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An equity parking area location model for transition from dockless to docked shared micromobility systems

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Simona De Bartolomeo ✉, Michele Ottomanelli & Leonardo Caggiani

The rise of micromobility shared vehicles has brought about a number of economic, environmental and social benefits. Specifically, there are two types of sharing systems: station-based (docked) and free-floating (dockless) systems. Although the latter allow users to release the vehicle at the exact point of destination, on the other hand it has generated disorder and obstruction on streets, blocking vehicle flow and pavements. To solve this issue, it is necessary to locate stations where the vehicles must be picked up and released, so avoiding illegal user behaviour. However, the location of stations may generate inequalities, i.e. one part of the population may cover higher walking distances to reach a station. For this reason, we propose a bi-objective parking area location model for shared micromobility systems considering walking distance equity aspects to convert a free-floating system into station-based. This model has been applied to the city of Bari (Apulia, Italy).

Sustainable mobility has become increasingly popular in recent years, particularly with the spread of shared micromobility systems, such as e-scooter and bicycle sharing. This type of transport may reduce polluting emissions and traffic congestion and may promote a more sustainable mode of transport allowing users to cover short to medium distances with the possibility of leaving vehicles at the closest station to their destinations (station-based or docked system) or anywhere within the operating area, provided this is in line with the highway code and service conditions (free-floating or dockless system)[1,2]. The location of parked vehicles in free-floating systems represents one of the critical issues related to this kind of transport. The incorrect parking of bicycles and e-scooters belonging to these systems creates disorder and danger on the streets, both for pedestrians and other traffic categories. Indeed, if they are irregularly parked on pavements (i.e. sidewalks) they could be an obstacle to pedestrian, and if they are released on street they may compromise the regular flow of other traffic categories. James et al.[3], for example, analysed the relationship between pedestrians and e-scooters. They showed that a percentage of about 16% of parked e-scooters were not correctly parked, 28% were not upright, 28% represented an obstacle to pedestrians, and 22% were on private property[3]. One way to solve this issue was the introduction of 'beautificators', a group of agents hired by a sharing company expressly to reposition e-scooters in order to guarantee urban decorum[4]. This operation consists of repositioning vehicles over short distances to adjust the position of parked vehicles in order to fix the irregular and disorderly parking that obstruct roads and pavements[4]. For example, in the study of Carrese et al.[4], a mixed integer programming model and a heuristic with the aim of tackling wild parking with beautificators were proposed[5]. This is different from the relocation process, which include medium-long distances with the aim of rebalancing shared systems and moving vehicles into stations or from a station to another (see Zhang et al. for more details)[6]. Literature suggests that it is a potential solution that could be further explored as it discusses the role of agents hired to reposition e-scooter to ensure proper parking and urban decorum. Indeed, for example, Carrese et al.[7] proposed a linear programming model to represent the problem of both beautificator and relocator actions operated overnight in a service area[7].

In addition to this partial solution, the presence of parking areas may reduce these issues, as shown in the study of Hemphill et al.[8] which analysed the spatial distribution of parking compliance[8]. They demonstrated that the proportion of correct parking is higher on blocks with designated e-scooter parking than blocks without and highlighted a statistically significant relationship between legally parkable areas and parking compliance. Moreover, the study of Gossling[9] investigated the role of e-scooters in urban transportation with problems and policies, considering the introduction of dedicated parking as a possible improvement[9]. The location of these parking areas becomes important for how the system functions.

In literature, a number of studies have focused on the station/parking location problem for shared micromobility systems. Two kinds of models are frequently used to define parking and station locations: the maximum coverage location problem and the p-median model.

