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# Understanding spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility

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ABSTRACT

The revolution in mobility-sharing services brings disruptive changes to the transportation landscape around the globe. The authorities often rush to regulate the services without a good knowledge of these new options. In Singapore and some other cities, dockless bike-sharing systems rose and fell in just one year and were followed by the booming of docking scooter-sharing systems. This study conducts a comparative analysis of bike-sharing and scooter-sharing activities in Singapore to help understand the phenomenon and inform policy-making. Based on the collected data (i.e., origin-destination pairs enriched with the departure and arrival time and the GPS locations) for one month, this study proposed methods to construct the paths and estimated repositioning trips and the fleet sizes. Hence, the spatio-temporal heterogeneity of the two systems in two discrete urban areas was investigated. It explored the impact of the fleet size, operational regulations (dockless versus docking), and weather conditions on the usages. We found that shared scooters have spatially compact and quantitatively denser distribution compared with shared bikes, and their high demands associate with places such as attractions, metros, and the dormitory. Results suggest that scooter sharing has a better performance than bike sharing in terms of the increased sharing frequency and decreased fleet size; however, the shareability still has potential to be improved. High repositioning rates of shared-scooters indicates high maintenance cost for rebalancing and charging. Rainfall and high temperatures at noon suppress the usages but not conclusively. The study also proposes several initiatives to promote the sustainable development of scooter-sharing services.

## 1. Introduction

Transportation has been undergoing a remarkable transformation in the past few years from planned public transit to customized individual mobility, such as ride-hailing (Vazifeh, Santi, Resta, Strogatz, & Ratti, 2018), car-sharing (Jorge & Correia, 2013; Martin, Shaheen, & Lidicker, 2010), ride-sharing (Alonso-Mora, Samaranayake, Wallar, Frazzoli, & Rus, 2017; Santi et al., 2014), and even the upcoming aircraft-sharing (Teo, 2019). However, the car-centric mindset has imprisoned us into unpleasant situations from congestion to parking shortages and pollution (Kan, Wong, & Zhu, 2020; Zhu, Wong, Guilbert, & Chan, 2017). As an alternative and refreshing approach, the first- or last-mile riding on shared-bikes (SBs) or electric shared-scooters (SSs) is increasingly becoming popular for citizens, since they allow fast and cheap short-trip in street blocks without any waiting-or-congestion caused delay (McKenzie, 2019; Shen, Zhang, & Zhao, 2018a; Wen, Chen, Nassir, & Zhao, 2018).

With the development of new techniques such as mobile payment and big-data computing, the sharing economy has penetrated the bike-sharing market with new dockless bike-rental services (Shen et al., 2018a; Shen, Zhang, & Zhao, 2018b). This service allows users to locate and unlock a bike through smartphones and return it anywhere (allowed for parking) when a trip is completed. However, like a short flash of fireworks, the dockless sharing systems have confronted many challenges and some of them have already failed due to the reasons such as unsustainable business model, over-sized fleets, and vandalism (Ma, Lan, Thornton, Mangalagiu, & Zhu, 2018;Shen et al., 2018b; Xu et al., 2019).

In the last two-years, scooter sharing has bloomed and shown its competitiveness in labor-saving and faster travelling compared with bike sharing (Hardt & Bogenberger, 2019; McKenzie, 2019), which becomes prominently superior in tropical cities as high temperatures have negative impacts on bike utilization (Shen et al., 2018b). Having learned a lesson from the challenges confronted by bike-sharing

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services that severe obstacle of public space may occur in a dockless system, the latest operations on scooter sharing have transformed from dockless systems to the adoption of the deterministic docking stations (Today, 2018). As such, a foreseeable problem may also be tackled. In a dockless system, the battery distance of scooters is limited to a few kilometers and SSs would be abandoned if the electricity is used up on halfway so that extra manpower is needed to recycle these scooters at a considerably high cost. Nevertheless, a vague image about the performance of a scooter-sharing system is still unclear comparing with a bike-sharing system.

Thus, this study aims to investigate the performance of the widely established dockless bike-sharing service versus recently operated scooter-sharing service with docking stations and hence reveal the pros and cons of the two services. To discover the similarities and differences between the two systems operated in the same urban areas and weather factors, our focus is to investigate the performance in terms of usage rates and fleet size management when transforming from SBs to SSs. As Singapore is one of the earliest adventurers on operating micro-mobility (Shen et al., 2018b; Xu et al., 2019), we collected usage information of SBs and SSs and constructed their trips using GPS locations at origins and destinations for one month in two study areas in Singapore. Then, we make a comparative analysis of the two services by focusing on the spatial-temporal distribution represented by seven proposed indices, quantitative changes about trips over weekdays and weekends, and weather influence on demand. Lastly, we summarize the findings and propose four initiatives for the sustainable development of micro-mobility.

The paper is organized as follows. Section 2 presents a review of the revolution of bike-sharing and scooter-sharing systems. Section 3 introduces the pre-processing of the data collected in Singapore and Section 4 introduces the estimation methods. Section 5 conducts a comparative analysis between the two systems in three different aspects. Then, we propose several initiatives to tackle the revealed problems in Section 6, followed by a conclusion in Section 7.

## 2. Literature review

### 2.1. Spatio-temporal analysis

Many studies have been conducted to reveal spatio-temporal patterns of micro-mobility. In New York City, the arrival and departure rates of SBs at one station were associated with bicycle flow rates between the nearby stations (Faghih-Imani & Eluru, 2016). One of the most recent studies compared SBs and SSs operated in Washington, D.C. and found that SBs were primarily used for commuting between homes and offices while SSs were for recreation (McKenzie, 2019). We will also make similar comparisons between the two services in Singapore but our focuses will in two discrete areas that potentially leads to different purposes of the trips.

Focusing on Singapore, one study used an eigendecomposition method to reveal usage patterns of SBs at several discrete places (Xu et al., 2019). The results show that substantial variations of the usages occurred across urban locations on weekdays, especially between 8 and 9 am; while usage became more uniform in weekends. Another study found that higher utilization of SBs positively correlated with larger fleet sizes with a decrease of the marginal impact (Shen et al., 2018b). It also emphasized that utilization of SBs was rather low in Singapore, which could be one of the major reasons that SBs was not profitable. This observation motivates us to find out whether the performance is improved in the case of a dock-based scooter-sharing service compared to the dockless bike-sharing service. Besides, our study will not only investigate spatio-temporal usage patterns but also reveal the reasons behind the performance differences and transformation from SBs to SSs.

### 2.2. Influential factors on shared trips

Further studies investigated the impacts of various influential factors on the usages of micro-mobility. For instance, socio-demographics (population density and median household income in Washington, D.C., and age, gender, and station accessibility in Minneapolis-St. Paul) and exogenous variables (transportation network infrastructure and point of interests in New York City) were investigated, both of which influenced the utilization of SBs (Buck & Buehler, 2012; Faghih-Imani & Eluru, 2015; Wang & Lindsey, 2019). It was also found that moral obligations incorporated in users' intentions promote responsible usage significantly (Si, Shi, Tang, Wu, & Lan, 2020), while further studies investigated the role of financial incentives in shaping user behavior (Lu, An, Hsu, & Zhu, 2019; Zhang, Meng, & Wang, 2019). In addition, many models were proposed to explore the impacts of built environments (e.g., residential and commercial densities, and land use mixture) on the usage of SBs through correlation analysis (Faghih-Imani & Eluru, 2016; Liu & Lin, 2019; Shen et al., 2018b; Xu et al., 2019). In Singapore, it was found that locations associated with a higher density of public housing could make fewer shared trips in the morning versus more shared trips in the evening (Xu et al., 2019). However, our study will not consider these factors because they only change in a longer temporal scale, thus are not expected to influence any difference in the usage of SBs to SSs.

Weather, as the other factor that may determine usages of micro-mobility, cannot be ignored. It was found that rainy and cold days have a decline in trips of SBs in Toronto and SSs in Munich (El-Assi, Mahmoud, & Habib, 2017; Hardt & Bogenberger, 2019), and the same trend was discovered with respect to hot weather for SBs in Singapore (Shen et al., 2018b). One important reason could be that riding bikes in high temperatures and under great sunshine is an exhausting exercise that will affect activities thereafter, such as working in the office. In comparison, riding scooters require much less effect, thus we expect the effect of hot weather to be less important; we explicitly explore this question in the current study.

