Decision support models for the fair redesign of free-floating micromobility sharing systems

LIBERATORIA PER L'ARCHIVIAZIONE DELLA TESI DI DOTTORATO

Al Magnifico Rettore
del Politecnico di Bari

Il/la sottoscritto/a Simona De Bartolomeo nato/a a Bari il 08/03/1998

residente a Bari in via Vassallo 3/a e-mail simona.debartolomeo@gmail.com

iscritto al 3° anno di Corso di Dottorato di Ricerca in Rischio, Sviluppo Ambientale, Territoriale ed Edilizio ciclo 37

ed essendo stato ammesso a sostenere l'esame finale con la prevista discussione della tesi dal titolo:

Decision support models for the fair redesign of free-floating micromobility sharing systems

DICHIARA

1) di essere consapevole che, ai sensi del D.P.R. n. 445 del 28.12.2000, le dichiarazioni mendaci, la falsità negli atti e l'uso di atti falsi sono puniti ai sensi del codice penale e delle Leggi speciali in materia, e che nel caso ricorressero dette ipotesi, decade fin dall'inizio e senza necessità di nessuna formalità dai benefici conseguenti al provvedimento emanato sulla base di tali dichiarazioni;

2) di essere iscritto al Corso di Dottorato di ricerca Rischio, Sviluppo Ambientale, Territoriale ed Edilizio ciclo 37, corso attivato ai sensi del "Regolamento dei Corsi di Dottorato di ricerca del Politecnico di Bari", emanato con D.R. n.286 del 01.07.2013;

3) di essere pienamente a conoscenza delle disposizioni contenute nel predetto Regolamento in merito alla procedura di deposito, pubblicazione e autoarchiviazione della tesi di dottorato nell'Archivio Istituzionale ad accesso aperto alla letteratura scientifica;

4) di essere consapevole che attraverso l'autoarchiviazione delle tesi nell'Archivio Istituzionale ad accesso aperto alla letteratura scientifica del Politecnico di Bari (IRIS-POLIBA), l'Ateneo archivierà e renderà consultabile in rete (nel rispetto della Policy di Ateneo di cui al D.R. 642 del 13.11.2015) il testo completo della tesi di dottorato, fatta salva la possibilità di sottoscrizione di apposite licenze per le relative condizioni di utilizzo (di cui al sito http://www.creativecommons.it/Licenze), e fatte salve, altresì, le eventuali esigenze di "embargo", legate a strette considerazioni sulla tutelabilità e sfruttamento industriale/commerciale dei contenuti della tesi, da rappresentarsi mediante compilazione e sottoscrizione del modulo in calce (Richiesta di embargo);

5) che la tesi da depositare in IRIS-POLIBA, in formato digitale (PDF/A) sarà del tutto identica a quelle consegnate/inviate/da inviarsi ai componenti della commissione per l'esame finale e a qualsiasi altra copia depositata presso gli Uffici del Politecnico di Bari in forma cartacea o digitale, ovvero a quella da discutere in sede di esame finale, a quella da depositare, a cura dell'Ateneo, presso le Biblioteche Nazionali Centrali di Roma e Firenze e presso tutti gli Uffici competenti per legge al momento del deposito stesso, e che di conseguenza va esclusa qualsiasi responsabilità del Politecnico di Bari per quanto riguarda eventuali errori, imprecisioni o omissioni nei contenuti della tesi;

6) che il contenuto e l'organizzazione della tesi è opera originale realizzata dal sottoscritto e non compromette in alcun modo i diritti di terzi, ivi compresi quelli relativi alla sicurezza dei dati personali; che pertanto il Politecnico di Bari

ed i suoi funzionari sono in ogni caso esenti da responsabilità di qualsivoglia natura: civile, amministrativa e penale e saranno dal sottoscritto tenuti indenni da qualsiasi richiesta o rivendicazione da parte di terzi;

7) che il contenuto della tesi non infrange in alcun modo il diritto d'Autore né gli obblighi connessi alla salvaguardia di diritti morali od economici di altri autori o di altri aventi diritto, sia per testi, immagini, foto, tabelle, o altre parti di cui la tesi è composta.

Luogo e data Bari, 07/01/2025 Firma

Il/La sottoscritto, con l'autoarchiviazione della propria tesi di dottorato nell'Archivio Istituzionale ad accesso aperto del Politecnico di Bari (POLIBA-IRIS), pur mantenendo su di essa tutti i diritti d'autore, morali ed economici, ai sensi della normativa vigente (Legge 633/1941 e ss.mm.ii.),

CONCEDE

- al Politecnico di Bari il permesso di trasferire l'opera su qualsiasi supporto e di convertirla in qualsiasi formato al fine di una corretta conservazione nel tempo. Il Politecnico di Bari garantisce che non verrà effettuata alcuna modifica al contenuto e alla struttura dell'opera.
- al Politecnico di Bari la possibilità di riprodurre l'opera in più di una copia per fini di sicurezza, back-up e conservazione.

Luogo e data Bari, 07/01/2025 Firma

D.R.S.A.T.E.

POLITECNICO DI BARI

01

Doctor in Risk and Environmental, Territorial and Building Development

2024

Coordinator: Prof. Vito Iacobellis

XXXVII CYCLE
ICAR/05- Transportation

DICATECh
Department of Civil, Environmental, Building Engineering and Chemistry

Simona De Bartolomeo

Decision support models for the fair redesign of free-floating micromobility sharing systems

Prof. Leonardo Caggiani
Prof. Michele Ottomanelli

Department of Civil, Environmental, Building Engineering and Chemistry (DICATECh)
Polytechnic University of Bari

D.R.S.A.T.E.

Dottore in Rischio e Sviluppo Ambientale, Territoriale ed Edilizio

Coordinatore: Prof. Vito Iacobellis

XXXVII CYCLE
ICAR/05- Trasporti

DICATECh
Dipartimento in Ingegneria Civile, Ambientale, del Territorio, Edile e di Chimica

POLITECNICO DI BARI

01
2024

Simona De Bartolomeo

Modelli di supporto alle decisioni per un'equa riprogettazione dei sistemi free-floating di micromobilità condivisa

Prof. Leonardo Caggiani
Prof. Michele Ottomanelli

Dipartimento di Ingegneria Civile, Ambientale, del Terirtorio, Edile e di Chimica (DICATECh)
Politecnico di Bari

Title: Decision support models for the fair redesign of free-floating micromobility sharing systems

***EXTENDED ABSTRACT** (eng)*

Sharing mobility is changing users' behaviour in urban areas, introducing a new way of movement. Vehicle-sharing systems are valid alternatives to the use of private modes of transport, since they allow users to cover short to medium distances with no emissions, promoting multimodality. There are two main types of vehicle-sharing systems: station-based and free-floating. Unlike former systems, free-floating ones are not based on stations and users can release a rented vehicle arbitrarily within a predefined operating area as close as possible to their destination and in an accessible place for others. Due to these characteristics, we have focused our research on free-floating systems that have significantly grown in the last few years, but they are also characterised by a number of issues related to safety features and urban decorum. One aspect of the evolution of these systems is the possibility (or obligation) to release vehicles in geofence areas, which are similar to stations, with the aim of avoiding disorderly parking (urban decorum) that can be an obstacle to pedestrians and vehicle flows (safety features). To this end, we proposed three decision support models for the redesign of free-floating micromobility systems. The first model proposed the conversion from free-floating systems into a station-based one. In this case, users must drop off vehicles at the nearest station to their destinations. It is a bi-objective model with the aim of minimising the walking distances that users face to reach the nearest station and minimising the inequality of the service offered. The second model is an equity-based optimisation model for the location of parking areas in free-floating sharing systems. In this case, it is not mandatory to drop off vehicles in these zones, users are simply incentivised to do so. This model takes into consideration the minimisation of demand outside parking areas and the minimisation of inequality. The third model is based on the conversion of a free-floating system into a mixed one with mandatory geofence areas in which vehicles can only be dropped off at stations which are identified with painted and geofenced spaces and/or through beacons. In particular, we propose a multi-objective model that maximises station demand, minimises user walking distances, and minimises inequality in walking distance changes due to the conversion to a mixed system. The proposed models aim to increase the equity of free-floating systems, which should be equally accessible for the entire population. The solutions found are a trade-off between municipal council needs (to solve the illegal parking problem) and operator needs (to adopt systems with arbitrary parking, maximising the use of each vehicle). Further research may involve dynamic aspects in the proposed methodologies, such as the dynamic location of hubs and the dynamic relocation of vehicles and battery swap, with the aim of further improving the accessibility and equity of the system

Keywords: *Equity, Location Problem, Micromobility, Free-floating shared system, Geofence areas, Multi-objective optimization, Parking areas*

Titolo: Modelli di supporto alle decisioni per un'equa riprogettazione dei sistemi free-floating di micromobilità condivisa

EXTENDED ABSTRACT *(ita)*

La mobilità condivisa sta cambiando il comportamento degli utenti nelle aree urbane, introducendo un nuovo modo di effettuare spostamenti. I sistemi di veicoli condivisi sono delle valide alternative all'uso di mezzi di trasporto privati, poiché consentono agli utenti di percorrere distanze medio-brevi senza emissioni, promuovendo la multimodalità. Esistono due tipologie principali di sistemi di veicoli condivisi: i sistemi a stazioni fisse (station-based) e quelli a flusso libero (free-floating). A differenza dei sistemi a stazioni fisse, i sistemi free-floating non sono basati su stazioni e gli utenti possono rilasciare arbitrariamente il veicolo noleggiato all'interno di un'area operativa predefinita, il più vicino possibile alla loro destinazione e in un luogo accessibile ad altri. La nostra ricerca si focalizza sui sistemi free-floating, che si sono sviluppati in modo significativo negli ultimi anni, ma sono anche caratterizzati da problematiche legate alla sicurezza e al decoro urbano. Una possibile evoluzione di questi sistemi è la possibilità (o l'obbligo) di rilasciare i veicoli in aree georeferenziate, che hanno una funzione simile alle stazioni, con l'obiettivo di evitare parcheggi disordinati che possono essere di ostacolo ai flussi pedonali e veicolari (problematiche relative al decoro urbano e alla sicurezza). A questo scopo abbiamo proposto tre modelli di supporto alle decisioni per la riprogettazione di sistemi di micromobilità free-floating. Il primo modello propone la conversione dei sistemi free-floating in sistemi basati su stazioni. In questo caso, l'utente deve rilasciare il veicolo alla stazione più vicina alla propria destinazione. Si tratta di un modello bi-obiettivo con la finalità di minimizzare le distanze che gli utenti devono percorrere per raggiungere

la stazione più vicina e di minimizzare l'ineguaglianza del servizio offerto. Il secondo modello è un modello di ottimizzazione basato sull'equità per la localizzazione delle aree di parcheggio nei sistemi di condivisione free-floating. In questo caso non è obbligatorio rilasciare i veicoli all'interno di queste zone, ma gli utenti sono più propensi a farlo in quanto localizzate in aree ad alta domanda. Questo modello prende in considerazione la minimizzazione della domanda al di fuori delle aree di parcheggio e la minimizzazione della disuguaglianza. Il terzo modello si basa sulla conversione di un sistema free-floating in un sistema misto con aree georeferenziate. All'interno di queste aree i veicoli possono essere rilasciati solo all'interno di stazioni identificate con spazi dipinti e georeferenziati e/o tramite beacon. In particolare, proponiamo un modello multi-obiettivo che massimizza la domanda di stazioni, minimizza le distanze a piedi degli utenti e minimizza l'ineguaglianza nelle variazioni delle distanze a piedi dovute alla conversione in un sistema misto. I modelli proposti hanno l'obiettivo di aumentare l'equità dei sistemi a flusso libero, che dovrebbero essere ugualmente accessibili a tutta la popolazione. Le soluzioni ottenute rappresentano un compromesso tra le esigenze delle amministrazioni comunali (risolvere il problema dei parcheggi abusivi) e quelle degli operatori (adottare sistemi con parcheggi arbitrari, massimizzando l'uso di ogni veicolo). Ulteriori ricerche potrebbero coinvolgere aspetti dinamici nelle metodologie proposte, come la localizzazione statica e dinamica degli hub e la ricollocazione dinamica dei veicoli e dello scambio di batterie, con l'obiettivo di migliorare ulteriormente l'accessibilità e l'equità del sistema.

keywords: *Equità, Problema di localizzazione, Micromobilità, Sistemi condivisi a flusso libero, Aree di geofencing, Ottimizzazione Multi-obiettivo, Aree di parcheggio*

INDEX

1. INTRODUCTION 1

1.1. Unauthorised and irregular parking 2

1.2. Proposed solution in literature 2

1.3. Types of parking areas 4

1.4. Willingness to walk 6

1.5. Contributions 7

2. LITERATURE REVIEW 8

2.1. Station location problem 8

2.2. Conversion from free-floating to station-based systems 9

2.3. Equity concept 12

2.4. Contributions 13

3. NOTATION 16

4. PROPOSED MODELS 21

4.1. Model 1: Free-floating system into station-based 21

4.2. Model 2: Location of parking areas in free-floating systems 23

4.3. Model 3: From free-floating to mixed shared micromobility systems 25

4.3.a. Framework for model and results definitions 26

4.3.b. Proposed optimisation multi-objective model 31

5. Case Studies and discussion of results 38

5.1. Case study and discussion of results of Model 1 39

5.2. Case study and discussion of results of Model 2 44

5.3. Case study and discussion of results of Model 3 48

5.3.1. Sensitivity analysis 62

5.3.1a. Increase in the maximum number of stations 63

5.3.1b. Variation of several input parameters 68

6. CONCLUSIONS 77

ACKNOWLEDGEMENTS 82

LIST OF FIGURES 83
LIST OF TABLES 84
BIBLIOGRAPHY 85
CURRICULUM 97

1. INTRODUCTION

Sustainable mobility has become increasingly popular in recent years, particularly with the spread of shared micromobility systems such as electric scooters (e-scooters) and bicycle sharing. These types of transport have been promoted due to the fact that they might help the transition towards a cleaner and more sustainable transportation system (Roig-Costa, Miralles-Guasch and Marquet, 2024), reducing polluting emissions and traffic congestion, improving individual health, giving flexibility and quick access from/to public transport terminals (Frondel and Vance, 2017; Yanocha and Allan, 2019). They are a valid alternative to private modes of transport, allowing users to cover from short to medium distances. It is possible to divide sharing systems into two main separate categories: station-based (docked) and free- floating (dockless). In the former, users can rent a vehicle from a station and then return it to another one to end the ride. In the latter, users can pick up and drop off a vehicle anywhere in the service area (except in zones which are private or not accessible to all users), always abiding to the highway code. Free-floating systems can appear more equitable and comfortable than station-based ones. Indeed, Meng and Brown (2021), analysing 32 USA cities, shown that the geographical distribution of docked systems is extremely unequal and dockless systems minimise these differences. On the other hand, parking freedom also poses a number of relevant issues. Unauthorised and irregular parking may hinder pedestrians and traffic flow in the city as well as compromise urban decorum. In the following subsections, we will illustrate the studies related to unauthorised and irregular parking; the possible solutions proposed include the location of stations or parking areas; the typologies of parking areas; the parameter of the willingness to walk as an important factor for station location and equity, and the contributions of our research.