As regards the first one, Park and Shon analysed optimal bicycle-sharing station locations with the use of location-allocation methods, focusing in particular on the minimum impedance model and maximum coverage location problem. The objective function aims to minimise the travel distance for each person to demand sites and the study is based on taxi

Polytechnic University of Bari, Bari, Italy. ✉e-mail: simona.debartolomeo@poliba.it

trajectory data[10]. Shi et al. proposed a framework for planning electric fences based on a dynamic land parcel subdivision algorithm and a regional coverage maximisation problem. The objective function aims to maximise the overall coverage provided by geofencing areas and data taken into consideration are related to dockless bikes and land parcels[11]. Zafar et al.[12], through a maximum coverage location problem, analysed correct electric vehicle fast charging station locations, using QGIS software. The objective function aims at maximising the number of served charging demands within desired driving distance by maximising coverage. The input data are related to highway traffic, population and GIS maps[12]. Amarilies et al.[13], through a maximum coverage distance problem, analysed parking positions and their capacity for dockless bike-sharing systems. The objective function aims at maximising the number of bikes that can be parked inside chosen parking facility and the input data are related to the geographic coordinate of bikes, the location of the candidate facilities, and the distances between them[13]. Colovic et al.[14] developed a novel multi-objective micromobility maximal coverage parking location model. The objective functions were about the maximisation of the population coverage, the maximisation of multimodal accessibility coverage and the maximisation of the attraction coverage considering the most important points of interest for each corresponding zone in large urban areas. They took into consideration factors such as population data, the location of points of interest, bus stops, green areas, etc[14].

Regarding the second approach, the p-median model, Cintrano et al.[15] analysed the best location of bike stations with the aim of allowing users to walk the shortest distance to reach them by minimising the distances between users and their closest facility. They took into consideration data such as bike trips, cycle lanes, traffic patterns, and points of interest[15]. Cintrano et al.[15] analysed the best station locations for shared bicycles with the use of a p-median problem. The objective function aims at minimising the weighted sum of distances between users and their closest bicycle station. They considered data such as real population, city maps, geographic locations of stations, bicycle collections, and deposits[16].

In addition, there are studies that focus on the identification of parking spaces within free-floating systems in order to incentivise or require users to end their rides in these zones. This may be an important strategy to reduce 'wild parking'' issues. Indeed, In the study of Zakhem and Smith-Colin[17], for example, they proposed the identification of free-floating parking areas to reduce disorder across cities. The aim was to provide incentives for users to drop-off vehicles in these areas[17]. The respective studies of Zhang et al.[18] and Sandoval et al.[19] propose the identification of geofence planning for free-floating bike-sharing systems and electric scooter parking locations, with the aim of incentivising or forcing the users to end the ride in these areas[18,19]. Conversely, Arif and Margellos [20] proposed an optimisation model to define parking hubs with the aim of forcing users to drop-off vehicles in those zones or penalised them for parking outside the defined areas[20]. At the same way, Xanthopoulos et al.[21] proposed a multi-stage design algorithm model to locate hubs in which users are obliged, not incentivised, to park vehicles[21].

Moreover, several authors have proposed the use of geofencing technology. Indeed, it is one of the latest innovative solutions that may deeply modify user behaviour. It is based on location-based services which controls entry or exit from or to a virtual boundary, named geofence, based on USA global positioning system. Through this method, it is possible to identify a vehicle and know if it is inside or outside the designated zones (for more details on the use of geofencing see Moran, Moran et al. and Liazos et al.[22–24].