Apart from the influential factors suggested in the above studies, the operational strategy either with or without docking stations is also one of the most distinctive characteristics of the rental services that may determine the landscape of the micro-mobility (Gu, Kim, & Currie, 2019; Shen et al., 2018b). Dockless systems are highly flexible but the utilization of dockless SBs in Singapore was unsatisfactory even though the fleet size was already large enough. One reason might be that SBs were either left in remote locations or vandalized. In comparison, dock-based systems show advantages in managing and utilizing SBs or SSs at determined locations even though they have lower flexibility and present an explicit challenge of rebalancing the fleets among stations. A recent study compared dock-based bike-sharing with dockless scooter-sharing services, and found that shared trips were similar in spatial distribution while substantially difference in temporal patterns (McKenzie, 2019). In contrast, our current study compares dockless bike-sharing with station-based scooter sharing, a case which, to the best of our knowledge, was not considered before in the literature.

### 2.3. Impacts of micro-mobility

Micro-mobility also has positive and negative impacts. For example, SSs and even SBs provide a faster means of travel in urban areas during the rush hour comparing with automobiles (Faghih-Imani, Anowar, Miller, & Eluru, 2017; McKenzie, 2020). A study found that life cycle cost of plug-in electric scooters is significantly lower than internal combustion engine mopeds with rather a small amount of carbon footprints (Chang, Wu, Lai, & Lai, 2016). It suggested that greenhouse gas emission, air pollution, noise pollution can be reduced completely with e-scooters (Cao & Shen, 2019; Voinov, Morales, & Hogenkamp, 2019) or bikes (Kou, Wang, Chiu, & Cai, 2020). In addition, one study investigated the social impacts of gasoline powered mopeds on traffic accidents in Netherlands, and suggested that the affected population will be increased from 30% at present to 38%–53% in the future as these mopeds share the same lanes with bicycles (Voinov et al., 2019). In a worse situation, pedestrian injuries caused by e-scooters or mopeds have been reported since pedestrians are unaware of them when they are approaching (Badeau et al., 2019; Sikka, Vila, Stratton, Ghassemi, & Pourmand, 2019; Voinov et al., 2019). In this regard, effective fleet-size management is vital to minimize the number of SSs for both environmental protection and pedestrian safety, which has not been emphasized by other studies. Therefore, an explicit understanding of the spatio-temporal usage patterns is an urgent need for making urban planning and policies or laws to promote sustainable development of the micro-mobility.

## 3. Data

### 3.1. Study area

In the past few years, Singapore has experienced the waves of rapid expansion and decline of dockless bike-sharing followed by the blooming of dock-based scooter-sharing services. SBs reached the peak of their popularity in 2017–2018 with multiple operators (e.g., Mobike, oBike, ofo, SG Bike, GBikes, and ShareBikeSG) flooding the market with bicycles, but faded quickly as they faced problems mainly with low utilization and frequent complaints about bikes parked in wrong locations. More recently, multiple companies entered the market of scooter-sharing services (e.g., Neuron Mobility, Telepod, GrabWheels, Beam, and ScootBee). Compared with the bike-sharing, these services were more helpful, allowing scooters only in limited and designated areas and requiring users to park the scooters at fixed stations or face a penalty, e.g., Neuron charged users 5 SGD for improperly parking scooters. The maximum speed was restricted in 25 km/h for safety and a full battery could support a continuous trip around 45 km.

In line with these rapid changes, our data comes from two distinct time periods, where the respective services were widely available and used. Since SSs became available by the time when SBs declined, comparing the two services for the same time period would introduce significant bias due to external economic factors, we believe it is more meaningful to compare the two services for time periods when usage was significant. At the same time, since scooter-sharing was only implemented in discrete areas, we restrict the geographic extent of our study to two areas where both shared-bikes (SBs) and shared-scooters (SSs) operated to make a fair comparison (Fig. 1). Study area in the South West (SW) district is 2.0 km × 2.6 km with a variety of land uses with the scooter operator focusing on serving the educational institutions (university campus) in this areas; study area in the Marina Bay (MB) district is 3.0 km × 3.5 km and mainly has office blocks in the downtown area.

### 3.2. Dataset collection

We have built a scraping tool and deployed it in dedicated servers to monitor the scooter in bike-sharing systems. For each round of scraping, the tool firstly obtains all stations in the system. Then, for each station, it further queries which scooters are being parked. Both scooters and stations can be identified based on their unique IDs. By continuously scanning the systems, we can understand when a scooter is rented or returned, and which station it is rented from or returned to. In the case of SBs, there are no stations, but the positions of the bikes are reported. The trips can thus be inferred. However, it should be noted that the trip is not associated with any personal information. In the interest of privacy, this study does not release operator details. Bike-sharing and scooter-sharing data has been collected in both SW and MB for four weeks. Bike-sharing is from 01 August 2017 to 28 August 2017, and scooter-sharing is from 01 February 2019 to 28 February 2019.

Several factors can influence on the usage of SBs and SSs, such as climate, land use, and pricing mode having long-term impacts versus weather, seasonal variation in tourism, and major events having short-term impacts. We consider that long-term impacts has little effect on comparing the patterns of SBs and SSs in this study because (i) seasonal variation in Singapore is not significant throughout a year as it is almost on the Equator line, (ii) land use in well-developed urban areas where the study focuses on has very little changes in the two years, and (iii) rental prices of SBs and SSs are fairly cheap that attract different users constantly. Since the number of the tourists has only a slight variation between 1.1 and 1.2 millions (SVA, 2019) without major events in the two months, we do not consider it an important factor for investigation as well. In comparison, weather can have instant and significant impact on the usage of SBs and SSs. Therefore, the two sharing systems are generally comparable even though the data was collected at different times.

Dockless bike-sharing data in the two areas is from a single operator while dock-based scooter-sharing data in the two areas are from two different operators, respectively. Therefore, the data can be organized into four sets, i.e., $\mathscr{R} = \{R_{SB}{}^{MB}, R_{SB}{}^{SW}, R_{SS}{}^{MB}, R_{SS}{}^{SW}\}$. For SBs in both areas, $r = \{id, t_o, t_d, o, d\}$ ($\forall r \in R_{SB}$), which means that each trip $r$ was recorded by the bike ID $id$, departure time $t_o$ and arrival time $t_d$, departure location $o$ and arrival location $d$ in GPS locations. For SSs in MB, $r = \{id, t_o, t_d, o, d, b_o, b_d\}$ ($\forall r \in R_{SS}{}^{MB}$), meaning that $r$ is enriched with the departure battery $b_o$ and arrival battery $b_d$ in percentage; however, it has no explicit station information. For SSs in SW, $r = \{id, t_o, t_d, o, d, b_o, b_d, i_o, i_d\}$ ($\forall r \in R_{SS}{}^{SW}$); in addition to the MB data, it also contains the departure station ID $i_o$ and arrival station ID $i_d$. As the location of SBs and SSs during the trips were not reported, road networks were obtained from OpenStreetMap (OSM, 2019) to construct paths of the trips.

Locations of scooter stations are only available in MB and recorded as $L^{MB}$. To obtain $L^{SW}$, we propose a simple and effective method. Since the origin $l_o$ and destination $l_d$ in $R_{SS}{}^{SW}$ are associated with the station IDs of $i_o$ and $i_d$, a tuple can be built as $s = \{\langle l, i\rangle\}$, which are filled by two complete sets of $\{\langle l_o, i_o\rangle\}$ and $\{\langle l_d, i_d\rangle\}$. As shown in Fig. 2, $s$ are mainly located in educational institutions and visualized in the group of $i$ and they are distributed as a set of spatial clusters due to GPS errors. Then, $L^{SW}$ can be estimated as the centroids of the clusters of $\{l\}$ categorized by $\{i\}$. We further verified these locations with field investigations; comparison on locations of estimated and real station locations suggests that the result is trustworthy. Besides, origins and destinations of SSs that are within a 200 m radius from the nearest station are also viewed as the cause of GPS errors since rare users returned SSs only a few steps away from stations based on our observation in both study areas; thus, they are relocated to the node of the station in this scenario.

To investigate the weather impacts on on-demand mobility, rainfall and air temperatures in the two months were collected online (RWRS, 2019). In the dataset, weather stations have an even distribution that recorded rainfall and air temperatures continuously with a frequency of 5 to 15 min. Particularly, two stations (S71 in SW and S118 in MB) recording rainfall and the other two stations (S116 closest to SW and S108 closest to MB) recording air temperatures were selected. Hence, the number of origins/destinations and rainfall/air temperatures during the same hour of a day for 28 days can be organized as a tuple for the calculation of Pearson correlation coefficients.