1.1. Unauthorised and irregular parking

There are numerous papers in which unauthorised and irregular parking have been studied. James et al. (2019) analysed 606 parked e-scooters along three mixed-use corridors in Rosslyn (USA) with the aim of investigating the relationship between the built environment and parking. They showed that 16% of these e-scooters were parked incorrectly and 6% were blocking the pedestrian right of way. Brown et al. (2020) collected data on 3,666 e-scooters, motor vehicles, bicycles, and sidewalk objects in various cities, such as San Francisco, Santa Monica and Washington. The objective was to analyse micromobility and motor vehicle parking practices. Brown (2021) analysed scooter parking regulations with data from 37 USA cities with the aim of highlighting the reasons for these choices. They found that 95% of cities allow users to park in the fourniture zone, 78% of cities allow users to park at bike raks, 70% against buildings, 62% on landscaping and 60% against singns. For these reasons, cities should approach reguations ad a fundamental piece for reclaiming streets and promoting mobility.

1.2. Proposed solution in literature

To address disorderly parking, operator-based processes and user-based regulations with mandatory or non- mandatory parking areas may be implemented. As regards the former, Carrese et al. (2020) introduce the figure of the "beautificators". Beautification differs from relocation which consists of redistributing vehicles around the city, even at greater distances from one part to another. Indeed, it aims to reposition e-scooters or bikes located in incorrect positions to optimise urban decorum. For example, Carrese et al. (2021a), with an integer linear programming and metaheuristic solution, proposed scooter repositioning of hired e-scooters in inappropriate positions. The search for incorrectly parked vehicles, to be implemented by the sharing company agents, could be facilitated, for example, using drones (Carrese et al., 2021b), through reports from other users (Voi Technology, 2024b) or, for vehicles lying on the ground, by vehicle gyroscopes. However, global navigation satellite systems have a bad signal in some places as garages, under bridges and tunnels. For this reason, Dawson et al. (2022) proposed a method to estimate the vehicle position through the use of on- board low cost inertial sensors such as accelerometers and gyroscopes. In that way it is possible to guarantee continuous positioning estimation for uninterrupted navigation. Also in the work of Zhou et al. (2022), they proposed a novel deep learning-based vehicle indoor positioning approach using smartphone built-in sensors such as accelerometer, gyroscope, gravity sensors, and magnetometer. They tested them in parking areas showing their good functioning.

Aside from “beautificators”, alternative key solutions could be to compel users of free-floating systems to park in designated spaces or provide them with the possibility to do so. In mandatory parking areas, users are forced to drop off vehicles in specific areas. Therefore, it is vital that these areas are clearly visible both in the service app and in the places where they are implemented. In non-mandatory parking areas, it is also helpful to implement app-based incentives to encourage users to park vehicles in designated areas. If they park in a place indicated in the app they can receive money, free rides or a discount on the app itself. Several studies have shown that this approach can overcome parking issues. For example, Su et al. (2020), using a randomised field experiment, showed that warning messages and monetary incentives promoting optimal behaviour reduce prohibited parking. Gao et al. (2021), through a logit model based on the theory of planned behaviour, analysed a sample of 453 users who parked their vehicles. This study showed that monetary rewards and penalties can motivate users to properly park their vehicles. The higher the intensity of the incentive, the lower the efficiency of financial penalty, especially when the distance to be travelled requires more than a 10-minute walk. Some operators directly implement parking incentives through their applications. In 2020, in Paris (France) Bird (Bird,

2020) introduced a “preferred product” for parking using app-based locations, messages, and real-time navigation to drive users to park in approved areas. An incentive is given to the users who park in these areas, accompanied by varying degrees of punishment for those who park irregularly.

1.3. Types of parking areas

Two main kinds of parking areas can be implemented: physical racks or dedicated spaces with no racks, marked with paint and/or geofenced or with beacons. Pilot projects, in particular with Voi logo racks (Voi Technology, 2024a) in Oslo (Norway) and painted parking spaces in Trondheim (Norway) and Oslo, were conducted to evaluate improvements in urban decorum. The results show that these parking solutions have a limited effect at a distance, but a good effect within the neighbourhood, especially if neutral and not linked to a rental company (TØI rapport, 2021).

Geofencing is one of the latest innovative solutions and it can change user behaviour. It is a location-based service which controls entry or exit from/to a virtual boundary, named geofence, based on a satellite navigation system, usually the USA Global Positioning System (GPS). In this way, it is possible to delimit a parking area and know whether a shared vehicle is parked inside it or not. Geofencing can be used for different purposes and not just to define parking areas. In transport, it can be used to delineate the service zone boundaries, to guarantee safety on the road with speed regulations and to deny access to certain roads or areas (Eurocities, 2020). For example, the operator Lime (Lime, 2024) and other companies use geofence zones. In the case of Lime, vehicles can stop, slow down or warn riders depending on the kind of zone they are in. There are “no locking” zones (in which a rider cannot stop or pause his ride), “low speed” zones (in which vehicle speed changes in relation of the type of street) and “no parking” zones (in which users can not end a ride) (Lime, 2020). Moran (2021) analysed bicycle and e-scooter geofences in San Francisco, USA, from 2017 to 2019. The aim was to show the importance of having regulations for defining geofencing areas. Moran, Laa and Emberger (2020) analysed the spatial variance in e-scooter geofences in Vienna, Austria, and how these differences are related to existing municipal regulations. In that way, they analysed differences between six operators highlighting geofence size, shape and placement, no-parking zone category and frequency of geofence modification. The goal was to establish a e-scooter sharing profile which can be used as a basis for future comparison cases worldwide. Geofencing can also be used for scheduling. In fact, Liazos et al. (2022), in their study, proposed a methodological framework for a geofence planning network design model with the aim of reducing cycle interaction with other kinds of traffic.

Geofencing technology is not suitable in city zones where there is a weak GPS signal with connection delays that lead to improper system operations. In these particular cases, it is possible to rely on a more precise technology: beacons. With this method, it is also possible to decrease irregular parking and increase the accuracy of locating each vehicle in zones with low satellite signals, i.e., zones with roads and parks surrounded by high buildings (Segway, 2022). For a more precise positioning of a shared vehicle, Superpedestrian (LINK, 2020) propose a digital based map named Ground Truth Maps, with the aim of illustrating urban landscapes with specific features. These maps are subsequently integrated with details of problematic areas with the support of residents and experts. All these data are mixed with existing digital maps. Periodic updates play a fundamental role because of continuous changes.

In addition, the presence of parking areas may reduce these issues, as shown in the study of Hemphill et al. (2022) which analysed the spatial distribution of parking compliance. 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 (2020) investigated the role of e-scooters in urban transportation with problems and policies, considering the introduction of dedicated parking as a possible improvement.

1.4. Willingness to walk

The location of these parking areas becomes important for how these system functions. The willingness of users to walk is an important factor in how these systems function. For this reason, distance decay is conceived to evaluate system efficiency and behaviour of users. Indeed, the shorter the distance, the higher the probability to make the trip, while the greater the distance, the less likely it is for travel to occur (AuX Platform, 2020). Fukushige, Fitch and Handy (2022) examined bike-sharing user willingness to walk to pick up/drop off a vehicle at various distances from their origins or destinations and underlined the factors influencing their choice. They show that 90% of users are willing to walk about 5 minutes (around 400 m); as a result, placing bikes at 800 metre intervals could satisfy users. The study of Kabra, Belavina and Girotra (2016) established that almost 80% of bike-sharing system users were willing to walk a maximum of 300 metres to reach a vehicle. The study of Gao et al. (2020), however, shows that characteristics such as population density, education facility density, branch road density and parking density affect distance decay in dockless bike sharing systems in a positive way. Due to these theories, as well as the fact that the freedom to drop off vehicles at the exact location of the user’s destination has generated disorder and obstacles on roads and pavements (Zhang et al., 2023), the introduction of stations in free-floating systems was developed in a few studies. For example, Zakhem and Smith- Colin (2021) proposed the introduction of dockless parking zones to reduce disorder as a result of the free-floating mode. Users could be incentivised (not obliged) to release vehicle in these zones. Sandoval et al. (2021) proposed a data-driven placement of parking facilities in free-floating systems to incentivise users to drop off vehicles without obstructing roads and pavements. The location of parking facilities may benefit one part of the population more than another. For this reason, the equity concept needs to be taken into consideration.

1.5. Contributions

To the best of our knowledge, so far nobody has proposed station location models considering equity aspects. Our research aims to provide municipalities and shared system micromobility operators with a tool to address disorderly parking, proposing three decision support models for the fair redesign of free-floating micromobility systems. The first bi-objective model proposed the conversion from a free-floating system into a station-based one. 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. The second model is an equity-based optimisation model for the location of parking areas in free-floating e-scooter sharing systems. This model takes into consideration the minimisation of demand outside parking areas and the minimisation of inequality. The third model is based on the conversion of a free-floating system into a mixed one with mandatory geofence areas in which vehicles can only be dropped off at stations identified with painted and geofenced spaces and/or through beacons. In particular, we propose a multi-objective model that maximises station demand, minimises user walking distances, and minimises inequality in walking distance changes due to the conversion to a mixed system. In the following section, we report recent studies on location problems and equity. In the third section, we report the mathematical notation of models. The proposed models are presented in the fourth section with their respective case study and discussion of results. Conclusions close the thesis.

2. LITERATURE REVIEW

The problem of parking location has been one of the most discussed topics related to vehicle sharing systems. In particular, the methodologies and models used to identify infrastructure or parking positions were taken into consideration, with the aim of improving the organisation of shared systems. The literature review is organised as follows: Section 2.1 discusses studies focused on the problem of station location; Section 2.2 examines studies proposing the conversion from free-floating to station-based systems; Section 2.3 analyses the concept of equity and how it is related to this research; Section 2.4 outlines the contributions and future developments of the proposed study.

2.1. Station location problem

The problem of station location has been an issue widely discussed in literature. Among the first works, we find a variety of papers focusing on this topic. Palomares, Gutierrez and Latorre (2012) proposed a GIS-based method to calculate the spatial potential demand distribution for trips with the aim of determining station capacity and the characteristics of the demand for stations. Park and Shon (2017) analysed optimal bike-sharing station locations with the use of location- allocation methods, concentrating on the minimum impedance model and maximum coverage location problem. This study was based on taxi trajectory data with the aim of localizing bike-sharing stations more efficiently to replace short car trips. They calculated demand through records of real-scale floating population data. Cintrano et al. (2018), using a p-median problem, analysed the best location of bike stations with the aim of allowing users to walk the shortest distance to reach them. The objective function is the minimisation of the average distance from users to the nearest bike station. Chen et al. (2018) proposed a multi-objective mixed-integer linear programming (MILP) model with the aim of optimally localizing e-scooter charging stations. Sun, Li and Zuo (2019) proposed a MILP model to optimise location assignment of virtual stations and to maximise user demand. They also proposed a clustering algorithm such as an alternative solution to solve the problem in real time They proposed maximising the number of bikes of virtual stations to maximise station demand. User demand was considered as the number of shared bikes from of all virtual stations. Cheng and Wei (2020) proposed a multicriteria decision-making model including the analytic hierarchy process and the weight-restricted data envelopment analysis method with the aim of determining the optimal bike-sharing parking points. They took into consideration the interests of users, the environment and safety issues. Fu et al. (2020), within a spatio-temporal clustering algorithm, analysed data of shared bicycles, flows and parking rules with the aim of identifying bicycle area divisions more clearly. Amarilies, Kamil and Adzkia (2020), through a maximum coverage distance problem, analysed parking positions and their capacity for dockless bike-sharing systems. Cintrano, Chicano and Alba (2020) analysed the best station locations for shared bicycles with the use of a p-median problem. The objective function is to minimise the average distance from users to the nearest bike station.