The location of stations or parking areas, as well as the distribution of free-floating vehicles, may be not equitable, i.e., it does not guarantee equal accessibility to the entire population, and there may be one part of the population which is more disadvantaged than the other. Therefore, it is important to consider equity criteria when positioning parking areas. Equity can be horizontal or vertical. Horizontal equity consists of offering the same opportunities in equal circumstances and vertical equity consists of distributing benefits among groups with different needs. In literature, equity was calculated through indicators; the most widely used are the Theil index and the Gini index. Theil index measures the inequality between groups and within groups and was used, for example, in the analysis of Hamidi et al.[26] based on inequalities of bicycle access at major transportation nodes in a city[25,26]. This index was also used in the study by Caggiani et al.[27] to propose a model for the location of bike-sharing stations that aims to minimise inequalities in bicycle-public transport multimodal mobility among observed groups and maintain certain levels of accessibility and coverage simultaneously[27]. Gini index is a measure of the inequality of a distribution (income) among a population and it is calculated from the Lorenz curve[28]. For example, Chen et al.[29] proposed a methodology to evaluate equity in bike-sharing systems[29]. They used measures to analyse horizontal and vertical equity. Related to the horizontal equity they took into consideration the Lorenz curve and Gini index, while in the case of vertical equity they used disaggregated data. Ronas-Satizábal et al.[30] examined the equality in the accessibility to employment and education among cycle-user adult in Bogotà. They estimated potential accessibility indicators and horizontal and vertical equity indicator, including the Gini index[30]. In the study of Giuffrida et al.[31], an evaluation of horizontal equity was conducted through the use of the Gini index based on the Lorenz curve as a measure used to assess the distribution of accessibility within the population[31]. Similarly, in the study of Berke et al.[32], the Gini index was used to evaluate spatial equity in access to public bike-sharing[32]. In the study of De Bartolomeo et al.[33], Gini index was used to evaluate vertical equity related to the accessibility to an e-scooter-sharing system considering the most disadvantaged sector of the population[33].

However, none of these studies proposed models which consider equity criteria and define the location of stations to convert a free-floating system into a station-based one. The location of parking areas without taking into account equity criteria could generate disparities between population groups because a part of the population can be forced or encouraged to walk greater or shorter distances than the rest. For this reason, in this paper, we propose a model to convert a free-floating system into station-based considering equity criteria. With this change, users may not drop off vehicles at the exact point of their destinations and have to walk a certain distance to reach the nearest station. In particular, we proposed a bi-objective model which, as well as minimising the total walking distances, as in p-median models, also reduces the inequality of the service offered. In the following section, we present the notation adopted in the paper and the proposed model. The case study and the discussion close the paper.

Proposed model

In the first part of this section, the mathematical notation adopted in the paper is reported. Then the proposed model was explained.

In a preliminary phase, the area under study has to be divided into m micro-zone i and z zones q by grouping micro-zones. These micro-zone clustering should be done with the aim of evaluating the fairness of the transformed station-based system among zones q population. In this section we proposed an equity-based bi-objective model (1)–(7) to convert a free-floating system into a station-based one. The aim was to locate mandatory stations in a free-floating system considering equity aspects. We proposed locating parking areas in car parking spaces (as per the study of Hemphill et al.[8] and in smaller quantities on pavements[8].

For each micro-zone, the first objective function, Eq. (1), aims at minimising the total walking distance that is the sum of the product between drop-offs of each micro-zone i, $nstop_i$, and walking distances d_i that users have to cover from the origin centroid of the micro-zone i to the nearest station. The function changes with the variable $\boldsymbol{S}$, which is the set of chosen stations. The second objective function, Eq. (2), is the minimisation of the Gini value, i.e. the maximisation of horizontal equity. This value is calculated according to the Lorenz curve, where $\boldsymbol{LOS}$, a level of service vector with generic los_q elements, is distributed in line with the resident population $\boldsymbol{POP}$, the population vector with generic pop_q elements.

In particular, los_q (Eq. (3)), is intended as the difference between the greatest total walking distances over the area under consideration and the sum of walking distances in zone q.

The zone with the highest level of service los_q is the zone with the lowest walking distance from centroids to the nearest chosen station. These distances were calculated in Eq. (4) for each zone q considering the distances from the centroid of each micro-zone belonging to zone q to the nearest chosen station. Equation (5) represents the total population in zone q.

$$\min_s dt = \sum_{i=1}^{m} nstop_i \cdot d_i \tag{1}$$

$$\min_s g = GINI(\boldsymbol{LOS}, \boldsymbol{POP}) \tag{2}$$

with

$$los_q = \lceil \max(\boldsymbol{D}) \rceil - \sum_{i=1}^{m_q} d_i \tag{3}$$

$$\boldsymbol{D} = \left[\sum_{i=1}^{m_1} d_i, \sum_{i=1}^{m_2} d_i, \ldots, \sum_{i=1}^{m_z} d_i \right] \tag{4}$$

$$pop_q = \sum_{i=1}^{m_q} pop_i \tag{5}$$

s.t.