## 4. Estimation methods

### 4.1. Construction of the paths

A probable path from $o$ to $d$ needs to be assigned for each $r$ since continuous locations during each trip are not available. To achieve this, a *weighted* and *undirected* graph is refined from OpenStreetMap. The edges of the graph contain all the possible sidewalks and pedestrian paths excluding steps, bike paths, and roads except highways (as almost

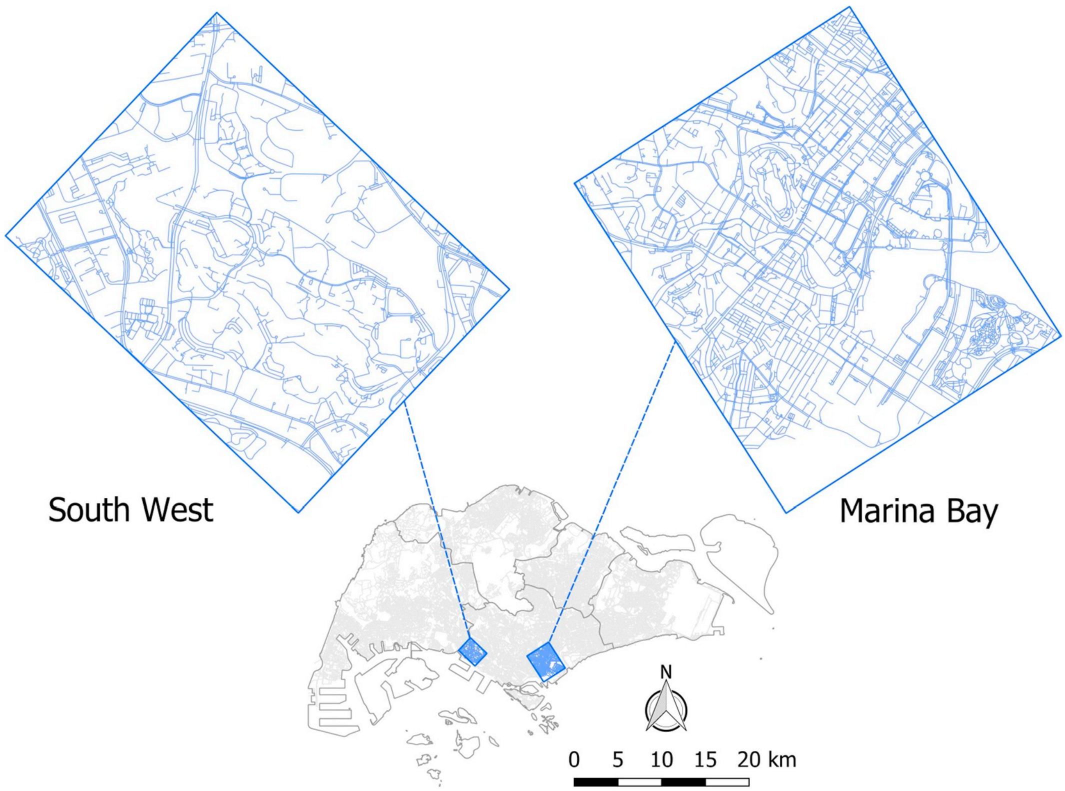


**Fig. 1.** Two comparative study areas in Singapore. One is in the South West district, and the other one is in the Marina Bay district.

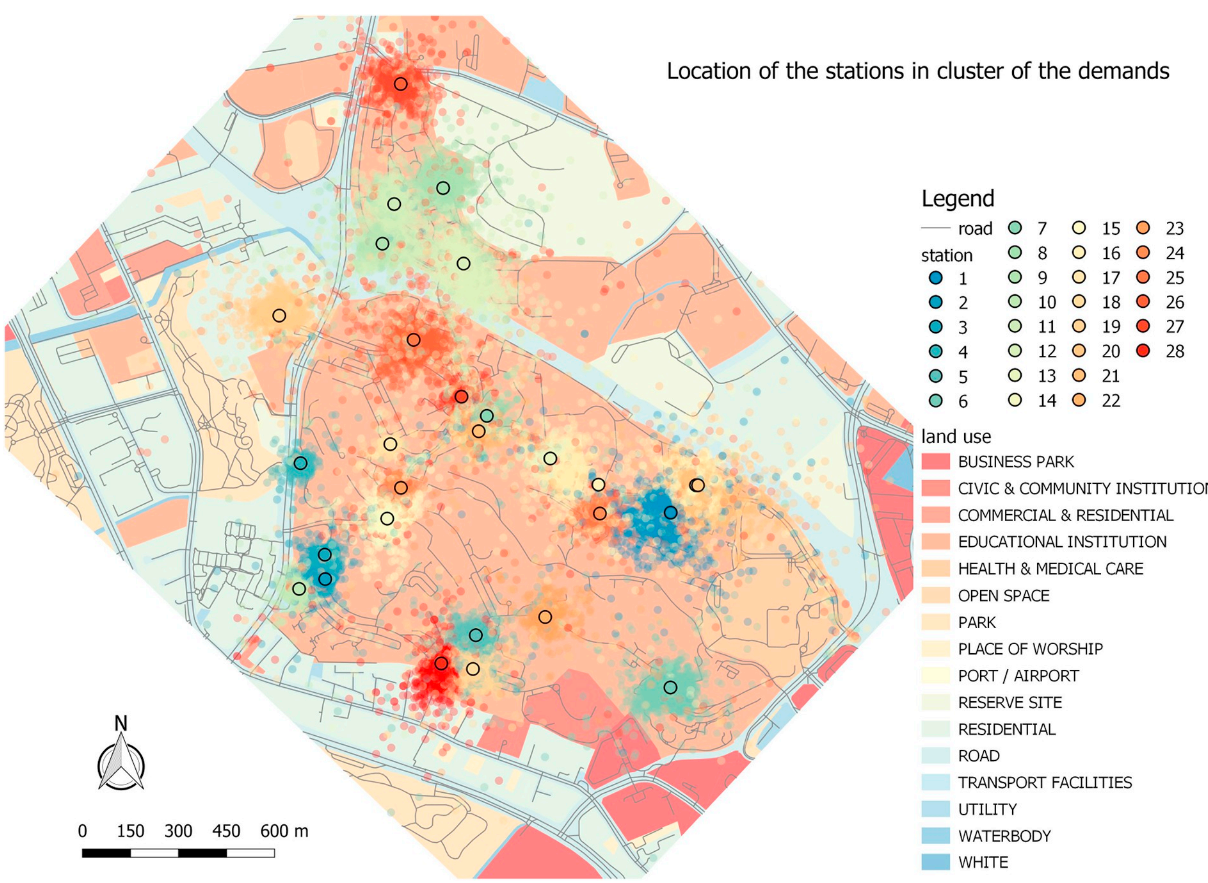


**Fig. 2.** Locations of scooter-stations and clusters of demands associated with station IDs.

all roads in Singapore are associated with sidewalks). In addition, we have noticed that users carried bikes or scooters and continued riding when their planned routes were interrupted by a few steps. Therefore, some of theses edges are topologically connected through manual editing when they are disconnected to increase the accessibility. Assuming that all the trips always follow the shortest path (denoted by $p$) on the road network, edge weights were set to be equal to the lengths of road segments.

In general $\{\langle o,d\rangle\}$ in $\mathscr{R}$ randomly shift away from the edges of the graph because of the GPS accuracy issue. Therefore, the complete set of $\{o\}$ and $\{d\}$ are repositioned onto the closest node in the graph and are associated with the corresponding node ID for the shortest path computation. Next, $\mathscr{R}$ is refined, by checking the condition that both $o$ and $d$ in each $r$ are in the study area.

The shortest path computation and spatio-temporal analysis were implemented as a set of hierarchical SQL functions in a spatial database management system (DBMS) of PostgreSQL 11.4 (PostgreSQL, 2019), with the support of pgRouting v2.x which provides geospatial routing functionality (pgRouting, 2019) (such as the Dijkstra's algorithm used in this study) and PostGIS 2.5 which provides a series of functions for 2D/3D geometrical computation (PostGIS, 2019). DBeaver 5.3 (Dbeaver, 2019) has been utilized as an administrative and management tool for the database development.

### 4.2. Estimation repositioning trips

Both SBs and SSs were repositioned to rebalance the distribution of the fleets so as to meet the on-demand mobility. However, repositioning trips of SBs were not recorded in $R_{SB}$. Alternatively, a bike-sharing repositioning trip can be detected if there is an obvious displacement between the destination and origin of two consecutive trips that share the same bike ID *id*. To account for possible GPS location shifting, a repositioning trip is constructed if the displacement is at least 200 m in this study. However, the departure and arrival time of the repositioning trip cannot be specified, which fall in a fuzzy interval between $(t_d, t_o)$ of two consecutive trips. For SSs, both *real* trips made by users and repositioning trips were recorded in $R_{SS}$. Benefiting from $b_o$ and $b_d$ in $r \in R_{SS}$, a trip can be classified into one of the three scenarios: (i) a *real* trip made by a user if $b_o < b_d$, (ii) a rebalance trip if $b_o = b_d$, and (iii) a charging trip possibly affiliated with the rebalance purpose if $b_o > b_d$.