2.2. Conversion from free-floating to station-based systems

Among the most recent works we find papers related to problem location focused on the conversion from free-floating systems to a geofenced or station-based one. For example, Fazio et al. (2021) proposed a spatial multicriteria GIS-based method for the prioritisation of locations of the cycle stations within urban areas, with the design of a cycle network. They considered spatial data related to public transport accessibility, attractiveness, presence of points of interest and socio- economic information. Zafar, Bayram and Bayhan (2021), through a maximum coverage location problem, analysed correct electric vehicle fast charging station locations, using QGIS software. The objective is to maximise the amount of charging demand required within the desired driving distance by achieving maximal coverage. Mahmoodian, Zhang and Charkhgard (2022) proposed dynamic hubbing (i.e., geofencing areas varying from one day to another) and hybrid rebalancing by combining user-based and operator-based strategies, using a novel multi-objective simulation optimisation approach. They proposed two models. In the first model, the objective is to minimise the distance between the location of the hub centre and the location of demand. The objective of the second model is to minimise the walking distance between zone and customers and the assignment of demand to that zone. Cai, Ong and Meng (2023) proposed a multi-objective integer non-linear programming model with the aim of converting an existing free-floating bike sharing system into a geofence-based one. They set out to define geofencing stations, their corresponding parking capacities, and deployment of bikes. The objective is to minimise monetary costs, user dissatisfaction, and the additional first/last-mile walking distance of users. Rojas et al. (2023) proposed a decision support system to guide free-floating bike-sharing system operators in deciding where to locate virtual bike stations in a medium-sized city, using a geospatial data wrangling methodology and open-source software such as GeoPandas. The objective is to minimise the sum of the distances between all demand nodes and the stations. Fu et al. (2023) constructed a site selection model with constrained service level through the use of a hybrid genetic and annealing algorithm. The aim is to adjust the location of electronic fences to balance the supply and demand of sharing bicycles, minimising the costs and ensuring service level. Deveci et al. (2023) developed a novel hybrid fuzzy multi-criteria decision-making model with the aim of determining optimal e-scooter parking locations by combining the logarithmic methodology of additive weights and the ranking of alternatives through functional mapping of criterion sub- intervals into a single interval method. Colovic et al. (2024) proposed a novel multi-objective micromobility maximal coverage parking location model with the aim to design shared e-kick scooter parking spaces in large urban areas. The objective functions are three and are about the maximisation of the population coverage, the maximisation of multimodal accessibility coverage and the maximisation of the attraction coverage considering most relevant points of interest for each corresponding zone belonging to large urban areas.

More specifically, there are a number of studies focusing on the location of stations, where users are incentivised to drop off vehicles. For example, Zakhem and Smith-Colin (2021) proposed two methodologies to identify areas of high parking demand and roadway segments of high micromobility vehicle demand. Their goal was to assign free-floating parking and reduce disorder across cities, in an attempt to improve identification of locations for road infrastructures, incentivizing users to drop off vehicles in those parking areas. The studies of Zhang, Lin and Mi (2019) and Sandoval et al. (2021) proposed an electric fence planning for free-floating bike-sharing systems and a data-driven method based on clustering algorithms with the aim of establishing shared e-scooter parking locations and their usage, respectively. In both studies users could be incentivised or obliged to drop off vehicles in those zones. In addition, Arif and Margellos (2022) proposed painted parking areas for bikes where users are either not allowed to end a journey outside of a parking hub or are penalized for parking outside the designed area. Conversely, in the paper of Xanthopoulos et al. (2024) users are obliged, not incentivised, to park vehicles in predefined areas. There are few studies involving mixed use of free-floating systems and station-based functioning. Zhao and Ong (2021), for example, proposed a procedure to identify potential bicycle parking facility locations and capacities, using a density-based spatial clustering of applications with noise method and k-means clustering algorithm. Shi, Liang and Seng (2022) proposed a framework for planning electric fences based on a dynamic land parcel subdivision algorithm and a regional coverage maximisation problem. Mangold et al. (2022) developed a Geographic information system based multi- criteria decision analysis framework for geofence planning of dockless bike-sharing systems based on available data. However, in all these studies, no models are proposed to define the boundary of the free-floating and station-based sub- areas, but these are set a priori.

2.3. Equity concept

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 (Theil, 1967) explicitly quantifies inequality both within and between groups (e.g., for mutually exclusive spatial regions or sociodemographic categories) and it is decomposable into these two quantities and the overall Theil is simply the sum of the between- and within-group inequalities (Karner et al., 2024) and it was used, for example, in the analysis of Hamidi et al. (2019) based on inequalities of bicycle access at major transportation nodes in a city. The Gini index (Gini, 1912) is a measure of inequality of a distribution and it is calculated from the Lorenz curve, which is represented on a diagram. On the horizontal axis, a chosen unit was represented (in most cases the population), while on the vertical axis the income was shown. If the curve is equal to a 45° straight line, the situation is equitable; if it shows a curvilinear trend, the situation is unfair. This index was used, for example, in the study of Giuffrida et al. (2023); an evaluation of horizontal equity was conducted through the use of the Gini index based on Lorenz curve as a measure used to assess the distribution of accessibility within the population. Similarly, in the study of Berke et al. (2024), the Gini index was used to evaluate spatial equity in access to public bike-sharing.

There are numerous studies in which equity aspects were analysed in relation to the problem of problem. Caggiani, Colovic and Ottomanelli (2020) in their study, for example, proposed a bike-sharing station location model with equality aspects, through a Theil index. The aim was to minimise inequalities in bike-public transport mobility, maintaining high levels of accessibility and coverage. Iravani (2022) used an innovative methodology to identify the locations of electric vehicle stations, improving accessibility with equity and efficiency aspects with the aim of maximizing system usage. Beairsto et al. (2022) carried out the ideal locations for future bike sharing stations in Glasgow, Scotland, combining demand modelling, with an ordinary least squares regression model with accessibility aspects, measured by two-step floating catchment area methodology and GIS weighted overlay analysis. Fan and Harper (2024) carried out a bi-objective optimisation model to show how stakeholder preferences towards equity impact the design of docked bike shared systems. The objective function is about maximizing the encircled demand of bike stations and maximizing total service weighted by disadvantaged level of census block groups. Blanco, Marin and Puerto (2022) introduced an equity criterion based on envy, which is defined with respect to the revealed preference of each demand point for sites of the potential serving facility. The aim was to locate facilities minimizing envy through a p-facilities location problem. Blanco and Gazquez (2023) proposed a general mathematical optimisation model to capture the notion of fairness in maximal covering location problems. They carried out a new fairness measurement based on a Gini index and other definitions. Bencekri et al. (2023) propose a single allocation p-median hub with a fixed cost model, where the fixed cost includes equity and coverage indices. Equity was explained through a Gini index derived using social quantile group data.

2.4. Contributions

To eliminate irregular and unauthorized parking, municipal councils can approve the total transition from free-floating systems to station-based. However, this solution may only be the best considering a high number of stations, due to the low walking distances that users have to cover on foot in a station-based system. It is not usually possible to implement a large number of stations to have the same distances as free-floating walking distances, due to the fact that it would be necessary to subtract spaces from pavements or other parking categories, such as cars and mopeds. On the other hand, non-mandatory parking areas may be insufficient to address the problems related to free parking. In both cases, stations could create advantages or disadvantages for a part of the population with higher or lower walking distances. A trade-off solution could be the conversion from a free-floating system to a mixed one, with geofenced sub-areas based on stations, considering equity aspects, as proposed in this thesis.

To the best of our knowledge, in literature there are no location models that consider equity aspects and suggest the conversion of a dockless system into a mixed one with free-floating and station-based service sub-areas. Therefore, in this work we propose a model that allows the definition of these sub-areas that can be implemented using geofencing technology. In station-based sub-areas, stations can be identified with painted and geofenced spaces and/or through beacons. Transforming a free-floating system into a mixed one can limit irregular parking but, at the same time, it can lead to a change (often a reduction) in the level of service. Indeed, if the distance among stations is not sufficiently low, users will be forced to walk longer, on average, compared to a purely dockless system. For these reasons, we suggest a multi-objective problem with the aim of finding a compromise solution among three objectives: 1) the maximisation of the number of users parking in stations (station demand) where vehicle parking is mandatory, to minimise irregular parking; 2) the minimisation of users' walking distances; 3) the minimisation of inequality in the accessibility of the system among service area residents to ensure that there are no population zones that will be more affected by the walking distance changes. All the details of the proposed model, including all its parameters and variables, are fully described in the next section.

The proposed model was applied to a case study which highlights how it can support municipalities and operators, allowing them to find a fair compromise system configuration between the entire transformation of a dockless system into a docked one and a system with no mandatory parking spaces, creating stations only where it is most necessary (where the vehicle drop-offs are higher) without neglecting a possible minimisation of users’ walking distances.

3. NOTATION

In this subsection, all the symbols used in the thesis with the relative description have been reported in alphabetical order.

$a_{s,r}$	number of car parking spaces belonging to paid category r that have to be removed to satisfy maximum number of shared vehicles simultaneously at station s, incremented with factor δ
b	generic buffer with $b \in [0, 1, 2, \dots, nb]$
β_b	percentage of system users that are willing to walk a distance less or equal to vb from their destinations to the nearest station to drop off a vehicle
c_i	centroid coordinates of micro-zone i
c_{j_i}	centroid coordinates of micro-zone j_i
cap_s	capacity of a generic station s (maximum number of parked shared Vehicles at station s)
cap_{s_k}	maximum number of shared vehicles that can be parked in the station s_k
cd_max	maximum distance among any pair of stations belonging to the same cluster
$\boldsymbol{CK}$	choice set of station clusters
$clim_r$	maximum number of car parking spaces of the category r to be removed
c_min	minimum number of stations belonging to a cluster of stations
γ_{j_i}	weight of the destination micro-zone j_i reachable from micro-zone i
δ	incremental factor of $peak_{s_k}$
$\boldsymbol{D}$	vector of z elements of the total of minimum distances between micro-zone centroids belonging to zone q and the nearest chosen

	stations
dem	total number of users parking in stations during ΔT function
d_i	minimum distance between micro-zone i centroid and the nearest station belonging to chosen stations $\boldsymbol{S}$
$dist$	distance function between two centroids
$dlim$	maximum distance that a user is forced to walk to pick-up or drop-off a vehicle in station-based sub-areas
$dmax$	maximum distance that users are willing to cover with a shared vehicle
$dmin$	minimum distance for which a user chooses to pick-up a shared vehicle instead of walking to the destination
Δg	difference between inequality Gini index of the existing free-floating micromobility sharing system and that of the mixed one ($g_{ff} - g$)
$\overline{\Delta g}$	number of times Δg is less than 0, calculated as a percentage, during the time interval ΔT
ΔT	total time interval in which the existing free-floating system trips data are available
e_{j_i}	drop-off walking distance at destination micro-zone j_i (drop-off distance at destination)
f_{j_i}	pick-up walking distance at destination micro-zone j_i (pick-up distance at destination)
g	inequality Gini index of the mixed micromobility sharing system function
g_{ff}	inequality Gini index of the existing free-floating micromobility sharing system function
i_{s_k}	generic micro-zone of station s_k with $i_{s_k} \in [1, 2, \dots, m_{s_k}]$
i	generic micro-zone with $i \in [1, 2, \dots, m]$
in_max	maximum value of average spacing among stations of the choice set calculated with Delaunay triangulation

j_i	generic destination micro-zone reachable from origin micro-zone i (destination centroid is at a distance between $dmin$ and $dmax$ from the origin centroid) with $j_i \in [1, 2, \dots, n_i]$
k	station cluster with $k \in [1, 2, \dots, nsc]$
$\boldsymbol{K}$	chosen set of station clusters (decision variable) with $\boldsymbol{K} \subseteq \boldsymbol{CK}$
los_q	level of service ratio of zone q
$\boldsymbol{LOS}$	level of service ratio vector with los_q elements
m	total number of micro-zones
$\boldsymbol{M}$	set of all micro-zones of service area
$\boldsymbol{MF}$	set of micro-zones of the free-floating sub-area whose centroids are at a distance greater than $dlim$ from at least one station of the chosen set of station clusters with $\boldsymbol{MF} \subseteq \boldsymbol{M}$
m_q	total number of micro-zones belonging to a zone q
$\boldsymbol{M}_q$	set of micro-zones belonging to a zone q
$\boldsymbol{MS}$	set of micro-zones of station-based sub-areas that are at a distance shorter than $dlim$ from at least one station of the chosen set of station clusters with $\boldsymbol{MS} \subseteq \boldsymbol{M}$; $\boldsymbol{MS} \cup \boldsymbol{MF} = \boldsymbol{M}$
$m_{s,b}$	number of micro-zones around station s with centroids located between buffer b with radius vb and buffer b − 1 with radius vb−1
m_{s_k}	total number of micro-zones whose centroids fall within a radius of $dlim$ from station s_k
$mwsb$	average user' walking distance in station-based sub-areas
nb	total number of considered buffers around each chosen station
n_i	total number of destination micro-zones which can be reached from the origin micro-zone i
n_r	number of car parking spaces category
ns	total number of chosen stations
nsc	total number of clusters belonging to $\boldsymbol{K}$
ns_q	total number of chosen stations in a generic zone q
nst	total number of stations in the service area

nst_k	number of stations belonging to cluster k
$nstop_i$	number of drop offs in a micro-zone during the period under consideration
$nstop_{i_{s_k}}$	number of drop-offs in a micro-zone i_{s_k} during the time interval ΔT
$nstop_{j_i}$	number of drop-offs in a destination micro-zone j_i during the time interval ΔT
pav	total number of stations on pavement
$peak_s$	maximum number of shared vehicles that could be simultaneously located at station s in the period under consideration
$peak_{s_k}$	maximum number of shared vehicles that could be simultaneously at station s_k
$\boldsymbol{POP}$	population vector with pop_q elements
pop_q	resident population in zone q
psp	total number of car parking spaces that have to be removed for the conversion from the free-floating system to the mixed one
psp_r	number of r category car parking spaces that have to be removed for the conversion from the free-floating system to the mixed one
$psp_{s_k,r}$	number of car parking spaces in category r that have to be removed to satisfy the maximum number of shared vehicles simultaneously dropped-off at station s_k, incremented with δ factor
q	generic zone in which the population is divided
r	car parking spaces category with $r \in [1, 2, \dots, n_r]$
s	generic station with s $\in [1, 2, \dots, ns]$
$\boldsymbol{S}$	set of chosen stations
sba	station-based sub-area percentage over service area
$\boldsymbol{SC}$	set of coordinates of stations belonging to $\boldsymbol{K}$

s_k	generic station within cluster k with $s_k \in [1, 2, \dots, nst_k]$
$slim$	maximum number of stations that could be realized
$stop_{s,b}$	number of drop offs around station s between buffer b with radius vb and buffer $b-1$ with radius vb−1
t	update time interval of the existing free-floating micromobility sharing system database
und	unsatisfied stations demand
v_b	radius of buffer b
$\boldsymbol{VC}_t$	set of coordinates of dropped-off vehicles that users may pick-up during the time interval t
w	sum of round-trip user walking distances function
$w1_i$	pick-up walking distance at origin micro-zone i
$w2_i$	sum of weighted drop-off walking distances at destinations j_i reachable from the micro-zone i
$w3_i$	sum of weighted pick-up distances at destinations j_i reachable from the micro-zone i
$w4_i$	drop-off walking distance at origin micro-zone i
$wf1_i$	pick-up walking distance at origin micro-zone i for the free-floating system
$wf3_i$	sum of weighted pick-up distances at destinations j_i reachable from the micro-zone i for the free-floating system
wsb	percentage increase in a user's average walking distance in station-based sub-areas compared to that of the free-floating system in the same sub-areas
z	total number of zones into which the population is divided

4. PROPOSED MODELS

In this thesis attention is focused on free-floating systems that allow users to pick up and drop off vehicles as close as possible to their destinations at any point within the operating area, as long as this follows the highway code. On the other hand, these systems are characterized by a number of issues. Indeed, disorderly parking affects urban decorum and parked vehicles on sidewalks are obstacles to pedestrians and compromise their safety.