$$ns \le slim \tag{6}$$

$$cap_s \ge peak_s \; \forall s \in [1, 2, \ldots, ns] \tag{7}$$

Equation (6) establishes that the total number of stations ns have to be fewer than the total number of stations that could be chosen ($slim$). Equation (7) is the capacity of each station, cap_s, that has to be equal or greater than the maximum number of shared vehicles that could be parked simultaneously at station s. To calculate this value ($peak_s$) each micro-zone was characterised by a trend of drop-offs. These are associated with the nearest station and the sum of trend of each station is the total trend, where the $peak_s$ is the highest value. The imbalance of the los_q between zones depends on the walking distance and the population. The minimisation of the first objective function does not imply the minimisation of the Gini, or vice versa. The aim is to balance the los_q with pop_q. Therefore, the solution for this proposed model was a Pareto front. Pareto optimality consists of a number of high-performing solutions which trade off the conflicting objectives considered in the study. For further details, see Deb [34]. These solutions can be represented through a bidimensional diagram where the values of the first objective function are shown on the x-axis and the values of Gini index are shown on y-axis. Considering the high number of hypothetical station locations among which to choose the stations that has to be implemented, the problem can be solved with a metaheuristic. In particular, we solved it with a Genetic Algorithm (GA), as better explained in the next section.

Case study and results

The proposed model was applied to an e-scooter sharing free-floating system in the city of Bari, Apulia Region (Italy). This city has a population of about 316,000 inhabitants with an urban area of 116 km^2. The system under analysis belongs to the BIT mobility operator. There are 640 e-scooters and the system is active in a defined operating area of about 33 km. The data were recorded during November 2020 and represent the trend of drop-offs with a 2 min time interval. We only took the city centre into consideration. This is the most important part of the city due to the fact that the majority of movements are focused within this zone. Because the configuration of roads is grid-like, distances were calculated through taxicab geometry[35]. We divided the area under consideration into micro-zones with a square mesh grid zoning of 25 m. The resident population was calculated for each micro-zone[36]. With the aim of evaluating the fairness of the transformed station-based system among specific areas, we grouped together these micro-zones into 30 population zones.

The number of hypothetical stations should be much higher than the number of stations to be chosen, and their location must be homogeneously distributed over the study area. Specifically, in our case we fixed a number of hypothetical stations equal to 482 by substituting car parking spaces and, where possible, new parking areas on pavements were established with the aim of preventing obstacles to pedestrians.

Figure 1 shows the city centre e-scooter sharing operating area divided into micro-zones i and zone q. Grey dots represent car parking spaces while orange dots show parking areas located on pavements, the total of dots represents 482 hypothetical stations.

We solved the bi-objective model (1)–(7) when the total number of stations to be chosen, $slim$, changed. We considered the total number of 50, 100, 150, 200, 250, 300, 350 and 400 stations, respectively. The higher values were considered to analyse how the model performs, but municipal councils are unlikely to have all these stations built as they would have to remove too