### 4.3. Estimation the fleet sizes

Since SSs are operated in two discrete areas, it is easy to obtain their fleet sizes by counting the distinct number of scooter-IDs in MB and SW. The static fleet size of SBs can also be estimated using the same method as their trips are recorded when both $o$ and $d$ are in one site. However, SBs are operated in the whole of Singapore so that the fleet size of SBs in a smaller area may vary continuously over time. In a short time, such as an hour of a day, the fleet size can only be computed for bikes that have been in service, filtering out a large number of unused ones. Therefore, the static fleet size derived from a long time (i.e., four weeks) is more reliable.

## 5. Comparative analysis

### 5.1. Spatio-temporal distribution

Seven indices are proposed to describe the performance of the two sharing services: $fs$ is the fleet size of bikes/scooters, $d(fs)$ is the density of the fleet size, $n(r)$ is the number of the *real* trips over 28 days, $f(r)$ is the sharing frequency per bike/scooter per day, $r(rp)$ is the overall the repositioning ratio, $r(rb)$ is the repositioning ratio for rebalancing, and $r(c)$ is the repositioning ratio for charging. Table 1 presents seven statistics to describe the performance of bike-sharing and scooter-sharing systems in the two study areas. The table shows that bike sharing has a significantly larger fleet size than scooter sharing in both areas, i.e., 4412 versus 348 in MB and 1144 versus 463 in SW. Consequently, it makes 420 bikes versus 67 scooters per km$^2$ in MB and 109 bikes versus 89 scooters per km$^2$ in SW. Even though bike sharing has a larger number of *real* trips than scooter sharing in MB (i.e., 58,109 versus 11,445 over 28 days); a bike is used on average only at 0.47 times per day, while a scooter achieves a higher utilization of 1.17 times per day. In comparison, bike sharing has a smaller number of *real* trips than scooter sharing in SW (i.e., 13,582 versus 40,830 over 28 days); the difference in utilization is even more striking with a bike being used on average at 0.47 times per day, while scooters are used 3.15 times per day at a much higher rate than even SSs in MB. One reason is the attractive promotion that provided half the standard rate at 50 cents for 30-min use or 30-min or even unlimited free-ride.

Based on the proposed method above, a number of repositioning trips of SBs (5809 in MB and 1431 in SW for 28 days) are detected so that their repositioning ratios of $r(rp)$ are 10.00% for MB and 10.53% for SW (Table 1). This means that 10 SBs in MB or SW are repositioned for every 100 *real* trips. In contrast, $r(rp)$ is 14.50% for SSs in SW, and it is significantly larger at 58.48% in MB, which is composed of 26.88% for rebalancing and 31.60% for charging (also possibly for rebalancing). The ratio at 31.60% is significantly high, which means that charging of SSs can be a great challenge since it is difficult to bridge national gird to all the stations in the downtown area.

Furthermore, Fig. 3 visualizes the “heatmap” of the paths produced by SBs and SSs in the two areas, i.e., path segments on the map are colored according to the number of times they travelled by bikes or scooters, accumulated over 28 days. Overall, it shows that usage of SBs in MB is more dispersed compared to SW. On the other hand, usage of SSs is more concentrated in both areas. In MB, hotspot paths have almost the same spatial distribution for SBs and SSs. However, in SW, hotspot paths shift from the west (residential communities) to the center (the campus of a university). One main reason is that the operational area of SSs does not include the residential neighbourhoods so that the comparison is essentially between two different locations: bikes along the coast and scooters on the campus. Moreover, SSs have significantly higher usage in the campus than SBs, contrary to the downtown area where the two are more comparable. This may be due to the steep slope on the campus, which makes it difficult to ride a bike. Besides, several phenomena can be revealed.

First, the fleet size is reduced dramatically. Operators made inappropriate competition by flooding SBs into entire Singapore (e.g., MB has 420 bikes in 1 km$^2$), which, however, could easily cause over-occupation and disruption of public spaces. The operators were closed down due to the unsustainable business model and all the SBs were removed from Singapore consequentially. With the arising of SSs, government learned a lesson from SB experience and regulated the new operators so that the fleet size of scooters has been controlled effectively.

Second, the sharing frequency is increased but there is still space to be improved. The transformation of the dockless bike-sharing system to the dock-based scooter-sharing system restricts the flexibility of a sharing system apparently, since routes are constrained between stations and spatial distribution of the mobility is contracted as shown in Fig. 3. However, also because of this reason, users can access scooters in the locational-determined dock-based stations more easily. As a result, the sharing frequency increases from less than 0.5 to more than 3 times per day. Nevertheless, a scooter used on an average of 3 times a day means that SSs may not be used most of the time, and the shareability still needs to be improved to create a profitable sharing system.

Third, the high repositioning ratio means a large number of “*unreal-demand*” trips and indicates costly and manpower-extensive maintenance, since employees have to collect and transport scooters between stations continuously. Even though the operators have followed regulations made by the government and charged a certain penalty from users if they return scooters away from the stations, the

**Table 1**
Statistics of the shared-bikes and shared-scooters in the two study areas.

| No. | Type | Area | fs | d(fs) | n(r) | f(r) | r(rp) | r(rb) | r(c) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | SBs | MB | 4412 | 420/km$^2$ | 58,109 | 0.47 | 10.00% | – | – |
| 2 | SBs | SW | 1144 | 109/km$^2$ | 13,583 | 0.42 | 10.53% | – | – |
| 3 | SSs | MB | 348 | 67/km$^2$ | 11,445 | 1.17 | 58.48% | 26.88% | 31.60% |
| 4 | SSs | SW | 463 | 89/km$^2$ | 40,830 | 3.15 | 14.50% | 6.63% | 7.87% |

considerably high repositioning ratio for rebalancing *r*(*rp*) (especially for SSs in MB, which can be as high as 58.48%) may be due to two reasons. For one reason, the penalty may not be high enough to incentivize users to properly return scooters. Since high demands are associated with many tourist attractions (Fig. 4A), we intuitively suppose that most users may be tourists. In this case, tourists are likely to return scooters away from stations for the best of their convenience, disregarding the penalty if it is affordable. Another reason might be the operation in a small and discrete area that causes few or excess demands at time-dependent stations more easily. Demands are unable to be served if the requested origin-destination (OD) matrices are beyond the operational area or there are no scooters available at the stations. Thus, repositions are needed to meet the demand and avoid repeating an embarrassing situation of over-occupation of public space and visual pollution. In SW, high demands are associated with a dormitory and a metro station on the campus (Fig. 4B). This reveals that people in the campus have regular demands overall, and they are likely to return SSs regularly at stations to avoid the penalty.


**Fig. 3.** heatmap of the paths produced by SBs and SSs in the two study areas. Colour corresponds to the number of the paths travelled by SBs or SSs. It visualizes usage for (A) SBs in MB, (B) SSs in MB, (C) SBs in SW, and (D) SSs in SW.

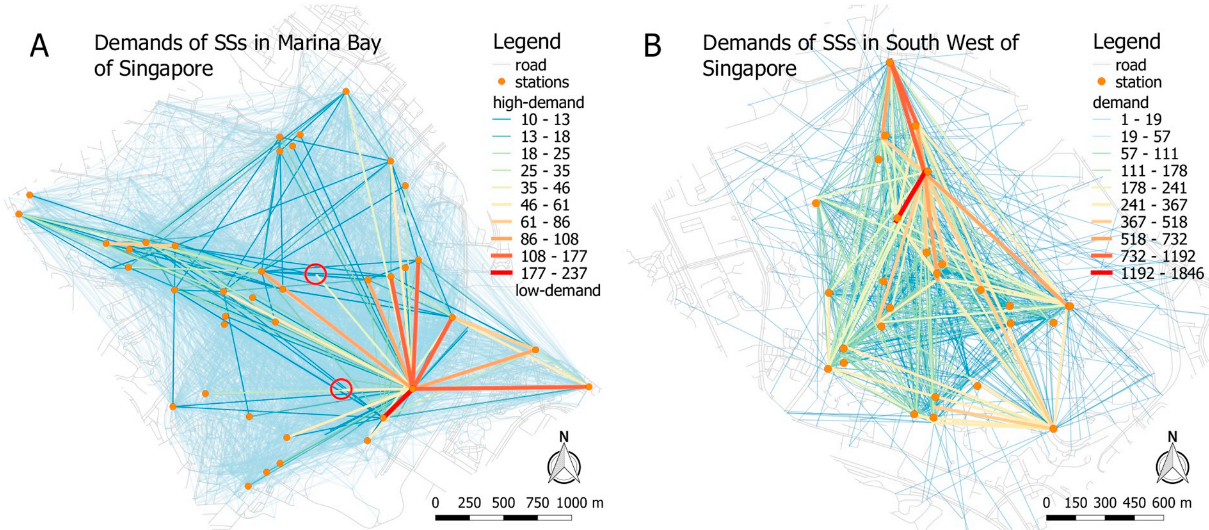


**Fig. 4.** Origin-destination matrices enriched with number of the *real* trips of SSs in MB and SW. (A) High demands are mostly associated with tourist attractions. (B) High demands are mostly associated with a dormitory and a metro station.