In this section, we propose three decision support models for the fair redesign of free-floating micromobility systems with the aim of avoiding the issues above. Model 1 (Section 4.1), Model 2 (Section 4.2) and Model 3 (Section 4.3) are reported as follows.

4.1. Model 1: Free-floating system into station-based

In this section we propose a model to convert a free-floating system into station-based. 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. However, the location of stations may not always allow for equitable access to the system for all the population. To the best of our knowledge, up to now nobody has proposed a station location model to convert a free- floating system into station-based considering equity aspects.

In this section we proposed an equity-based bi-objective model (4.1.1)-(4.1.7) 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., 2022) and in smaller quantities on pavements.

For each micro-zone, the first objective function (4.1.1) 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 (4.1.2) is the minimisation of 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. (4.1.3)), is intended as the difference between total walking distances in zone q compared to zones with the greatest total walking distances over the area under consideration.

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. (4.1.4) for each zone q considering the distances from the centroid of each micro-zone belonging to zone q to the nearest chosen station. Eq. (4.1.5) represents the total population in zone q.

$$\min_{\boldsymbol{S}} dt = \sum_{i=1}^{m} nstop_i \cdot d_i \tag{4.1.1}$$

$$\min_{\boldsymbol{S}} g = GINI(\boldsymbol{LOS}, \boldsymbol{POP}) \tag{4.1.2}$$

with

$$los_q = \lceil max(\boldsymbol{D}) \rceil - \sum_{i=1}^{m_q} d_i \tag{4.1.3}$$

$$\boldsymbol{D} = \left[\sum_{i=1}^{m_1} d_i , \sum_{i=1}^{m_2} d_i , \dots , \sum_{i=1}^{m_z} d_i \right] \tag{4.1.4}$$

$$pop_q = \sum_{i=1}^{m_q} pop_i \tag{4.1.5}$$

s.t.

$$ns \leq slim \tag{4.1.6}$$

$$cap_s \geq peak_s \qquad \forall\, s\, \epsilon\, [1, 2, \dots , ns] \tag{4.1.7}$$

Constraint (4.1.6) establishes that the total number of stations ns have to be fewer than the total number of stations that could be chosen ($slim$). Constraint (4.1.7) 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 viceversa. The aim is to balance the los_q with pop_q. Therefore, the solutions for this proposed model were 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 (2001).

4.2. Model 2: Location of parking areas in free-floating systems

In this section, we propose a bi-objective model (4.2.1)-(4.2.8) with the aim of defining parking areas for free-floating e-scooter sharing systems. In these zones, it is not mandatory to drop off vehicles; users are simply incentivised to do so. We considered as possible locations the conversion from paid and/or unpaid car parking spaces into micromobility parking areas and the possibility to locate a smaller quantity of parking areas on pavements. The first objective function (4.2.1) aims at minimising micromobility shared vehicles outside stations. The equation is a difference between two sums. The former is the total of drop offs $nstop_i$ for each micro-zone m, the second is the total number of drop offs around station s between buffer b with radius v_b and buffer $b-1$ with radius v_{b-1}, which are considered as the users that would leave the vehicles inside the stations, for each m. Eq. (4.2.3) represents the total number of drop offs around station s between buffer b with radius v_b and buffer $b-1$ with radius v_{b-1}. This is equal to the product of the $nstop_i$, and the percentage of users who could be willing to walk a distance less than or equal to v_b from their destinations to the nearest station to drop off a vehicle, for each $m_{s,b}$; i.e., number of micro-zones around station s with centroids located between buffer b with radius v_b and buffer $b-1$ with radius v_{b-1}.

The second objective function (4.2.2) aims at minimising the Gini value. The Gini value is calculated taking into consideration the departure and the return to origin of a circular journey. It is calculated from the Lorenz curve and depends on the level of service vector $\boldsymbol{LOS}$ (y-axis) and population vector $\boldsymbol{POP}$ (x-axis). These are composed of the level of system service in zone q equal to the total number of drop offs outside stations in the period under consideration and the number of stations in zone q, named los_q, and total resident population in zone q, named pop_q, respectively. Eq. (4.2.4) represents the probability of finding available vehicles near users and it is the difference between the $nstop_i$ for each micro-zone m_q belonging to zone q, and the sum of $stop_{s,b}$ and the total number of chosen stations, ns_q, in a generic zone q. Eq. (4.2.5) shows the total of the population for each micro-zone m belonging to zone q. Eq. (4.2.4) and Eq. (4.2.5) have to be balanced to guarantee a good level of equity.

$$\min_{\boldsymbol{S}} dem = \sum_{i=1}^{m} nstop_i - \sum_{s=1}^{ns} \sum_{b=2}^{nb} stop_{s,b} \tag{4.2.1}$$

$$\min_{\boldsymbol{S}} g = GINI(\boldsymbol{LOS}, \boldsymbol{POP}) \tag{4.2.2}$$

with

$$stop_{s,b} = \sum_{i=1}^{m_{s,b}} \left(nstop_i \cdot \left(\frac{\beta_b}{100} \right) \right) \tag{4.2.3}$$

$$los_q = \sum_{i=1}^{m_q} nstop_i - \sum_{s=1}^{ns_q} \sum_{b=1}^{nb} stop_{s,b} + ns_q \tag{4.2.4}$$

$$pop_q = \sum_{i=1}^{m_q} pop_i \tag{4.2.5}$$

s.t.

$$ns \leq slim \tag{4.2.6}$$

$$\sum_{s=1}^{ns} a_{s,r} \leq clim_r \qquad \forall\, r \; \in [1, 2, \dots, nr] \tag{4.2.7}$$

$$cap_s \geq \; peak_s + \delta \qquad \forall\, s \; \in [1, 2, \dots, ns] \tag{4.2.8}$$

Constraint (4.2.6) establishes that the total number of chosen stations ns has to be lower than the total number of stations that could be chosen, slim. Constraint (4.2.7) shows the number of car parking spaces belonging to paid category r that have to be removed to satisfy maximum number of shared vehicles simultaneously at station s, increased with factor δ, $a_{s,r}$, have to be lower than the maximum number of car parking spaces belonging to paid category r to be removed to establish a shared-vehicle station, $clim_r$. Constraint (4.2.8) states that the capacity of a generic station, cap_s, has to be greater than the maximum number of shared vehicles that could be simultaneously located at station s in the period under consideration, $peak_s$, incremented with factor δ.

4.3. Model 3: From free-floating to mixed shared micromobility systems

This section is divided into two subsections. The first (4.3.a) shows the entire procedure for defining the input data, the model and the results while the second (4.3.b) shows the proposed optimisation multi-objective model.

4.3.a. Framework for model and results definitions

In this subsection, through a flowchart divided in 3 parts (Figure 1), we describe all the procedures for defining the model inputs (part 1 and part 2) and a summary description of the model itself with possible solutions processing (part 3).

Part 1 of the entire framework, to the left of the flowchart, focuses on the definition of the sharing system and population data. To reduce the complexity of the problem, we divide the service area into m micro-zones, using for example a square or a hexagonal mesh grid. Trip data, updated at a high frequency every t minutes, of an existing free- floating micromobility sharing system, are assumed to be available. Starting from this database containing data for a ΔT total time interval, we can associate the drop-off trends and their locations to each centroid of the micro-zones. In this way, it is possible to calculate the drop-off demand and the distances between the centroids and all the nearest drop-off locations.

The population in each micro-zone can be found starting from the resident population database. Subsequently, micro- zones are grouped together to create population zones among which we want to minimise disparities in the accessibility changes of the mixed vehicle sharing system.

Part 2, to the right of the flowchart, focuses on the definition of the station choice set. To promote shared micromobility by removing parking spaces from car drivers, where it is possible, we proposed to select station locations among city car parking spaces, as suggested also in the study of Hemphill et al. (2022). In addition, a (possible smaller) number of stations can even be located on pavements exclusively where they are sufficiently wide to allow pedestrians to walk without obstructions. The database for available parking spaces for transformation into shared system stations and suitable pavements can be provided by the municipality or can be defined according to their urban mobility technicians. It is important to know the coordinates for each car parking space/pavement area (named stations from here on) and their capacity, i.e., the maximum number of micromobility vehicles that can be dropped off inside them.

This choice set could include stations very close to each other. Therefore, it may be appropriate to eliminate extra stations from this database by ensuring that the average spacing between them are less than or equal to in_{max}. Spacing is calculated using a Delaunay triangulation, which is a triangulation net where each triangle satisfies the Delaunay condition: for each circumcircle created for a Delaunay triangle, there are no vertices of other triangles inside (Delaunay, 1934). The goal was to generate a mesh to represent continuous surface. The input of this triangulation is a set of points, while the result is a set of triangles which do not overlap (Dinas and Banon, 2014).

To find a subset of stations with average spacings among them less than or equal to in_{max}, the following step-by-step heuristic procedure is proposed:

Step 1: Delaunay triangulation among station choice set.

Step 2: calculation of the average spacing between each station and those connected to it via Delaunay triangles.

Step 3: if the smallest average spacing is less than or equal to in_{max}, then the station with this average spacing is deleted from the station choice set, thus generating a station choice subset, otherwise the procedure ends.

Step 4: Delaunay triangulation among the station choice subset.

Step 5: calculation of the average spacing among each station and those connected to it via Delaunay triangles.

Step 6: if the smallest average spacing is greater than in_{max}, then the station deleted in Step 3 is inserted again in the station choice subset and the procedure ends; otherwise, the procedure restarts from Step 3.

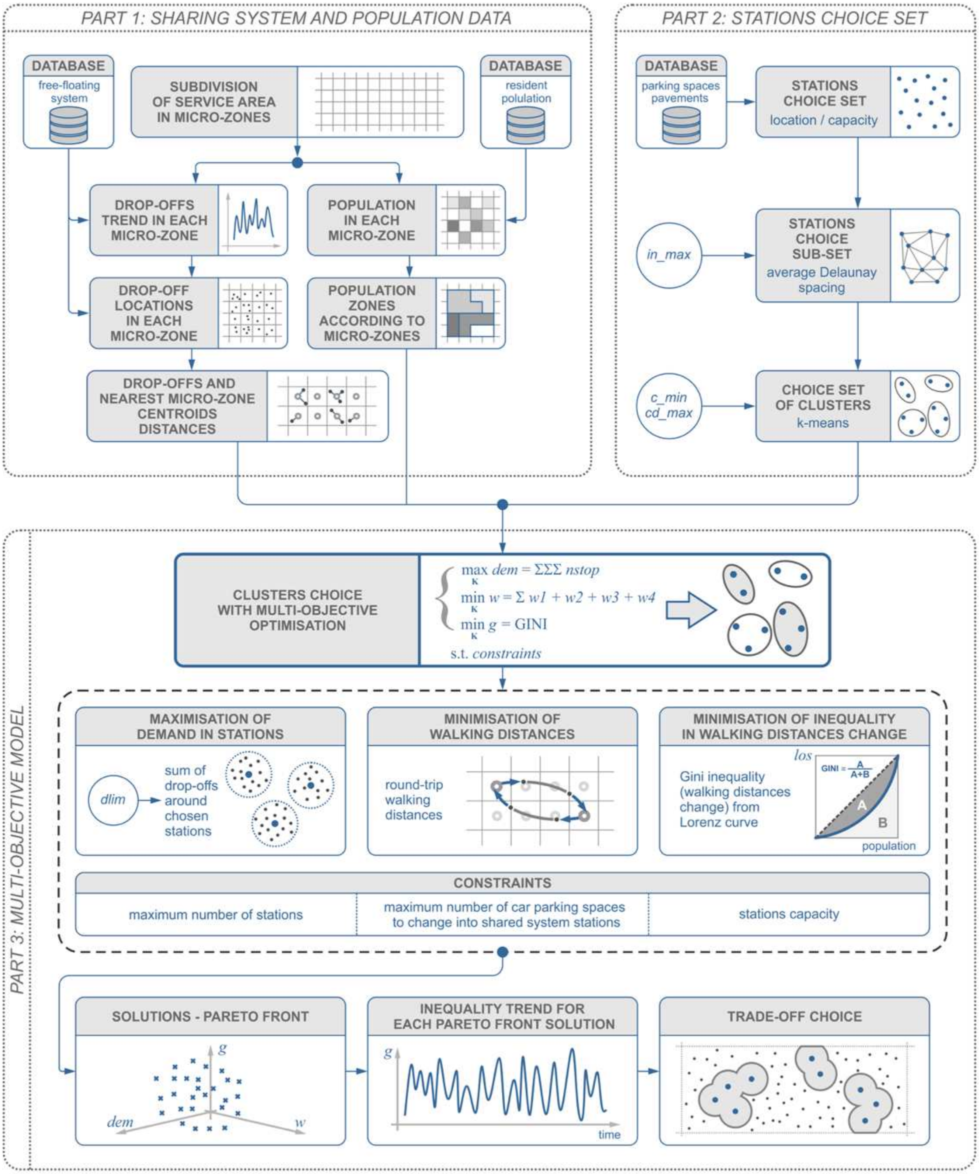

Fig. 1- Proposed framework flowchart

The final result of our proposal is to identify areas within which it is mandatory to drop off shared vehicles at stations. These areas should not be too small to make it easier for users to recognise them and so that there are not too many discontinuities among free-floating based and station-based sub-areas. Subsequently, it is necessary to cluster the stations of the choice subset through that the optimisation model can choose among clusters of stations and not among individual stations. The choice set of station clusters, CK, could be defined using k-means algorithm (Kaur and Kaur, 2013) with c_{min} (the minimum number of stations a cluster must have) and cd_{max} (the maximum distance among any pair of stations within a cluster) as constraints. The total number of clusters will be the smallest integer that allows these two constraints to be satisfied.