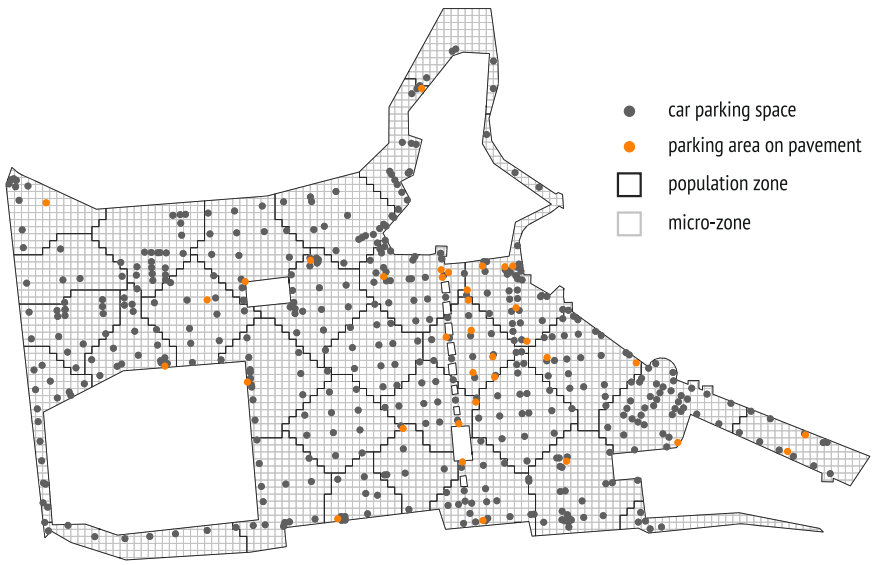

Fig. 1 | E-scooter sharing operating area with zones and hypothetical stations. The operating area was divided into square micro-zones (light grey) and population zones (deep grey). The different coloured dots represent car parking spaces (grey dots) and parking areas located on pavements (orange dots). The dots represent 482 hypothetical stations.

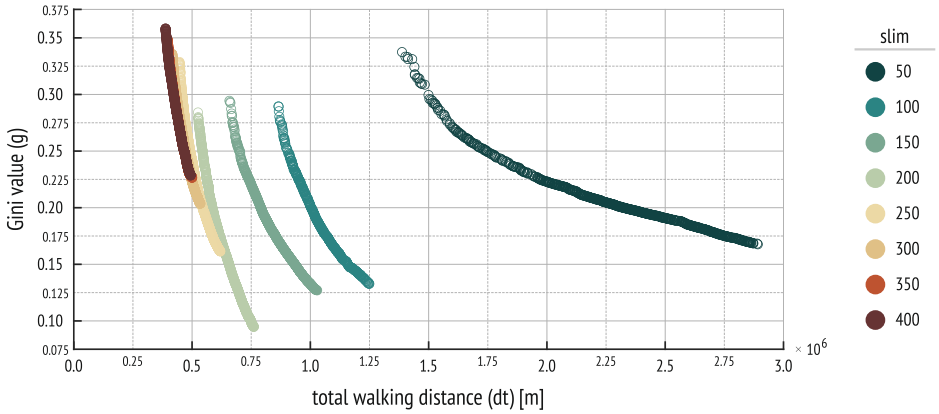

Fig. 2 | Pareto front for each *slim* value. The diagram is characterised by the value of the first objective function on the x-axis and the value of the second objective function on the y-axis. The diagram shows the solutions for a maximum number of stations that could be chosen from 50 to 400.

many car parking spaces to the detriment of people using cars or other vehicles and residents who would have no private parking. Furthermore, the model makes more sense when the number of *slim*, stations to be chosen, is much smaller than the total number of hypothetical stations. Due to the complexity of the proposed model, results were found using a genetic algorithm.

A solution to the problem (GA chromosome) consists of a binary string with a length equal to 482 (the number of the hypothetical station). The unitary elements in the string correspond to the near-optimal stations that should be implemented. Fitness functions were defined equal to the total walking distance (*dt*) and Gini index (*g*). After some empirical tests, the following GA parameters were set. The population size was set equal to 4 times the number of clusters. The maximum number of generations was set at 350 and the algorithm stops before reaching the maximum generation number if the average relative change is less than or equal to 10E-18 in the best fitness function value over 50 generations. The genetic operators used to generate offspring are the Tournament selection, the Scattered crossover, and the Gaussian mutation. The GA was implemented using MATLAB software (for further details see The MathWorks Inc.)[37].

Values of the two objective functions, calculated through the optimisation for each *slim* were reported in the Pareto front diagram shown in Fig. 2.