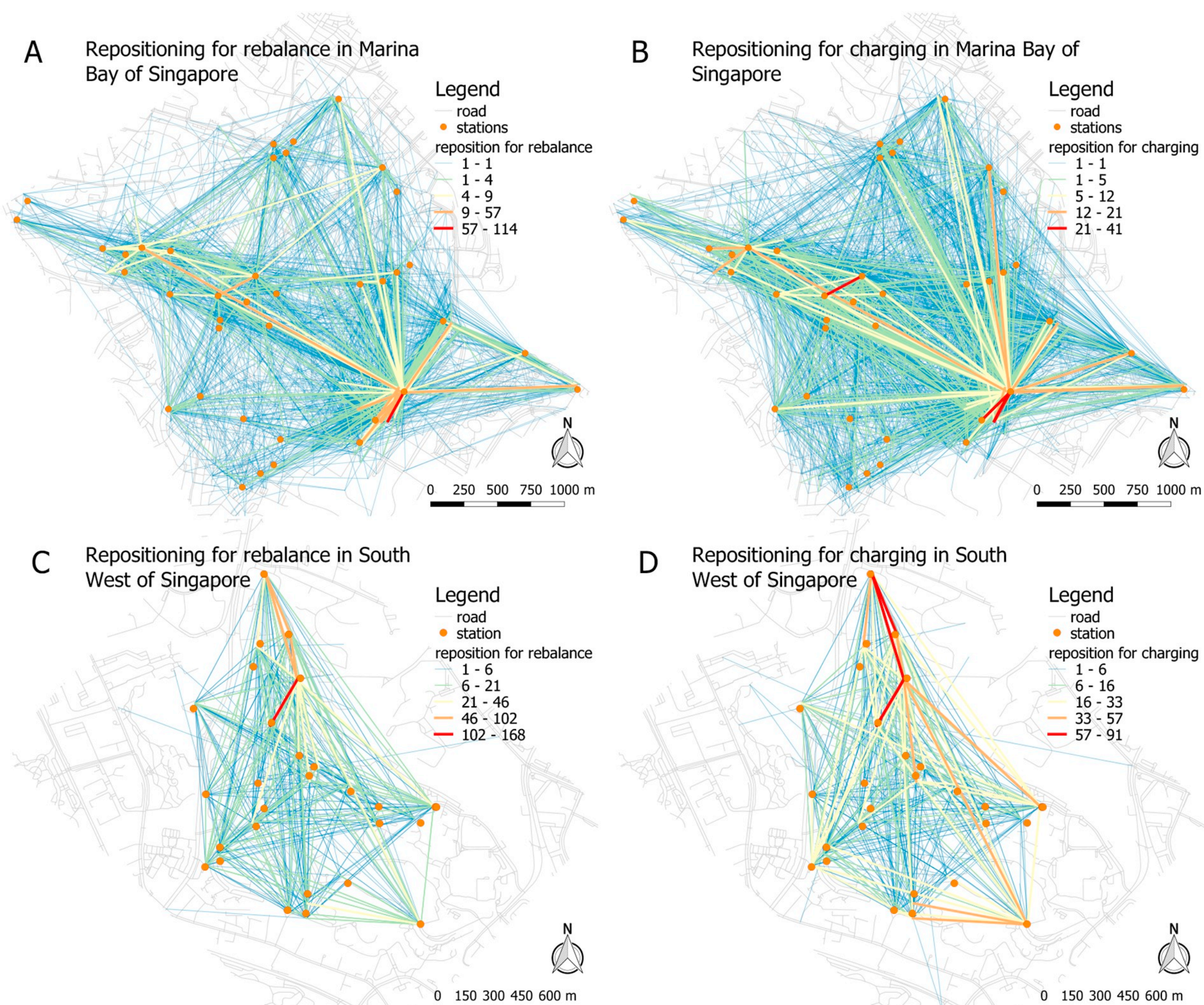


**Fig. 5.** Origin-destination matrices enriched with number of the repositioning trips of SSs in Marina Bay and South West areas. (A) Repositioning for rebalancing in MB. (B) Repositioning for charging in MB. (C) Repositioning for rebalancing in SW. (D) Repositioning for charging in SW.

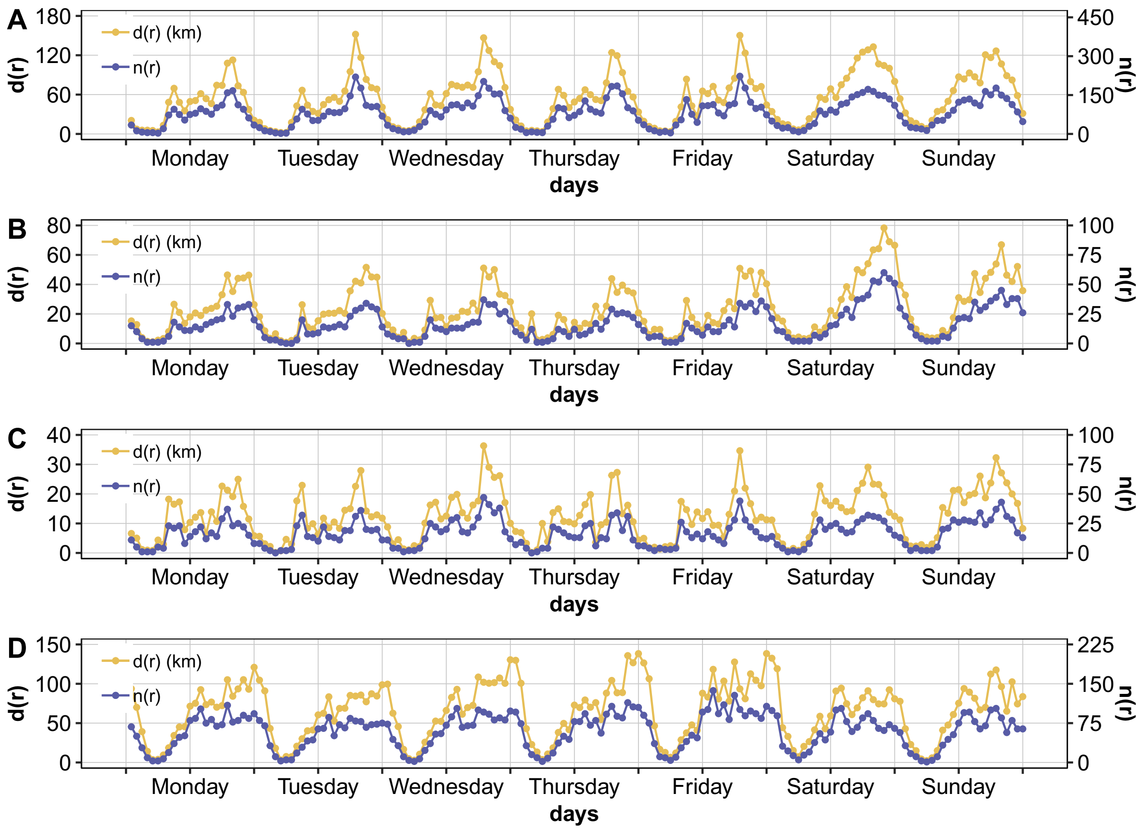


**Fig. 6.** The total distance of the rides ($d(r)$ in the left y-axis) and the total number of the rides ($n(r)$ in the right y-axis) over weekdays and weekends (in the x-axis), accumulated for four weeks. The four plots are for SBs in MB (A), SSs in MB (B), SBs in SW (C), and SSs in SW (D), respectively.

Fourth, for SSs, major repositioning trips for rebalancing and charging have a strong association between a few pairs of stations. The repositioning trips are decomposed as rebalance trips (Fig. 5A, C) and charging trips (Fig. 5B, D). In MB, rebalance trips are made between a few stations while charging trips are associated with only one station, locating at the Marina Bay Sands hotel. The same pattern occurs in SW where rebalance trips and charging trips are associated with the University Town. Notably, the charging trips may also serve for the rebalance purpose so that their spatial distributions of origin-destination matrices display some similarity. This would make the operation effective when stations have both the charging functionality and the largest number of repositioned scooters.

Fifth, the higher utilization of SSs is achieved at the expense of higher rebalancing costs. According to our statistics, *real* trips departed from and arrived at non-stations were unexpectedly at 28.50% and 26.32%, respectively. This means that most of the inappropriately returned scooters were utilized by users. Thus, the repositioning ratios for rebalancing and charging at 26.88% and 31.60% are mostly made between stations. This can also be confirmed from Fig. 5 that these trips are between stations.