Part 3, at the bottom of the flowchart, focuses on the proposed multi-objective model and possible solutions processing. The main inputs of the model are those deriving from the previous parts of the framework. This model presents three objectives. The first concerns maximising station demand (dem), which is the number of users parking in stations during ΔT. Assuming that the maximum distance that a user is forced to walk to pick up or drop off a vehicle in a station-based sub-area is equal to $dlim$, the dem function is the total of the number of drop-offs for each micro-zone whose centroids fall within a radius of $dlim$ from the stations. In other words, all micro-zones whose centroid is within the buffer will contribute to the total number of drop-offs for that station, and each user leaving the vehicle in that buffer will travel a distance less or equal than $dlim$.

The second objective regards minimising the total of round-trip users' walking distances (w) considering as origins and destinations the micro-zone centroids.

The third objective focuses on minimising the inequalities (g) among resident population zones in the changes of round-trip users' walking distances due to the conversion from the free-floating system to a mixed one. The inequality is calculated using the Gini index based on the Lorenz curve.

The constraints of the problem are related to the maximum number of stations ($slim$), the maximum number of car parking spaces to change into micromobility shared system stations ($clim_r$), and the need for station capacities to be greater than or equal to demand. The first two limit values ($slim$ and $clim_r$) may be fixed, for example, by municipal councils, who should consider other traffic categories when making these decisions.

These three objectives, which will be described in detail with the problem constraints in the next subsection, may be incompatible with each other. If demand at stations is maximised, it is not guaranteed that user walking distances and walking distance inequalities will be minimised. This is the same for other combinations.

The multi-objective model offered a variety of solutions, which are represented through a Pareto front. Pareto optimality is a state in which it is impossible to make any objective function value better off without making at least one other objective function value worse off. For further details, see Deb, 2001. These solutions are shown in a three-dimensional diagram. Each solution represents chosen clusters of stations. The related station-based sub-areas are defined by superposition of buffers with radius $dlim$ centred at each station. Municipal councils and experts may choose a trade-off solution from these results. To this end, for each Pareto front solution, we can consider the trend of g during ΔT due to the change in station demand over time. Therefore, it is possible to calculate the differences Δg, during ΔT, between the trends of the Gini index in the case in which the system remained free-floating (g_{ff}) and the trend of g. The desirable solutions are those with fewer repetitions of negative Δg during ΔT, i.e., with their percentage ($\overline{\Delta g}$) as low as possible. Subsequently, the choice of station clusters and the related station-base sub-areas could fall on one of the solutions with the lowest $\overline{\Delta g}$ value, as we will see better in the case study, with the support of figures.

4.3.b. Proposed optimisation multi-objective model

In this subsection, the formulation of the proposed multi-objective model is described in detail. This model presents three objective functions and three constraints as follows, where the decision variable is a set of station clusters, $\boldsymbol{K}$, belonging to the choice set $\boldsymbol{CK}$, defined in part 1 of the proposed framework.

$$\max_{\boldsymbol{K}} dem = \sum_{k=1}^{nsc} \sum_{s_k=1}^{nst_k} \sum_{i_{s_k}=1}^{m_{s_k}} nstop_{i_{s_k}} \tag{4.3.b.1}$$

$$\min_{\boldsymbol{K}} w = \sum_{i=1}^{m} w1_i + w2_i + w3_i + w4_i \tag{4.3.b.2}$$

$$\min_{\boldsymbol{K}} g = Gini(\boldsymbol{LOS}, \boldsymbol{POP}) \tag{4.3.b.3}$$

$with$

$$w1_i = \begin{cases} mode\{\min\,[dist(c_i\,, \boldsymbol{VC}_t) \;\; \forall t \in \Delta T\} \text{ if } i \in \boldsymbol{MF} \\ \min[dist(c_i, \boldsymbol{SC}\,)] \text{ if } i \in \boldsymbol{MS} \end{cases} \tag{4.3.b.4}$$

$$w2_i = \sum_{j_i}^{n_i} e_{j_i} \cdot \gamma_{j_i} \tag{4.3.b.5}$$

$$w3_i = \sum_{j_i=1}^{n_i} f_{j_i} \cdot \gamma_{j_i} \tag{4.3.b.6}$$

$$w4_i = \begin{cases} 0 \text{ if } i \in \boldsymbol{MF} \\ \min[dist(c_i, \boldsymbol{SC}\,)] \text{ if } i \in \boldsymbol{MS} \end{cases} \tag{4.3.b.7}$$

$$e_{j_i} = \begin{cases} 0 \text{ if } j_i \in \boldsymbol{MF} \\ \min\left[dist\left(c_{j_i}, \boldsymbol{SC}\right)\right] \text{ if } j_i \in \boldsymbol{MS} \end{cases} \tag{4.3.b.8}$$

$$f_{j_i} = \begin{cases} mode\left\{\min\left[dist\left(c_{j_i}, \boldsymbol{VC}_t\right) \ \forall t \in \Delta T\right\} \text{ if } j_i \in \boldsymbol{MF} \\ \min\left[dist\left(c_{j_i}, \boldsymbol{SC}\right)\right] \text{ if } j_i \in \boldsymbol{MS} \end{cases} \tag{4.3.b.9}$$

$$\gamma_{j_i} = \frac{nstop_{j_i}}{\sum_{i=1}^{m} nstop_i} \tag{4.3.b.10}$$

$$los_q = \frac{\sum_{i_q=1}^{m_q} wf1_i + wf3_i}{\sum_{i=1}^{m_q} w1_i + w2_i + w3_i + w4_i} \quad \text{with } i \in \boldsymbol{M}_q \tag{4.3.b.11}$$

$$wf1_i = mode\{\min\left[dist(c_i, \boldsymbol{VC}_t) \ \forall t \in \Delta T\right\} \quad \text{with } i \in \boldsymbol{M}_q \tag{4.3.b.12}$$

$$wf3_i = \sum_{j_i=1}^{n_i} mode\{\min\left[dist(c_i, \boldsymbol{VC}_t) \ \forall t \in \Delta T\right\} \cdot \gamma_{j_i} \quad \text{with } i \in \boldsymbol{M}_q \tag{4.3.b.13}$$

$$pop_q = \sum_{i=1}^{m_q} pop_i \quad \text{with } i \in \boldsymbol{M}_q \tag{4.3.b.14}$$

$s.t.$

$$\sum_{k=1}^{nsc} nst_k \leq slim \tag{4.3.b.15}$$

$$\sum_{k=1}^{nsc} \sum_{s_k=1}^{nst_k} psp_{s_k,r} \leq clim_r \ \ \forall r \in [1, 2, \dots, n_r] \tag{4.3.b.16}$$

$$cap_{s_k} \geq peak_{s_k} + \delta \ \ \forall k \in [1, 2, \dots, nsc], \forall s_k \in [1, 2, \dots, nst_k] \tag{4.3.b.17}$$

The first objective (4.3.b.1) aims at maximising the station demand (dem), that is the sum of $nstop_{i_{s_k}}$ drop-offs inside each of the m_{s_k} micro-zone i_{s_k} whose centroid falls within a radius of $dlim$ from each of the nst_k stations s_k belonging to each of the nsc cluster k of the set of chosen station clusters $\boldsymbol{K}$.

The second objective (4.3.b.2) represents the minimisation of round-trip user walking distances (w) for each eligible pair of micro-zone centroids. Indeed, we assume that all trips occur between centroids, but not all pairs of centroids are suitable. The nearest micro-zone centroids from the origin centroid, within a distance less than $dmin$, were not considered as possible destinations since it is possible to reach them on foot. Additionally, destination centroids at a distance greater than $dmax$ from the origin were not considered reachable with micro-mobility vehicles. Therefore, only the micro-zones whose centroids are at a distance between $dmin$ and $dmax$ from the origin centroid were considered. In general, w is the sum of four distances: the walking distance $w1_i$ on the outward journey between the origin centroid i and the nearest shared vehicle named pick-up distance at origin (4.3.b.4), the walking distance $w2_i$ between the vehicle drop-off location and the destination centroid named drop-off distance at destination (4.3.b.5), the walking distance $w3_i$ on the return journey between the destination centroid and the nearest vehicle named pick-up distance at destination (4.3.b.6), and the walking distance $w4_i$ between the vehicle drop-off location and the origin centroid i named drop-off distance at origin (4.3.b.7). Given that the objective is to define a mixed shared system, the walking distance values depend on whether the origin or destination centroid belongs to a free-floating or to a station-based sub-area. Furthermore, while the origin centroid is fixed, the destination centroid could be any, as long as it is suitable. Thus, for these reasons it is necessary to explain the four walking distances in detail with the equations from (4.3.b.4) to (4.3.b.10). In general, given the variability of these walking distances over time, to reduce the complexity of the problem, their modes (the configuration that repeats itself most often over time) are considered as set out below.

Eq. (4.3.b.4): if a user starts the trip in a free-floating micro-zone ($i \in \boldsymbol{MF}$), $w1_i$ is the mode of the distances between the origin centroid i, with coordinates

c_i, and the nearest vehicle in each time interval t, whose set of coordinates $\boldsymbol{VC_t}$ is known. If the starting micro-zone is in a station-based sub-area ($i \in \boldsymbol{MS}$), $w1_i$ is the minimum walking distance between the origin centroid i and the nearest station belonging to the chosen station clusters $\boldsymbol{K}$ with the set of coordinates $\boldsymbol{SC}$.

Eq. (4.3.b.5): in general, the destination micro-zone j_i, reachable from i, is not known, but, given that some micro-zones are more requested for drop-off than others, we calculate $w2_i$ as the weighted sum of all possible drop-off distances at destination. These distances, e_{j_i}, are calculated according to Eq. (4.3.b.8) while the weights γ_{j_i} are calculated according to Eq. (4.3.b.10). A drop-off distance at destination is equal to 0 in a free-floating sub-area, because the vehicle is dropped off exactly at the destination point. In a station-based sub-area, it is the minimum distance between the destination centroid j_i, with coordinates c_{j_i}, and the nearest station belonging to the chosen station clusters $\boldsymbol{K}$ with the set of coordinates $\boldsymbol{SC}$. The weights are calculated as the ratio between the number of drop-offs, $nstop_{j_i}$, in a micro-zone j_i and the total number of drop-offs in all the micro-zones m during the time interval ΔT. The higher the ratio, the greater the weight of that destination micro-zone.

Eq. (4.3.b.6): similarly to Eq. (4.3.b.5), $w3_i$ is calculated as the weighted sum of all possible pick-up distances at destination. These distances, f_{j_i}, are calculated according to Eq. (4.3.b.9) that is as the pick-up distances at origin (4.3.b.4). The weights γ_{j_i} are obtained according to Eq. (4.3.b.10).

Eq. (4.3.b.7): the drop-off distances at origin, $w4_i$, are calculated as the drop-off distances at destination (4.3.b.8).

The third objective (4.3.b.3) focuses on the minimisation of Gini index (g), calculated as the ratio between the area between the equal distribution line and the Lorenz curve, and the area under the Lorenz curve (Figure 2). Unlike the classical formulation of the Gini, we propose to evaluate the inequalities among resident population zones in the changes of round-trip user walking distances due to the conversion from the free-floating system to a mixed one. This definition was applied to all models.

