve these goals allowed by a truly reliable service, high \( v_R \) relocation speeds and thus improved path and road infrastructure will be necessary.

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 be essential for SRSPMDs to gain acceptance.

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. Nowadays competition between private cars and mass transit shall 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.

4 Materials and Methods

4.1 Data

Our dataset covers one week of bicycle locations of one of the largest dockless bike-share operators in Singapore, between 2017.09.11. and 2017.09.17; data collection and preprocessing procedures were presented in more detail in Refs. [8, 9]. 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 a one week period in our dataset. We show basic statistics of trips and bike usage in our dataset in Fig. S9 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, finding the shortest path for each trip and assuming it is the route taken. Currently, it is only allowed to use PMDs on sidewalks and cycle paths in Singapore; their use on roads is forbidden. It is uncertain what regulations will apply to SRSPMDs, thus we apply the same restrictions. We consider any future upgrades to be parallel to current segments in this network as well. After assigning shortest paths to each trip, we calculate average travel speeds and filter out trips that have an average speed above 30 km/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 278,826 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 S2) and on average, each bike is used for 26.2 minutes each day (see SI Fig. S9). 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.

4.2 Oracle model for estimating minimum fleet size

We use the methodology of shareability networks [48] to estimate a theoretical minimum for the fleet size. While shareability networks were originally proposed to estimate minimum possible size of taxi fleets, the methodology can be easily applied to this problem as well. 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). We then calculate a minimum path cover on this graph which results in an optimal dispatching strategy that serves all trips with the minimum number of vehicles. Since the graph constructed with this method is always a directed acyclic graph (edges can only point forward in time), calculating a minimum path cover can be done efficiently by converting the problem into calculating a maximum matching on a bipartite graph [48, 58].

In practice, we calculate a weighted maximum matching, where edge weights are defined as $w = D_{max} - d$ where $d$ is the distance of the connecting trip considered and $D_{max}$ is a maximum allowed connecting distance; the solutions then minimize the total distance traveled by the fleet as well. Resulting total travel distance during relocation trips is given in Tables S4 and S5 in the Supplementary Material.

To offer a better comparison with current dockless bike-share operations, we repeat the same analysis without self-repositioning capabilities. This essentially means that instead of considering vehicles that can travel to reach the starting location of their next trip, we assume that users are willing to walk up to a $d_{walk}$ maximum distance to find a suitable vehicle when starting their trip [59]. This way,
we can still construct a shareability network, with the limitation that trips are only connected if the distance between end and start locations is less than \(d_{\text{walk}}\). Solving the minimum fleet problem in this case gives an approximation of the minimum fleet size that the bike-share operator could have. In practice, we used \(d_{\text{walk}} = 100\) m, which we believe is a reasonable choice given Singapore’s warm and humid climate and the fact that trips are typically short.

4.3 Online model for estimating operational characteristics

We use a combination of greedy heuristics \([16, 17]\) and batched maximum matching in short time windows \([48]\) 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 \(t_b = 1\) 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. \(t_w = 5\) min, in line with the on-demand nature of our setting.

The proposed online model is reactive and can be further improved by using predictive demand modeling techniques to re-balance the fleet of vehicles which can drastically improve the performance. \([7, 34, 35]\). We note that the main benefit of self-repositioning capabilities is the elimination of labor costs associated with fleet rebalancing, thus we expect realistic solutions to achieve better performance at significantly reduced cost.

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## Supplementary Material

### Table S1: 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      | trips | shared bikes available | used | ideal | 1 km/h | 2.5 km/h | 5 km/h | 10 km/h | maximum utilization |
|----------|-------|------------------------|------|-------|--------|----------|--------|---------|---------------------|
| Monday   | 31058 | 35350                  | 13512| 10944 | 3531   | 2461     | 1890   | 1501    | 800                 |
| Tuesday  | 38030 | 35355                  | 1556 | 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 average vehicle utilization (trips / vehicle).

| day      | avg. trips / vehicle |
|----------|----------------------|
|          |                      |
| Monday   | 2.30                 |
| Tuesday  | 2.44                 |
| Wednesday| 2.48                 |
| Thursday | 2.48                 |
| Friday   | 2.37                 |
| Saturday | 2.75                 |
| Sunday   | 2.63                 |

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

| day      | avg. time used / vehicle [min] |
|----------|-------------------------------|
|          |                               |
| Monday   | 23.21                         |
| Tuesday  | 24.09                         |
| Wednesday| 24.37                         |
| Thursday | 24.80                         |
| Friday   | 23.76                         |
| Saturday | 32.40                         |
| Sunday   | 29.40                         |

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      | original trips | total distance traveled [km] |
|----------|----------------|-------------------------------|
|          |                | connecting 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   |

The distance traveled by the vehicles without a user (in connecting trips) can exceed 50% of the distance traveled with a user.
Table S5: Average distance traveled by each vehicle in the fleet.

| 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 |

Figure S1: 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 ($v_R \geq 5 \text{ km/h}$), $N_I$ quickly becomes very small compared to the fleet size determined by the vehicles performing trips or engaged in relocation movements.
Figure S2: Reductions in fleet size due to upgrading parts of the path network with original $v_R = 1 \text{ km/h}$ (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 S3: Increase in average fleet utilization due to upgrading parts of the path network with original $v_R = 1 \text{ km/h}$ (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 S4: Reductions in fleet size in the online model due to upgrading parts of the path network with original $v_R = 1 \text{ km/h}$ (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 S5: Increase in average fleet utilization in the online 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: Average waiting times in the online model and improvements due to infrastructure upgrades for original travel speed \( v_R = 1 \text{ km/h} \) (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 S7: 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 $v_R = 1$ 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 S8: 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.
Figure S9: 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 lengths. 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.