### 5.2. Quantitative changes over time

To find out quantitative changes of the trips over time, we firstly investigate the hourly distribution of the total distance $d(r)$ of the trips and the number $n(r)$ of the trips on weekdays and weekends (Fig. 6). Overall, $d(r)$ and $n(r)$ in each sub-figure have almost the same trend over days, and the highest demands are at night-time. As Singapore has a tropical rainforest climate having no distinctive seasonal changes, it is supposed that high temperatures and strong sunshine suppress outdoor activities in the day-time, which thus shifts to the night-time. Specifically, the demands of SBs in MB (Fig. 6A) and SW (Fig. 6C) do not have large changes on weekdays and weekends, while shape peaks are smoothed on weekends specifically on Saturday. This indicates that major trips of SBs in the two areas may be local citizens who have regular mobility (e.g., workers in office blocks). In comparison, the demands of SSs in MB are increased in weekends (Fig. 6B) but decreased in SW (Fig. 6D). This suggests a distinct usage pattern of the users, i.e., the majority of the trips in MB could be citizens or tourists for leisure trips, while the majority of the trips in SW could be university students for education-related purposes. Also, Fig. 6D shows that the highest demands always happen in the middle night from Monday to Friday. This indicates that people may use SSs as bridging services when public transit (e.g., buses and metro trains) are unavailable.

To compare the distribution of trip distances and durations of the two services, Fig. 7 draws the curves of the average distance $d(r)$ and the number of the trips $n(r)$ over the trip duration (*minutes* in the x-axis). Overall, $d(r)$ grows stably and approaching an upper boundary at 2 km with the increase of the trip duration versus $n(r)$ has a dramatic increase followed by a long and decreasing tail for SSs in all situations. Yet, there are three patterns between SBs (Fig. 7A,C) and SSs (Fig. 7B,D). First, trips of SBs are overwhelmingly shorter than 10 min, while trips of SSs can reach up to 1 h in MB (Fig. 7B) and 30 min in SW (Fig. 7D). In more detail, a larger number of the trips of SBs take around 1 min only while it can take 5 to 8 min for SSs, as shown in the red band. For bike-sharing trips around 1 min, one of the reasons could be that users realized that the rented bike was unusable due to some defect after starting the trip. Second, SSs make longer distances than SBs for trips that are shorter than 20 min; while they have almost the same distances for trips that are longer than 20 min. For instance, for 10-min trips, they are slightly longer and shorter than 1 km for SSs and SBs respectively; for 30-min trips, both are slightly over 1 km. Trips shorter than 20 min and has a linear regression roughly between the travel time and distance, suggesting that such trips mainly follow the shortest paths

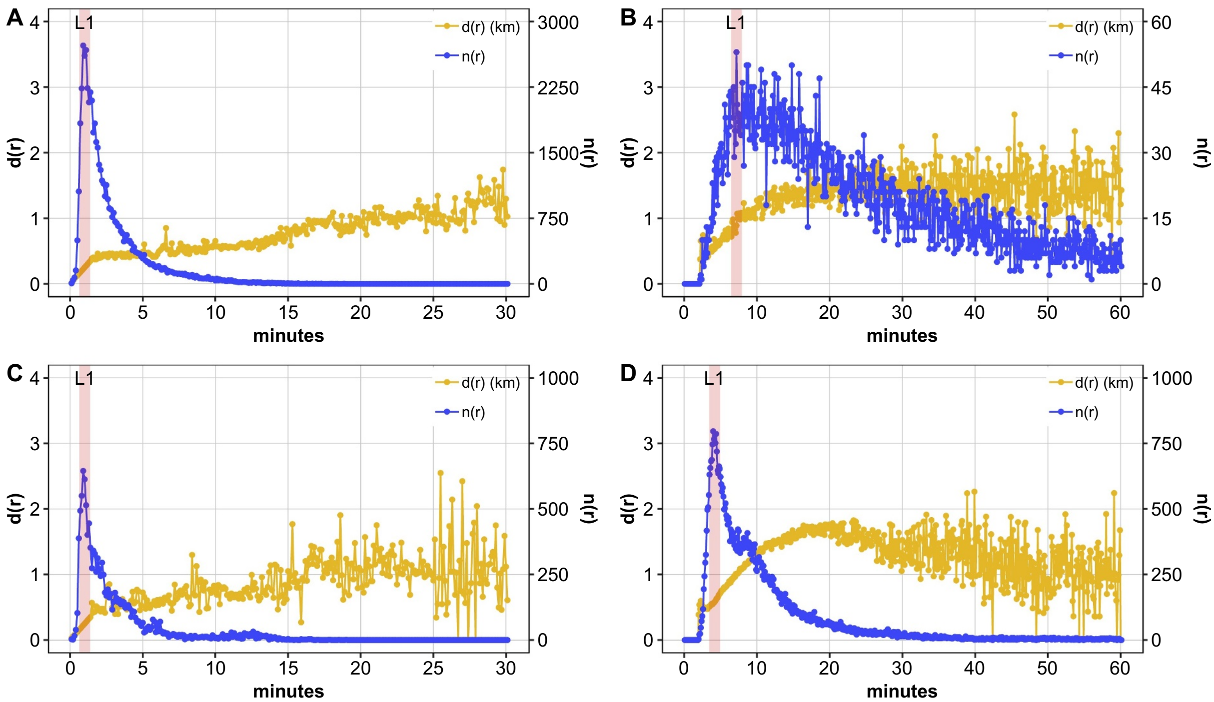


**Fig. 7.** The average distance of the rides ($d(r)$ in the left y-axis) and the corresponding number of the trips ($n(r)$ in the right y-axis) over the trip duration (minutes in the x-axis) for four continuous weeks. The four plots are (A) SBs in MB, (B) SSs in MB, (C) SBs in SW, and (D) SSs in SW, respectively.

at a constant speed from origins to destinations. This explanation is reasonable since these SB trips were also suggested as commuting trips in Singapore (Shen et al., 2018b; Xu et al., 2019).

Another important finding is that, when SS trips are longer than 30 min, the distances have an insignificant increase in MB or even perform a slight decrease in SW. It means that these trips probably serve for tourism having stops and/or detours before arrival, which thus prolongs trip duration, but underestimates trip distances based on the shortest path assumption. A similar explanation was provided that SBs were mainly used for commuting and tourism, and commuting had non-stops following the shortest paths while tourism likely had longer trip duration because of several stops along the trip (Kou & Cai, 2019).

The above finding suggests that trips shorter than 20 min probably follow the shortest paths so that their spatial distribution can be drawn with a negligible obstruction of detours. Fig. 8 shows the *heatmap* of trips that have duration indicated by red bands of Fig. 7, which corresponds to the largest number of the trips having the same trip duration shorter than 10 min. It shows that the most travelled paths of SBs in MB are discrete along the major roads in a larger area (Fig. 8A). This suggests that the majority of users can be citizens for short trips. An opposite phenomenon occurs for SSs in MB that two of the most intensive paths are respectively concentrated in the Singapore River and the Marina Bay Sands hotel (Fig. 8B). This indicates that the major users could be tourists as the two places are scenic spots. In SW, users with SBs and SSs usually have a single travelling purpose, i.e., commuting between residences in Fig. 7C and bridging between teaching buildings in Fig. 7D. This makes contiguous paths that overlap with each other, which thus forms short and hotspot paths.

### 5.3. Weather influence

As Singapore has a tropical rainforest climate, on-demand mobility of SBs and SSs can be influenced instantly and significantly by short-term weather. To account for this, rainfall and air temperatures are used to investigate the influence by making correlation analysis. Since on-demand mobility is also dependent on the time of a day (e.g., high demands in the morning peak hours versus low demands at late night), correlations are thus made in a unit of hour-of-day (*hod*). Fig. 9 presents Pearson correlation coefficient between arrivals and rainfall ($r(d,ra)$) and departures and rainfall ($r(o,ra)$) (left y-axis) together with hourly accumulated rainfall (right y-axis). It has more rainfall in August (Fig. 9A, C) than in February (Fig. 9B, D). Because of this reason, more occurrences of $r$ are derived for SBs than SSs in both MB and SW. Overall, the analysis shows moderate and negative correlations, which suggests that rainfall hurts the demands of SBs and SSs. Also, $r(o,ra)$ are slightly smaller than $r(d,ra)$ when they are negative, meaning that fewer departures occur than arrivals during raining. Also, SBs are more negatively correlated with rainfall than SS, which might be due to the effect of dock-based stations that in a sense “force” users to return the scooters at the stations even if it starts raining; on the other hand, with a dockless bike-sharing system users may drop the bikes immediately when it starts raining.