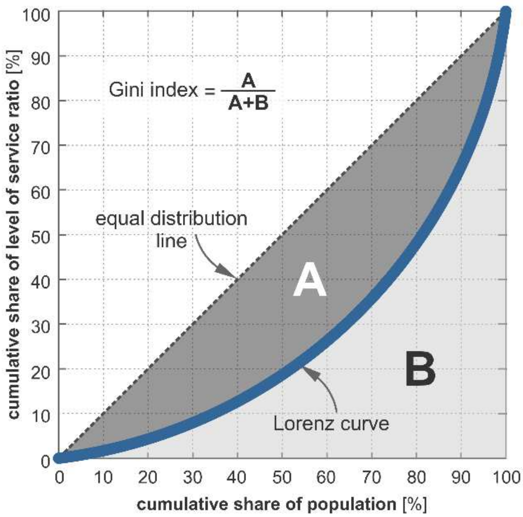

Fig. 2- Lorenz curve and Gini index

The change in walking distance, los_q (elements of the $\boldsymbol{LOS}$ vector), is calculated according to Eq. (4.3.b.11). It is the level of service ratio of population zone q between the sum of user walking distances of the free-floating system of the m_q micro-zones belonging to the zone q, ($i \in \boldsymbol{M}_q$), and the sum of the same distances after the implementation of the mixed system. The walking distances of the free-floating system (Eq. (4.3.b.12) and the Eq. (4.3.b.13)) are the pick-up distance mode at origin $wf1_i$ and the pick-up distance mode at destination $wf3_i$ calculated with the same expressions of (4.3.b.4) and (4.3.b.6) for the free-floating case, respectively. It is worth noting that drop-off distances at destination and at origin do not appear in the los_q numerator since they are always equal to 0 because in a free-floating system, vehicles can be dropped off exactly at the destination/origin points. Instead, in the los_q denominator, all four walking distances and their total for all micro-zones $i \in \boldsymbol{M}_q$ are considered. Through the los_q value, it is possible to understand if the conversion to a mixed system has improved or worsened the accessibility of the system among zone q residents of the service area. If los_q is equal to 1, the accessibility, for the zone q residents, is not changed because the walking distances stay the same. If los_q is smaller than 1, the situation has worsened. In this case, with a mixed system users have to walk more than with a free-floating system. If los_q is greater than 1, the accessibility improves, although this case may be unusual as it may imply higher station density compared to the individual scattered vehicle density of a free-floating system. In general, it is possible that in some zones, the level of service ratio decreases while it increases in other zones. If the distribution of the level of service ratio is fair compared to the zones q resident population, pop_q (elements of the $\boldsymbol{POP}$ vector), calculated according to Eq. (4.3.b.14), the Lorenz curve shows a 45° line; on the contrary, the curve will follow a curvilinear trend. In other words, the closer the g value is to zero, the closer horizontal equity is achieved, where horizontal equity consists of offering the same opportunities to all the zone q residents.

Three constraints are taken into consideration in the proposed model. Constraints (4.3.b.15) and (4.3.b.16) depend on the available car parking spaces and suitable pavements but, most of all, on the municipal administrations' willingness to replace them with shared system stations. Eq. (4.3.b.15) establishes that the total number of stations belonging to the chosen station clusters $\boldsymbol{K}$ has to be less than $slim$. Eq. (4.3.b.16) ensures that $psp_{s_k,r}$, the total number of car parking spaces in each category r that has to be removed to satisfy the maximum number of shared vehicles simultaneously dropped off at each s_k station, incremented with δ factor, has to be lower or equal to $clim_r$. The n_r categories can concern, for example, the different hourly rates for parking associated with each car parking space. Constraint (4.3.b.17) establishes that the capacity of a station, cap_{s_k}, must be greater than the maximum number of shared vehicles that could be simultaneously dropped off in the s_k station, $peak_{s_k}$, incremented by δ factor. This factor is added to compensate for any increases in station demand that may occur, for example, following the conversion of the free-floating system to the mixed one.

With the resolution of the problem (4.3.b.1)-(4.3.b.17), it is possible to find a Pareto front set of station cluster configurations. The stations belonging to the chosen clusters can be realized with painted and geofenced spaces and/or through beacons. By setting a buffer with a radius equal to $dmax$ for each station, it is possible to define station-based sub-areas to be implemented through geofencing. The proposed multi-objective model was applied to a real case study and several sets of station cluster configurations have been found considering different parameter values, as shown in the following section.

5. Case Studies and discussion of results

The following case study is the same for all models. These models were 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 square kilometers. 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 square kilometres. The data were recorded during November 2020 and represent the trend of drop offs with a 2 minute 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 (Krause, 1973). We divided the area under consideration into micro-zones with a square mesh grid zoning of 25 metres. The resident population was calculated for each micro-zone (ISTAT, 2024). These micro-zones were grouped to obtain 30 population zones among which we verified the level of fairness of the transformed station-based system.

A number of hypothetical stations was chosen by substituting car parking spaces and, where possible, new parking areas on pavements were established with the aim of preventing obstacles to pedestrians.

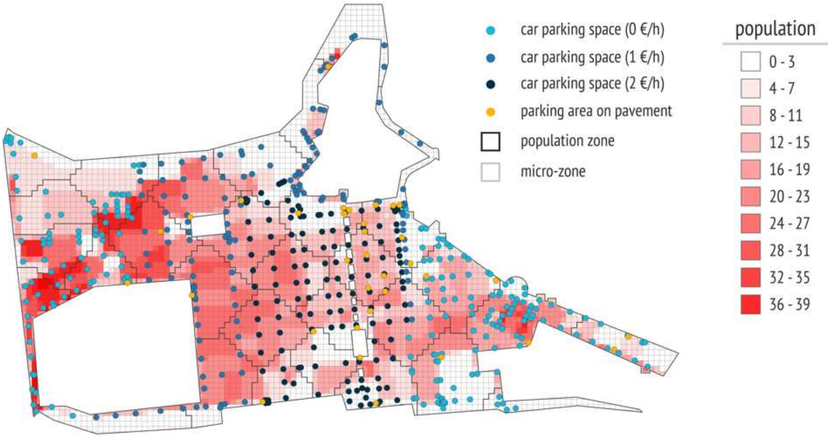

Fig. 3 - E-scooter sharing operating area with zones and hypothetical stations.

Fig. 3 shows the city centre e-scooter sharing operating area divided into micro-zones i and zone q. Dots represent car parking spaces while orange dots show parking areas located on pavements, the total of dots represents 482 hypothetical stations. The colour of the dots represents the paid category of car parking spaces. Micro-zones vary from white to red, from a low population number to a high number, respectively. In the following sections, we have analysed the case studies of Model 1 (Section 5.1), Model 2 (Section 5.2) and Model 3 (Section 5.3) by assuming the previous information related to the common characteristics of the case study and analysing each application in more detail.

5.1. Case study and discussion of results of Model 1

We solved the bi-objective model (4.1.1)-(4.1.7) when the total number of stations to be chosen, slim, changes. 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 many car parking spaces to the detriment of people using cars or other vehicles and residents who would have no private parking. Due to the complexity of the proposed model, results were found using genetic algorithm. Values of the two objective functions, calculated through the optimization for each slim were reported in the Pareto front diagram shown in Fig. 4.

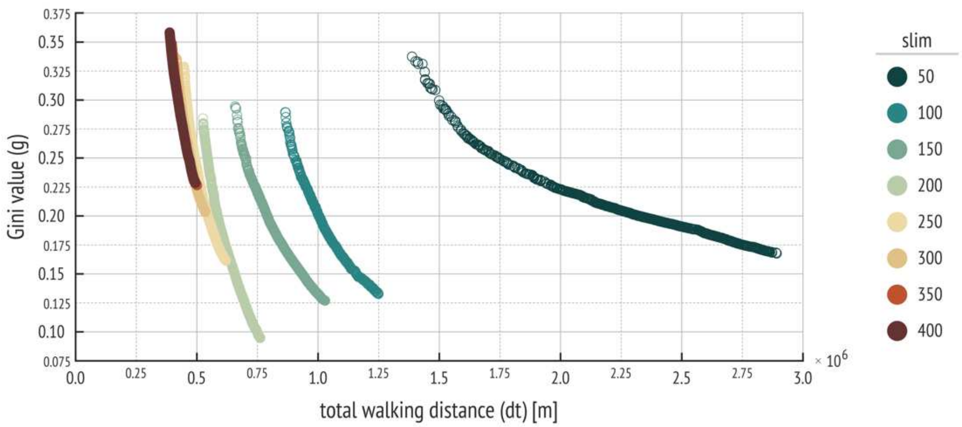

Fig. 4 - Pareto front for each $slim$ value.

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 were 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 fixed at half of the total walking distances of the corresponding Pareto front. 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}).

Table 1. Main results.

case	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
com	50	50	2313	0.201	80	0	468	803.4	170.2
g_{min}	50	50	2891	0.168	76	0	449	821.6	191.2
dt_{min}	100	100	865	0.289	114	4	652	448.4	84.0
com	100	100	1048	0.181	127	1	638	465.4	93.3
g_{min}	100	98	1249	0.133	124	2	627	475.9	103.8
dt_{min}	150	150	658	0.294	155	6	775	386.3	65.7
com	150	150	859	0.173	161	7	746	465.4	79.3
g_{min}	150	147	1029	0.127	159	6	698	465.4	87.0
dt_{min}	200	200	525	0.284	200	10	895	337.0	54.9
com	200	200	644	0.158	204	9	862	332.1	62.4
g_{min}	200	190	761	0.095	196	9	815	332.1	69.1

case	slim	ns	dt [km]	g	ppl	ppv	eps	wd_{max} [m]	wd_{mean} [m]
dt_{min}	250	250	447	0.329	245	14	988	305.9	46.9
com	250	250	527	0.214	243	16	967	332.1	54.2
g_{min}	250	245	619	0.161	243	14	930	332.1	59.7
dt_{min}	300	300	416	0.336	289	18	1059	257.8	43.0
com	300	300	471	0.252	291	17	1051	332.1	48.9
g_{min}	300	288	535	0.204	280	17	1012	332.1	54.2
dt_{min}	350	350	396	0.349	333	23	1145	257.8	40.2
com	350	349	441	0.277	333	23	1128	305.9	45.6
g_{min}	350	333	500	0.227	322	19	1086	332.1	50.5
dt_{min}	400	400	388	0.358	378	28	1198	257.8	38.4
com	400	368	436	0.283	350	24	1152	305.9	44.9
g_{min}	400	339	494	0.228	327	20	1095	332.1	50.4
	482	459	374	0.512	432	31	1268	222.5	34.6

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 metres. This is a good result because these values are less than 300 metres, which is the walking distance beyond which the users may not consider the vehicle convenient to drop off or pick up, considering e-scooter sharing user behaviour similar to bike-sharing (Kabra et al., 2016). On the other hand, the maximum distances are around 800 metres to drop off a vehicle in the case of 50 stations. 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 with a value of 300 metres, between 200 and 400 stations. 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 correspond 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 (ppl = 196, ppv = 9, eps = 815, wd_{max} = 332.1, wd_{mean} = 69.1). The best solution related to walking distances is the case with 400 stations (ppl = 378, ppv = 28, eps = 1198, wd_{max} = 257.8, wd_{mean} = 38.4). However, municipal councils may not be willing to propose so many stations and a compromise solution needs to be found.

It is interesting to observe the spatial distribution of chosen stations. For example, Fig. 5 shows the e-scooter parking areas within the operating area, considering the solutions with slim equal to 100 stations. Fig.5(a) represents the parking area location with the minimum walking distance of the Pareto front, while Fig.5(b) shows the parking area location with the corresponding Gini value of the Pareto front equal to 0.133.

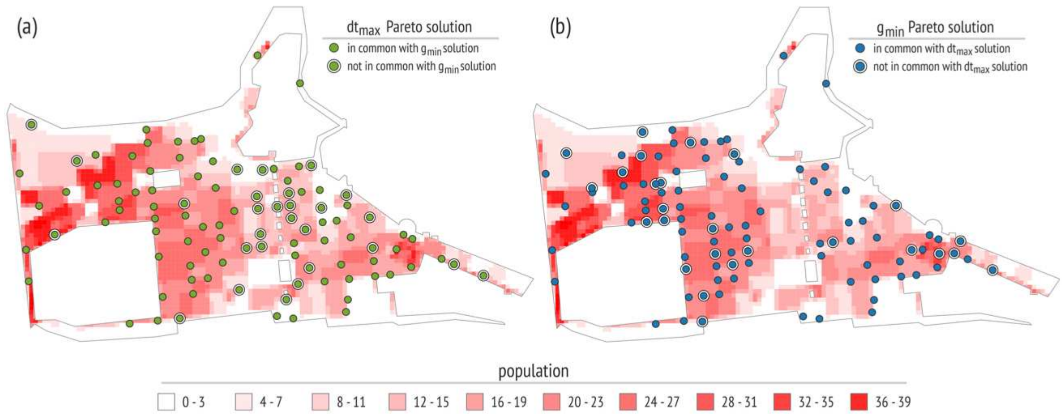

Fig. 5 - E-scooter parking areas for $slim$=100.

The micro-zones in Fig.5 change from white to red to represent resident population. Dark red shows a high value of resident population (major density) while white represents a lower value (less density). In Fig.5(a) 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.5(b), 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.

5.2. Case study and discussion of results of Model 2

Parameter values used in the application are: $nr = 3$; $r = 0$ (0 euro/hour); $r = 1$ (1 euro/hour); $r = 2$ (3 euro/hour); $clim_0 = clim_1 = clim_2 = 100$; $\delta = 2$; $nb = 5$; $\beta_0 = 100\%$; $\beta_1 = 100\%$; $\beta_2 = 80\%$; $\beta_3 = 60\%$; $\beta_4 = 40\%$; $\beta_5 = 20\%$; $v_0 = 0$ m; $v_1 = 20$ m; $v_2 = 40$ m; $v_3 = 60$ m; $v_4 = 80$ m; $v_5 = 100$ m. The β_b and v_b values were established as an example to better understand the model, but they need to be calibrated with the aim of obtaining results that explain the behaviour of users in the real context. We solved the bi-objective model (4.2.1)-(4.2.8) considering the maximum number of stations that could be chosen, $slim$, equal to 50, 100, 150, 200 and 250 stations, respectively, with steps of 50. The problem is highly complex, and due to multiples combinations, it was solved through the use of a genetic algorithm (for further details, see Deb (2001)). The results are shown in the Pareto front diagram in Fig. 6.