The horizontal axis shows the value of the first objective function (*dt*) and the vertical axis represents the Gini value (*g*). The diagram shows that the greater the number of stations, the shorter the total distance (*dt*) that users must cover to drop off vehicles, i.e. the distances increase as the number of stations decreases. It also could be said that the greater the total walking distance, the lower the Gini value. For this reason, it is necessary to choose a compromise solution. In the case of 200 stations, the Gini value was the lowest, around 0.09. In the results from 250 stations to 400, when the number of stations increase, the lower Gini value rises. Indeed, in the diagram both the maximum and minimum Gini value shift upwards. This is due to the fact that in increasing *slim*, the choice of stations becomes limited.

Other main results are reported in Table 1. For each *slim*, we took into consideration three solution cases: the lowest value of the first objective function belonging to Pareto front (*dt*), the lowest value of the second objective function belonging to Pareto front (*g*), and a compromise solution, named *com*. For the same *slim*, this solution corresponds to the average total walking distance between the total walking distance of the Pareto solution with the lowest Gini value and the total walking distance of the Pareto solution with the highest Gini value. This compromise solution is an example and has to be chosen by policy-makers depending on whether they want to favour solutions with lower Gini values or solutions related to lower total walking distances. Results for each *slim* value and each case were reported. The last line of the table considered, as chosen, all the hypothetical stations. The columns of the table represent the total number of chosen stations (*ns*), the number of car parking spaces which have to be converted into micromobility parking areas (*ppl*), the number of parking areas on pavements (*ppv*), the total number of parking spaces (*eps*) considering parking areas related to car parking spaces and pavements, the maximum distance which a user has to cover to drop off the vehicle starting from a centroid ($wd_{\max}$), and the average walking distance throughout all the area (wd_{mean}).

This table shows that the number of parking areas in car parking spaces and on pavements increases as the *slim* value increases. On the other hand, the maximum walking distances decrease as the number of stations increases, and this is the same for the average walking distances. The average walking distance values are between 124 and 191 m in the case of *slim* = 50. Considering e-scooter sharing user behaviour similar to bike-sharing, this is a good result because these values are less than 300 m. Indeed, Kabra et al.[38] established that almost 80% of bike-sharing system users were willing to walk a maximum of 300 m to reach a station[38]. The greater the number of chosen stations, the lower the wd_{mean} values that reach very low values starting from 200 stations with an average walking distance around 60 m. On the other hand, the maximum distances are around 800 m to drop off a vehicle. These values improve with the maximum number of 250 stations. There is a reduction in these values until a number of 150 chosen stations and then they become stable and more acceptable, between 200 and 400 stations. In these cases, even the maximum value of the walking distance is about 300 m. Gini values are between a maximum value of 0.358 and a minimum value of 0.095. Considering for the *slim* all the 482 hypothetical stations, only 459 were selected since the others would have remained empty due to the better positioning of the other stations. In this case, the total distance is the lowest and corresponds the highest value of Gini equal to 0.512. The best solution considering the lower Gini value and higher equity value is the one with the constraint of 200 stations. The best solution related to walking distances is the case with 400 stations. However, municipal councils may not be willing to propose so many stations and a compromise solution needs to be found. For example, choosing solutions where the maximum value of the walking distance is around 300 m, such as solutions with 150 or 200 stations accepting that a part of have to walk for more than 300 m.

It is interesting to observe the spatial distribution of chosen stations. For example, Fig. 3 shows the e-scooter parking areas within the operating area, considering the solutions with *slim* equal to 100 stations. Figure 3a represents the parking area location with the minimum walking distance of the Pareto front, while Fig. 3b shows the parking area location with the corresponding Gini value of the Pareto front equal to 0.133.

The micro-zones in Fig. 3 change from white to red to represent the resident population. Dark red shows a high value of resident population (major density) while white represents a lower value (less density). In Fig. 3a the highest density of stations is located in the centre of the operating area under consideration. This is different from the location of stations in Fig. 3b, where the number of stations is lower in white zones but increases in zones with higher density (red zones). To achieve equity, the greater the population density, the shorter the walking distances need to be.