Furthermore, correlations between air temperatures and arrivals ($r(d,tp)$) and departures ($r(o,tp)$) are investigated, which excludes the rainfall time so that the impact of air temperatures will not be influenced by rainfall. It shows that daily air temperatures in February (Fig. 10B, D) have slightly larger variation than in August (Fig. 10A, C). For SBs (Fig. 10A, 10C), both $r(d,tp)$ and $r(o,tp)$ are negative for 2 h from 12:00 to 13:00 in MB and from 13:00 to 14:00 in SW. Even though the negative correlations are weak, it suggests that high temperatures in the middle of the day can suppress the usage of SBs. In comparison, for SSs in MB (Fig. 10B), $r(d,tp)$ is positive but $r(o,tp)$ is negative at noon, meaning more arrivals but fewer departures of scooters with the increase of the temperatures. While, $r(d,tp)$ and $r(o,tp)$ are negative at 13:00, which means that riding of SBs and SSs can be suppressed in the hottest time in the early afternoon. On the other hand, $r(d,tp)$ and $r(o,tp)$ are positive between 16:00 to 18:00 in MB (Fig. 10A, B), and between 15:00 to 17:00 in SW (Fig. 10C, D). This means that higher temperatures can promote the usage of SBs and SSs in the late afternoon when the temperatures have already cooled down below certain degrees. One possible explanation is that with higher temperatures, scooters provide a more attractive alternative for walking. On the other

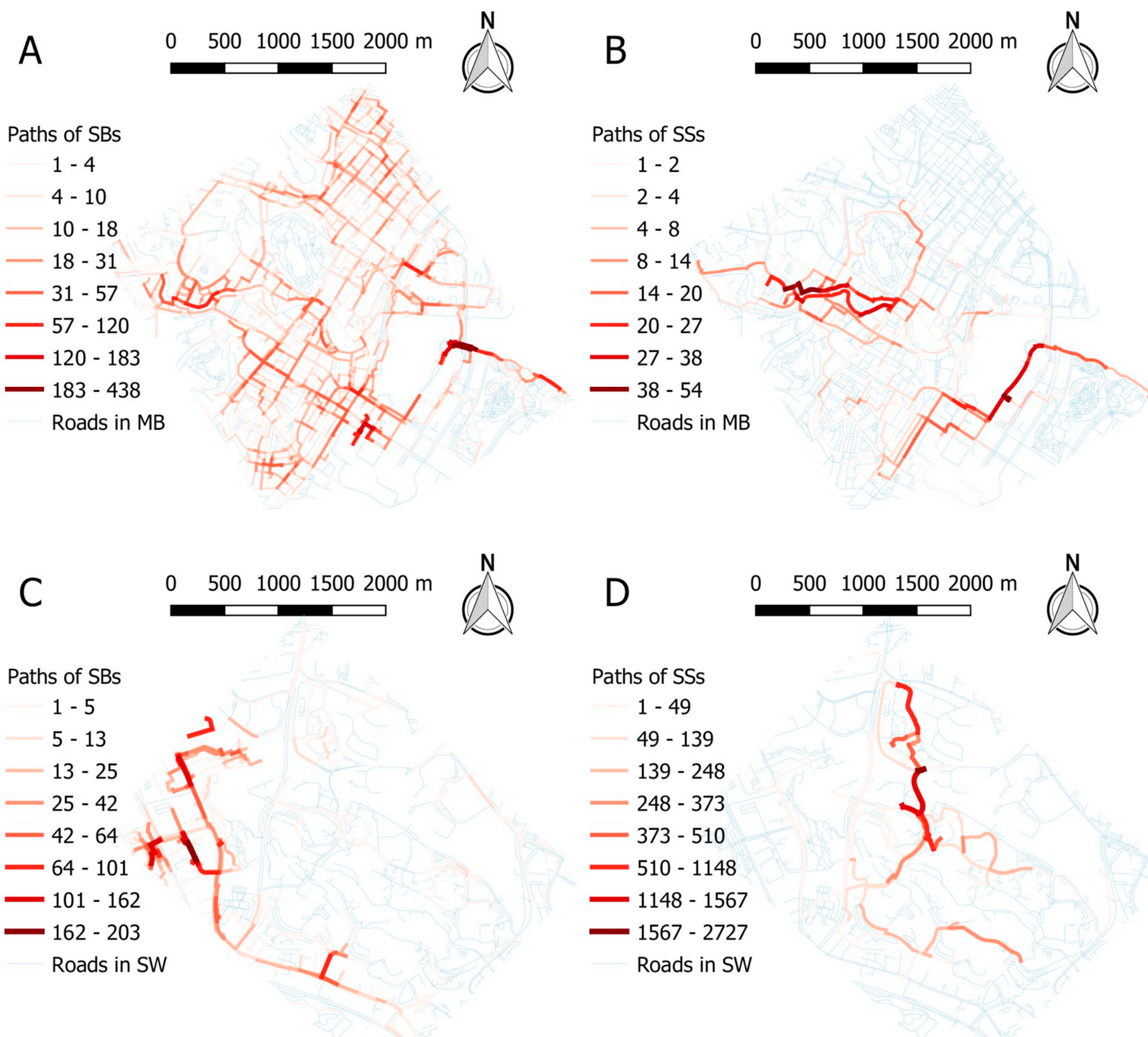


**Fig. 8.** The number of the travelled paths made by SBs and SSs in the red band of Fig. 7. The number of the paths made by (A) SBs in MB, (B) SSs in MB, (C) SBs in SW, and (D) SSs in SW. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

hand, at noon, using a bus service becomes the most attractive option as buses are air-conditioned and bus stops have shelters.

## 6. Discussion

Scooter sharing has a better performance than bike sharing in terms of the increased utilization and decreased fleet size. However, a scooter is still only used for 3.15 times per day on average and mostly used for less than 20 min, which suggests that scooters are not used most of the time every day. Also, SSs had high repositioning ratios at 15% in South West and 58% in Marina Bay in Singapore. The repositioning is mainly for two reasons: (i) scooters parking out of the stations are with low accessibility by other users and/or without permission in certain public space, and (ii) scooters need to be repositioned for battery charging. Since the repositioning of SSs was conducted by using automobiles, it means more vehicular trips and thus cause more greenhouse gas emissions (Hollingsworth, Copeland, & Johnson, 2019) and considerably higher operational cost. Additionally, rainfall and high temperatures at noon suppress the riding of scooters, and the mobility patterns with peak and off-peak hours make it difficult to improve the shareability and profitability of the system. All these suggest that sustainable development of a scooter-sharing system in Singapore still faces many challenges. Several initiatives are discussed to tackle the above problems.

1. Optimize the fleet size of stations and their locations. For instance, as shown in the two red circles in Fig. 4A, nodes of two yellow-lines do not associate with established stations, suggesting two spontaneously formed hotspots with high origins and/or destinations so that new stations may be established there.
2. Regulate returning behaviors more strictly. An increase of the penalty could induce more users to return scooters only at stations so that less repositioning is needed and more scooters are available with high accessibility to users. However, it may also become a double-edged sword that more users have doubt and even antipathy on riding shared-scooters if the penalty is significantly high. Thus, not only financial measures should be adopted, but also training and education for potential users becomes necessary.
3. Enable scooters to have autonomous repositioning functionality to meet the on-demand mobility. Besides hardware devices which allow real-time vehicle and pedestrian detection and lane detection (Andersen et al., 2016), this would require a module that provides a real-time, demand-aware shareability network to dispatch scooters to the users. This can be achieved by adopting a two-stage stochastic approximation scheme (Warrington & Ruchti, 2019) or incorporating into algorithms that have been used in ride-sharing