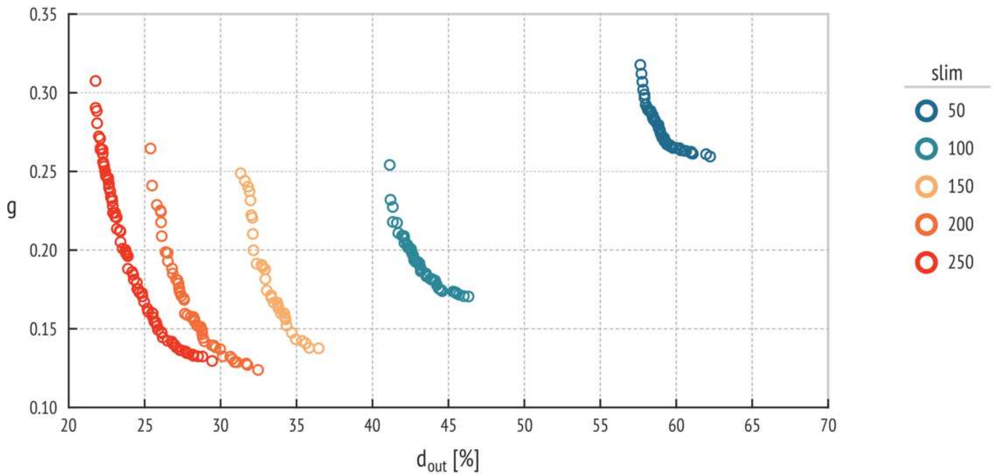

Fig. 6- Pareto front for each maximum number of chosen stations ($slim$)

The vertical axis represents the Gini value, g, and the horizontal axis shows the percentage of demand outside the stations, d_{out}, i.e. the free-floating demand. The lower the number of stations, the greater the d_{out}, for example around 70% in the case of 50 stations. From 50 to 100 stations, the percentage of free-floating outside demand decreases. With 100 stations the percentage of d_{out}, is between 48% and 42%. In the case of 200 stations the outside demand is equal to 20%. The higher the number of stations and the lower the number of scooters outside stations, the lower the minimum of Gini value, until slim=200. The variability of the Gini index increases as the number of stations rises. Indeed, in the case of 250 stations, the Gini value changes from 0.12 to 0.32. The main results are shown in Table 2 with all $slim$ considered.

Table 2. Main results.

		d_{out}	d_{in}	d_{out}[%]	d_{uns}[%]	g	ns	psc
0		7626	0	100.00	0	0.459	0	0
50	dem_{min}	4395	3231	57.63	0	0.318	50	48
	g_{min}	4745	2881	62.23	0	0.259	50	48
100	dem_{min}	3137	4489	41.14	0	0.254	100	97
	g_{min}	3532	4094	46.32	0	0.170	100	96
150	dem_{min}	2389	5237	31.32	0	0.249	150	147
	g_{min}	2780	4846	36.46	0	0.138	147	143
200	dem_{min}	1936	5690	25.39	0	0.265	200	191
	g_{min}	2476	5150	32.47	0	0.124	193	182
250	dem_{min}	1660	5966	21.77	0	0.307	250	237
	g_{min}	2245	5381	29.44	0	0.130	228	212
482		1244	6382	16.32	0.20	0.370	436	409

		r = 0	r = 1	r = 2	psp	eps	wd_{max}	wd_{mean}
0		0	0	0	0	0	-	-
50	dem_{min}	12	5	31	7	286	1129.0	195.3
	g_{min}	10	6	32	7	272	1227.1	276.3
100	dem_{min}	26	15	56	8	462	522.5	118.9
	g_{min}	25	11	60	9	443	837.4	172.8
150	dem_{min}	44	27	76	8	590	497.5	80.5
	g_{min}	41	23	79	9	577	519.1	106.8
200	dem_{min}	58	42	91	14	694	336.9	63.8
	g_{min}	55	35	92	16	657	444.0	88.5
250	dem_{min}	87	56	94	18	801	313.8	50.4
	g_{min}	67	51	94	20	738	444.0	79.8
482		170	107	132	29	1049	222.5	34.6

The first line of the table represents the free-floating case without stations, while the last line shows the case of all the hypothetical stations chosen. For each slim, two cases are shown: the lowest value of the first objective function belonging to the Pareto front, demand outside stations (dem_{min}), and the lowest value of the second objective function belonging to the Pareto front (g_{min}). The columns of the table show the total demand outside stations (d_{out}), the total demand inside stations (d_{in}), the percentage of demand outside stations (d_{out} [%]), the percentage of demand not satisfied (d_{uns}[%]), i.e. the number of users that wanted to drop off a vehicle at stations but these were full, the Gini value (g), the total number of stations (ns), the total number of car parking spaces (psc), free car parking spaces ($r = 0$), the 1 euro/hour car parking spaces ($r = 1$), 2 euro/hour car parking spaces ($r = 2$), parking areas on pavements (psp), the number of e-scooter parking places considering car parking spaces converted into micromobility parking and parking on pavements (eps), the maximum and the average walking distance between centroids of micro-zone i and parking areas (wd_{max} and wd_{mean}, respectively).

In the case of no chosen stations (free-floating functioning) the d_{out} [%] is 100% and the g is equal to 0.459. This shows an initial inequality, due to the imbalance of the vehicle distribution related to population.In the case of 50 stations, the d_{out} [%] is less than the starting condition (free-floating mode), and the lowest value of g is equal to 0.259, which is lower than the free-floating case (0.459) and higher than the lowest Gini (0.12). The greater the number of stations, the higher the variation of Gini value and the lower the d_{out} [%]. Parking areas increase in line with the number of stations. The need to use pavements for parking increases when the number of stations rises. Starting from 200 stations, maximum walking distances become acceptable from around 300-450 m maximum, according to the study of Kabra, Belavina and Girotra (2016). The wd_{mean} are good starting from a number of 50 stations, with a value of around 230 m, until a number of 150 stations, with values around 90 m. Two solutions belonging to the Pareto front with 50 stations are shown in Fig. 7.

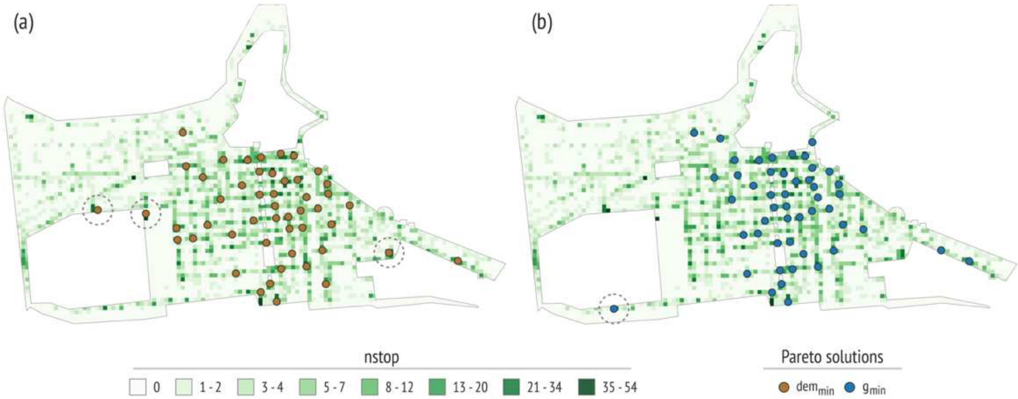

Fig. 7- Two Pareto solutions with 50 stations (dem_{min}, g_{min})

The $nstop$ are reported in shade of green with Jenks natural breaks: white represents the absence of drop offs and dark green represents a high number of drop offs. Fig. 7(a) represents the chosen stations (brown dots) considering the case of dem_{min}, while Fig. 7(b) shows the location of stations according to the

g_{min} (blue dots). In Fig. 7(a) the brown dots are mainly located near the dark green micro-zones, because they absorb more demand (see, for example, the three dots highlighted through dashed circles). Conversely, in Fig. 7(b) the stations are mostly located in the city centre where the population values are lower (see Fig. 3). This result was obtained due to the lower imbalance of the level of service among population. Also in this case, some blue dots are located on dark green micro-zones; conversely to the case of Fig. 7(a), they are related to a low population, as shown in the blue dot highlighted through a dashed circle. This shows how the two objective functions are in contrast with each other, due to the fact that the first objective function (4.2.1) is related to the minimisation of the number of drop offs outside the station, while the second objective function (4.2.2) aims to balance the level of service among population.

5.3. Case study and discussion of results of Model 3

The service area (Figure 8) was divided into m = 3922 micro-zones, using a square mesh grid with square side equal to 25 metres. The holes in the service area show zones where e-scooter drop-offs/pick-ups were forbidden. Trip data were available, updated every t = 2 minutes, for a time interval ΔT = 1 month (November 2020). The month of November was divided into two sub-intervals. Our multi-objective optimisation was applied considering only the first sub-interval trip data from November 1st to 21st (named opt period). The rest of the month data were considered as a hold-out sample (hos), to validate model results. Starting from the given database, vehicle drop-off locations and trends were associated to each micro-zone, with the aim of defining the drop-off demand and the distances among centroids and vehicles. As the centre of Bari has a prevailing Manhattan street configuration, the distance function ($dist$) between points, i.e. among centroids and vehicles/stations, was considered according to the taxi cab geometry (Krause, 1973). For example, Figure 5 shows the drop-offs of the e-scooters in the opt period and in each micro-zone according to a colour scale that goes from white (no drop-off) to dark green (from 48 to 78 drop-offs) and the positions of the individual e-scooters at 12:00 pm on November 11th. It is worth noting that the highest demand is in the centre of the service area i.e., the commercial area of the city full of shops and offices.

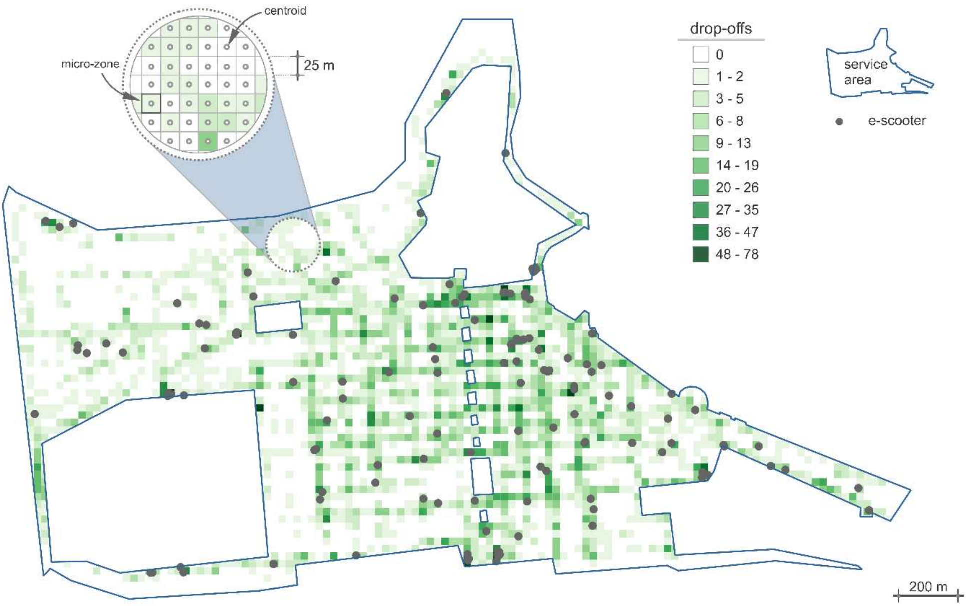

Fig. 8- Service area with a summary of system database

The service area includes a population of about 36,940 inhabitants. Starting from census population data (ISTAT, 2024), residents in each micro-zone were calculated. Subsequently, micro-zones were grouped together to create q = 30 population zones among which we want to minimise disparities in the accessibility to the mixed vehicle sharing system (see Figure 9).

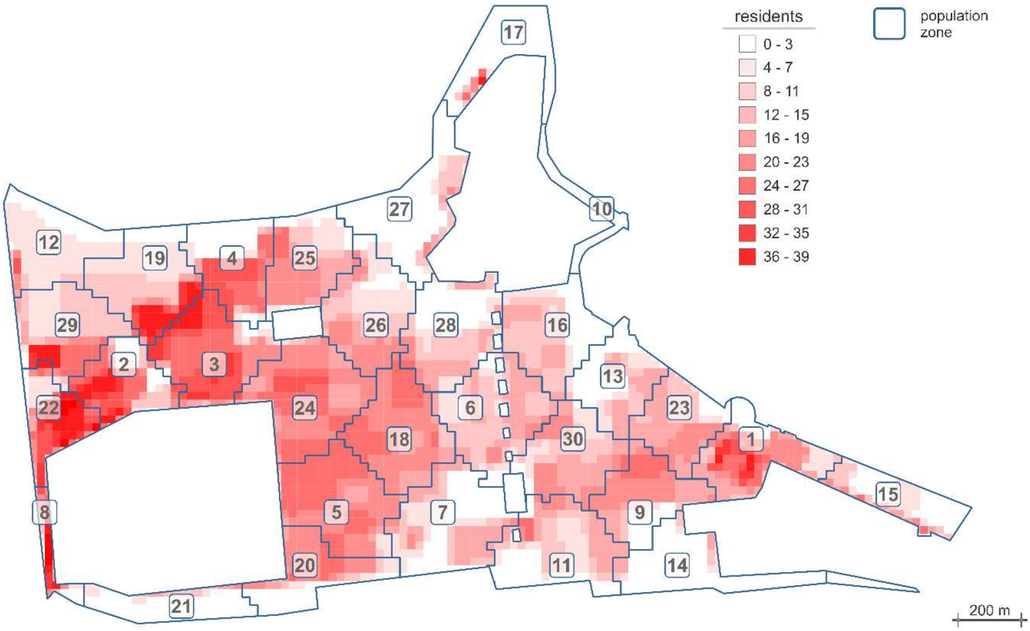

Fig. 9- Service area with resident micro-zones and population zone

Based on the described data sets, through the g function, it is possible to calculate the Gini index of the free-floating system in the opt period. It turned out that the system is inherently unfair with a Gini index equal to 0.3634. As described in Subsection 4.3.b, this value was calculated considering in the los_q equation (4.3.b.11) the mode of the minimum distances among e-scooter positions and micro-zone centroids (with $w1_i$ = $w4_i$ = 0 for the free-floating system). If instead of the mode of the minimum distances on the opt period, we considered the minimum of the distance every t = 2 minutes, then we would obtain a different Gini index every 2 minutes, given that drop-off demand changes over time. The trend of the Gini index for the free-floating system from November 1st to 21st (g_{ff}) is shown in Figure 10.