Table 1 | Main results.

case	slim	ns	dt [km]	*g*	ppl	ppv	eps	wd_{max} [m]	wd_{mean} [m]	slim	ns	dt [km]	*g*	ppl	ppv	eps	wd_{max} [m]	wd_{mean} [m]
dt_{min}	50	50	1388	0.337	76	1	496	653.2	124.0	250	250	447	0.329	245	14	988	305.9	46.9
com	50	50	2313	0.201	80	0	468	803.4	170.2	250	250	527	0.214	243	16	967	332.1	54.2
g_{min}	50	50	2891	0.168	76	0	449	821.6	191.2	250	245	619	0.161	243	14	930	332.1	59.7
dt_{min}	100	100	865	0.289	114	4	652	448.4	84.0	300	300	416	0.336	289	18	1059	257.8	43.0
com	100	100	1048	0.181	127	1	638	465.4	93.3	300	300	471	0.252	291	17	1051	332.1	48.9
g_{min}	100	98	1249	0.133	124	2	627	475.9	103.8	300	288	535	0.204	280	17	1012	332.1	54.2
dt_{min}	150	150	658	0.294	155	6	775	386.3	65.7	350	350	396	0.349	333	23	1145	257.8	40.2
com	150	150	859	0.173	161	7	746	465.4	79.3	350	349	441	0.277	333	23	1128	305.9	45.6
g_{min}	150	147	1029	0.127	159	6	698	465.4	87.0	350	333	500	0.227	322	19	1086	332.1	50.5
dt_{min}	200	200	525	0.284	200	10	895	337.0	54.9	400	400	388	0.358	378	28	1198	257.8	38.4
com	200	200	644	0.158	204	9	862	332.1	62.4	400	368	436	0.283	350	24	1152	305.9	44.9
g_{min}	200	190	761	0.095	196	9	815	332.1	69.1	400	339	494	0.228	327	20	1095	332.1	50.4
										482	459	374	0.512	432	31	1268	222.5	34.6

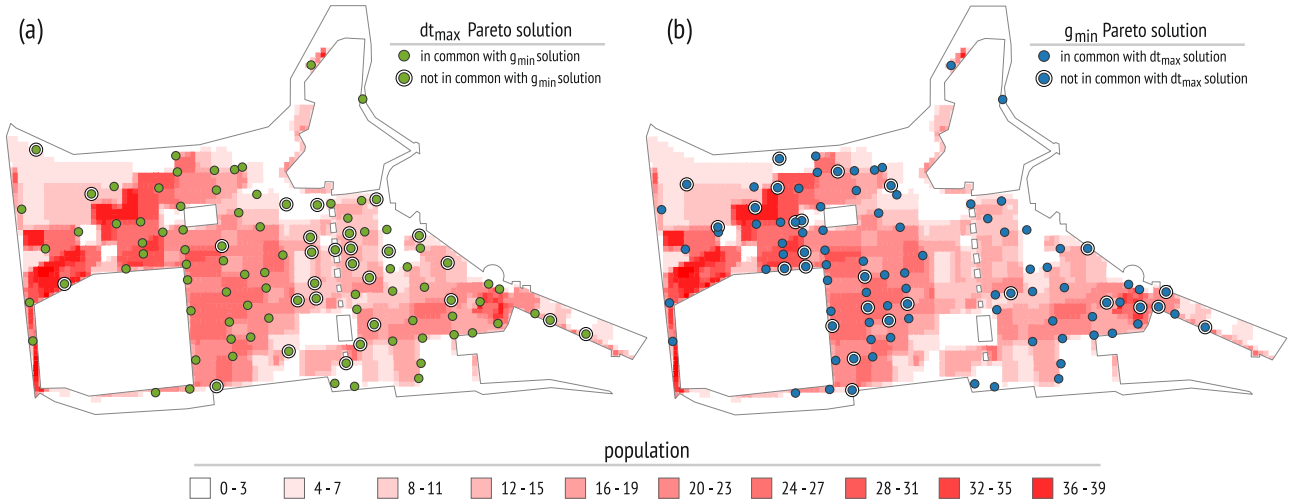

Fig. 3 | E-scooter parking areas for *slim* = 100. a The parking area location with the minimum walking distance of the Pareto front. **b** The parking area location with the minimum Gini value of the Pareto front.