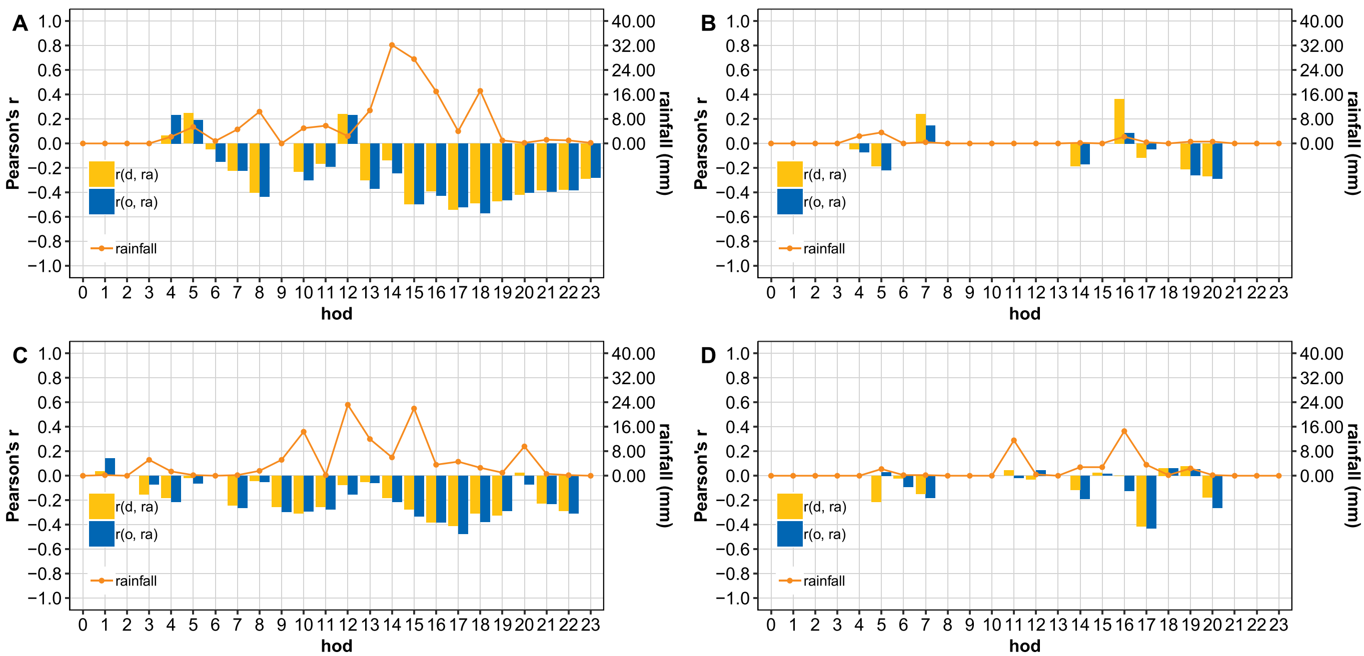


**Fig. 9.** Pearson correlation coefficient (*r* in the left y-axis) between the amount of rainfall and the number of origins/destinations over hour-of-day (hod in the x-axis) accumulated for four weeks. (A) *r* for SBs in MB. (B) *r* for SSs in MB. (C) *r* for SBs in SW. (D) *r* for SSs in SW.

systems (Santi et al., 2014). In this case, on-line reservation with a temporal horizon in the future is also required to allow the computation and dispatching of scooters to users.

4. Increase the effective battery life of scooters. One way is installing a photovoltaic module on scooters so that they can have solar charging during the trip and parking time (Ridden, 2019). The other way could equip conventional dock-based stations with grid charging or battery-exchange platforms (Chen, Cheng, Lie, & Yu, 2018), or solar charging platforms (Shah, 2019). Charging scooters at the parking space could be a simple and effective solution, which needs the equipment of charging platforms connecting to either the national grid or photovoltaic cells. However, bridging the platforms to the national grid needs the authorization from several government departments and systematic supports of the urban utility, which challenges its wide utilization. Solar charging might become particularly effective when the national grid is hard to be accessed. Stations should be placed at locations with large annual solar irradiation to maximize the generated electricity, which thus needs the accurate estimation of annual solar irradiation in an urban environment. Solar charging has four foreseeable advantages: generating electricity autonomously, spatially optimizable at solar-abundant locations, temporally configurable throughout the day

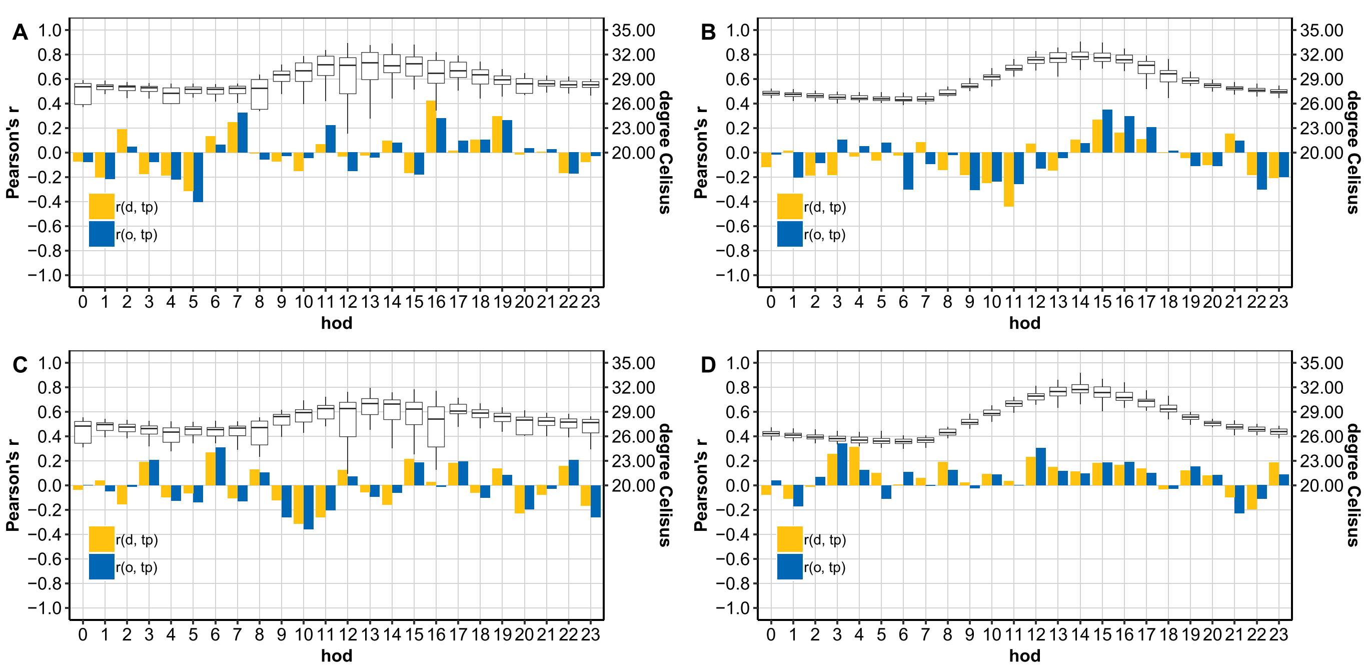


**Fig. 10.** Pearson correlation coefficient (*r* in the left y-axis) between air temperatures and the number of origins/destinations over hour-of-day (hod in the x-axis) accumulated for four weeks, which has excluded the raining time. (A) *r* for SBs in MB. (B) *r* for SSs in MB. (C) *r* for SBs in SW. (D) *r* for SSs in SW.

supported by storage batteries, and environmental friendly (Platt, El Haddad, Pieber, & Huang, 2014; Tulpule, Marano, Yurkovich, & Rizzoni, 2011, 2013).

Spatio-temporal heterogeneity of bike sharing and scooter sharing is not only influenced by the business model (e.g., transformation from a dockless system to a dock-based system), behaviors of users (e.g., returning scooters away from stations) and weather, but also significantly impacted by government policy. For instance, some vital measures are directly driven by government regulations, such as controlling the fleet size rigorously and changing the market from all the city to discrete areas when transforming from bike-sharing to scooter-sharing. Most recently, new problems occur that scooter-sharing has made inconvenience and injuries since scooters share sidewalks with pedestrians. They can be used on separate cycling paths, which severly restricts their reach and makes the shared scooter services analyzed in our work unfeasible. More research is thus needed on designing and developing the proper infrastructure and regulations for the safe use of scooters so that their benefits for urban mobility can be realized. Thus, supportive policies from the government also play a very important role in the sustainable development of the new transportation mode.

Lastly, observations are made from the comparison of the findings of this study and the study in Washington D.C. (McKenzie, 2019), which has a broad scope in the whole city with a symbiosis of SBs and SSs in the same spatio-temporal domain. In contrast, our study focused on two discrete areas experiencing a transformation from SBs to SSs. Nevertheless, both suggest that bike sharing is dominantly used for commuting while scooter sharing mainly serves for recreation or tourism activities in the downtown area even though the two cities have an entirely opposite operation method for SBs and SSs, i.e., dockless versus dock-based. Since built environments such as the residential and commercial densities have impacts on usage patterns of micro-mobility in Singapore (Xu et al., 2019), it draws our attention to incorporate these factors in the near future to promote sustainable development of the micro-mobility services, such as optimization of locations of parking spaces and planning of specialized paths for scooters.

## 7. Conclusion

This study conducts a comparative analysis to understand spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility in two discrete areas in Singapore. SSs have spatially compact and quantitatively denser distribution compared with SBs, and their high demand is associated with places such as attractions, metros, and dormitories. Weather in terms of rainfall and high temperatures at noon could suppress the usage of SBs and SSs, but not dominantly. On the contrary, higher temperatures below certain degrees Celsius in the late afternoon may promote the riding of SSs. It is also found that SSs have a better performance than SBs regarding the increased sharing frequency and decreased fleet size. Benefiting from the adoption of a dock-based system with a smaller fleet size for SSs, disruption of public space and orders is not expected, indicating a sustainable development for SSs. However, the relatively low sharing frequency and riding time of SSs indicates that they are still not in use most of the time, so that several measures as those proposed herein could be used to improve the sharing economy in micro-mobility.

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