Discussion

The rise of micromobility shared vehicles has brought about a number of economic, environmental and social benefits. In particular, free-floating systems have allowed users to rent a vehicle and drop it off anywhere within the operating area, provided this is in line with the highway code. The freedom to release the vehicle at the exact point of destination has generated disorder and obstruction on streets, blocking vehicle flow and pavements. To solve these issues, a station-based system, obliging users to drop off and pick up vehicles only to and from stations, could be a solution. However, the location of stations may create disadvantages for one part of the population compared to another. For this reason, we propose a bi-objective model with the aim of defining the location of stations to convert a free-floating system into station-based, also according to equity criteria. The first objective function aims at minimising the total walking distances for each micro-zone, while the second objective function aims at maximising horizontal equity, i.e. minimising the Gini value. Results show that a minimisation of total walking distances does not correspond to a minimisation of the Gini value. Indeed, the Pareto front shows that when the total walking distances decrease, the Gini values increase. Municipal councils could choose a compromise solution between extreme values of Pareto front. The calculation of the Gini index was made taking into consideration the resident population. This could be a limitation for the problem due to the presence of many activities in central areas that attract scooters at peak hours, but at the same time we may have few residents in these areas. For further study, we aim to propose other indicators that do not only taking into account the resident population. Other further studies may involve a multi-objective optimisation approach that aims to maximise the population coverage, multimodal accessibility, and attraction of key points of interest in addition to minimising walking distances and addressing equity concerns. Additionally, further research may focus on the combined station location and network design of cycle lanes to improve station accessibility, and the proposal of a station location model for free-floating systems without the obligation to park inside stations.

Data availability

The data that support the findings of this study are not publicly available due to contractual restrictions from the data provider but are available (as aggregate data) from the corresponding author upon reasonable request.

Code availability

The scripts of the proposed model cannot be publicly released due to contractual restrictions with the data provider.

Abbreviations

$\boldsymbol{S}$	set of chosen stations
ns	total number of chosen stations
s	generic station with $s \in [1, 2, \ldots, ns]$
m	total number of micro-zones
i	generic micro-zone with $i \in [1, 2, \ldots, m]$
$nstop_i$	number of drop offs in a micro-zone during the period under consideration
d_i	minimum distance between micro-zone i centroid and the nearest station belonging to the set of chosen stations $\boldsymbol{S}$
z	total number of zones into which the population is divided
q	generic zone in which the population is divided with $q \in [1, 2, \ldots, z]$
m_q	total number of micro-zones belonging to a generic zone q
$\boldsymbol{D}$	vector of z elements of the sum of minimum distances between micro-zone centroids belonging to zone q and the nearest chosen stations
$\boldsymbol{LOS}$	level of service vector with generic los_q elements
los_q	level of service of zone q equal to the difference between the ceiling of the maximum of $\boldsymbol{D}$ and the sum of minimum distances among micro-zone centroids belonging to zone q and the nearest chosen stations
$\boldsymbol{POP}$	population vector with generic pop_q elements
pop_q	total resident population in zone q
$slim$	maximum number of stations that could be chosen
cap_s	capacity of generic station s (maximum number of shared vehicles that could be parked at station s)
$peak_s$	maximum number of shared vehicles that could be simultaneously located at station s

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Author contributions

S.D.B. investigated the literature, curated the data, developed the conceptual model, performed the presented studies, and wrote the manuscript. M.O. supervised the research and administrated the project. L.C. developed the conceptual and the mathematical model, implemented the software model, reviewed the manuscript and supervised the research.

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to Simona De Bartolomeo.

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