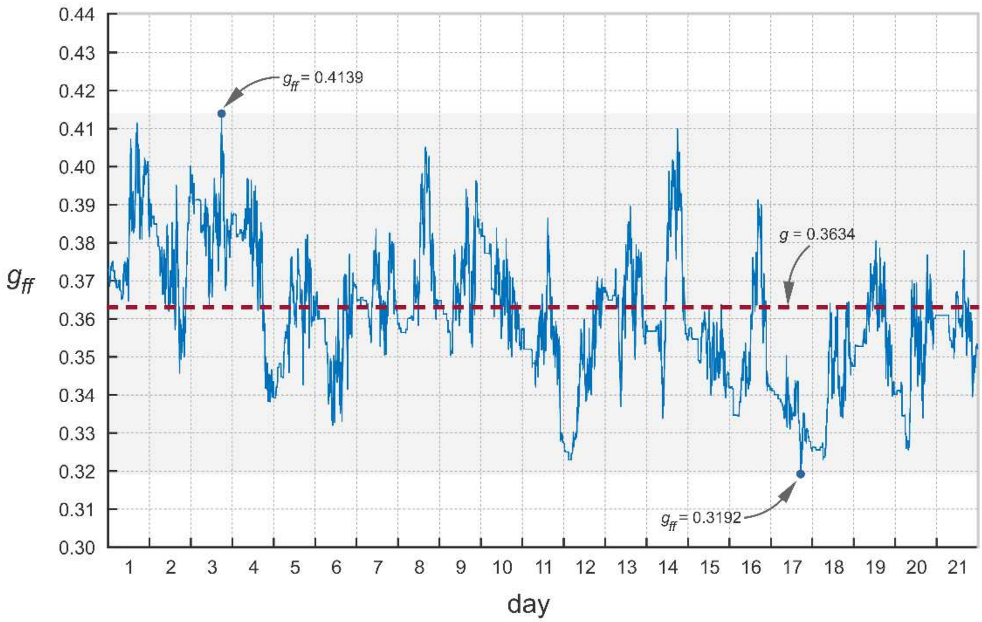

Fig. 10- Gini index of the free-floating system every 2 minutes in the *opt* period

We found that g_{ff} values are between 0.3192 and 0.4139. As we will see later, this trend will be useful for choosing the trade-off solution among those found by solving problems (4.3.b.1)-(4.3.b.17).

The station choice set was defined starting from the city car parking spaces database and the map of pavements. In the city centre there are n_r = 3 categories of car parking spaces with different parking hourly rates: the first (r = 1) is free of charge, the second (r = 2) is 1 €/hour, and the third (r = 3) is 2 €/hour. We assume all car parking spaces in the service area as available. The corresponding station locations were set at each road network intersection (see Figure 11) given their greater visibility compared to the location in the middle of the road links as stated by Nacto (2018).

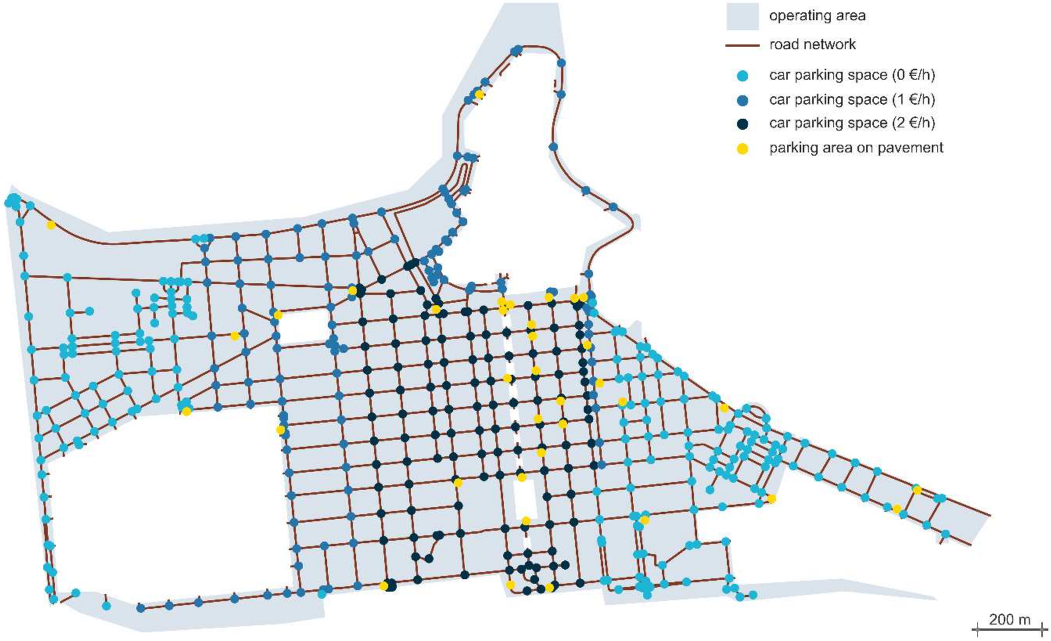

Fig. 11- Station choice sets and road network map

The capacity of each station has been calculated distributing parking spaces of a road link equally between stations belonging to the same road link and considering two e-scooter parking places for each linear metre of an equivalent parallel car parking place. Furthermore, we have selected stations on pavement areas exclusively where they are sufficiently wide to allow pedestrians to walk without obstructions. This choice set includes 488 stations very close to each other. Therefore, it may be appropriate to eliminate extra stations from the database. In this case study, we find a subset of stations, $\boldsymbol{CK}$, with the heuristic procedure based on Delaunay triangulation described in the Subsection 4.3.a, by ensuring that there are no stations with average spacings less than or equal to in_{max} = 150 metres. Subsequently, the selected 222 stations were grouped together in 27 clusters (Figure 12), using k-means algorithm with c_{min} = 2 stations and c_{max}= 600 metres.

To complete the model inputs, the following parameters were set relating to the first objective (4.3.b.1) and to the problem constraints (4.3.b.15)-(4.3.b.17): maximum distance that a user is forced to walk to pick up or drop off a vehicle in station-based sub-areas, $dlim$ = 150 m; the possible maximum number of stations that could be created, $slim$ = 50 stations; the maximum number of car parking spaces to be removed, $clim = clim_1$ = $clim_2$ = $clim_3 = 100$; incremental factor, δ = 2 e-scooters.

Since the choice set of clusters consists of 27 elements, the number of possible cluster combinations to be selected through the proposed multi-objective optimisation is rather high. For this reason, a heuristic or meta-heuristic optimisation method may be the best approach to solve the problem. Specifically, we use a Genetic Algorithm (GA) with the aim of finding near-optimal solutions.

Compared to other algorithms, we chose GA because we could effectively parallelize the computation (Désidéri et al., 2000), speeding up the convergence of the algorithm. Note that in this study, we suggest solving the problem using a GA; despite the good performance of the algorithm, further methods could be explored and compared in future works in order to understand which is the most suitable in solving the proposed optimization.

A solution (GA chromosome) consists of a binary string with a length equal to 27 (the number of station clusters). The unitary elements in the string correspond to the near-optimal clusters that should be implemented. Fitness functions were defined equal to station demand (dem), user walking distances (w) and the Gini index (g). After some empirical tests, the following GA parameters were set. The population size was set equal to 40 times the number of clusters. The maximum number of generations was set at 200 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 10 generations. The genetic operators used to generate offspring are the Tournament selection, the Scattered crossover, and the Gaussian mutation. The GA were implemented using MATLAB software (for further details see The MathWorks, (2022)).

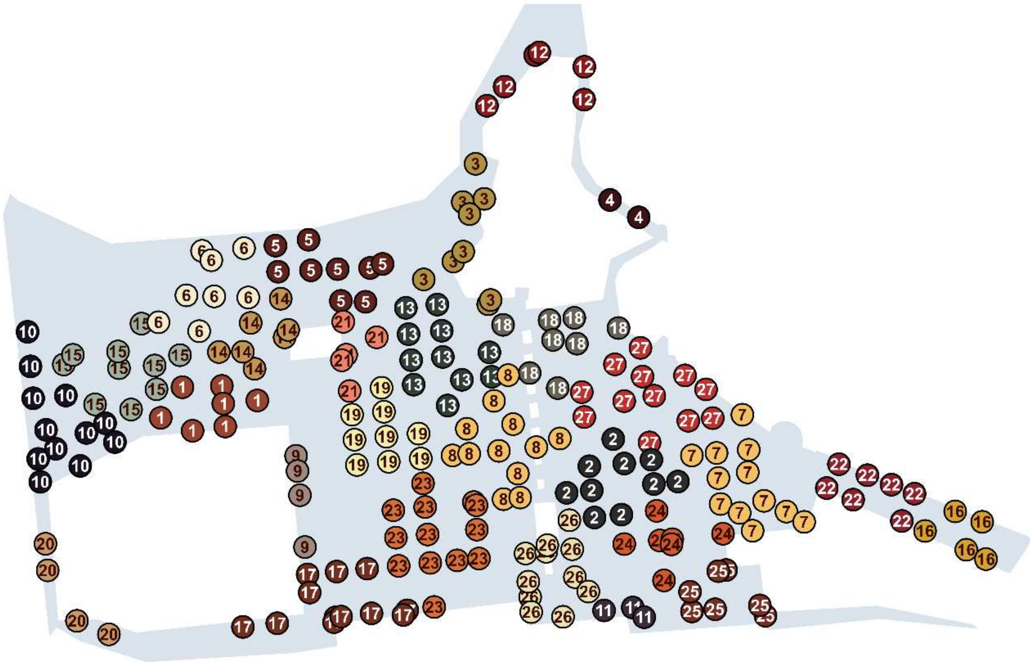

Fig. 12- Subset of stations ($\boldsymbol{CK}$) and the choice set of 27 clusters.

We represent the near-optimal solutions found through a Pareto front in a three-dimensional space (Figure 13(a)). Each solution, drawn with a cross symbol, represents chosen clusters of stations.

Municipal councils and experts may choose a trade-off solution from these results. A first consideration to make is that a solution should be chosen with a g value lower than 0.3634 (Gini index of the free-floating system), which is a solution below the dotted red line of Figure 13(b).

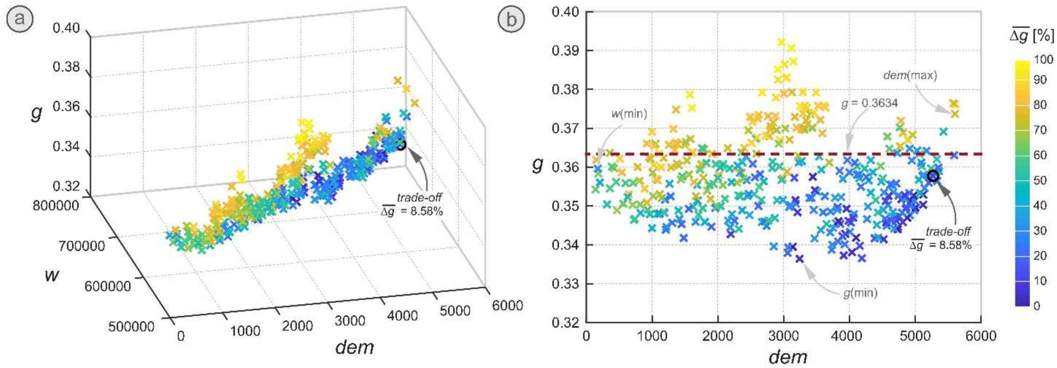

Fig. 13- Pareto front solutions in a three-dimensional (a) and two-dimensional (b) space.

However, these solutions are not all equally good because they present a variable trend over time of the Gini index due to the change in station demand. Therefore, for each Pareto front solution, we can consider the difference, every 2 minutes during the opt period, between the Gini index of the existing free-floating system and that of the mixed one: Δg = $g_{ff} - \ g$. The desirable solutions are those with fewer repetitions of negative Δg during the opt period, i.e., with their percentage ($\overline{\Delta g}$) as low as possible. Subsequently, the choice of station clusters and the related station-based sub-areas could be one of the solutions with the lowest $\overline{\Delta g}$ value. In Figure 13, each solution has been coloured based on this percentage value. The lower the percentage, the closer the colour is to dark blue. The solutions with colours closer to blue are mainly positioned below the dotted red line and for higher station demand values (dem) but with higher values of the sum of round-trip user walking distances (w). As an example, in order not to excessively reduce station demand (dem), accepting higher values of walking distances, the solution to choose could be the one with the lowest $\overline{\Delta g}$ value among the first 10 solutions below the dotted red line (called trade-off). This chosen solution, with a Δg shown in Figure 14, has $\overline{\Delta g}$ = 8.58% during the opt period and a near-zero value (0.23%) during the hos period.

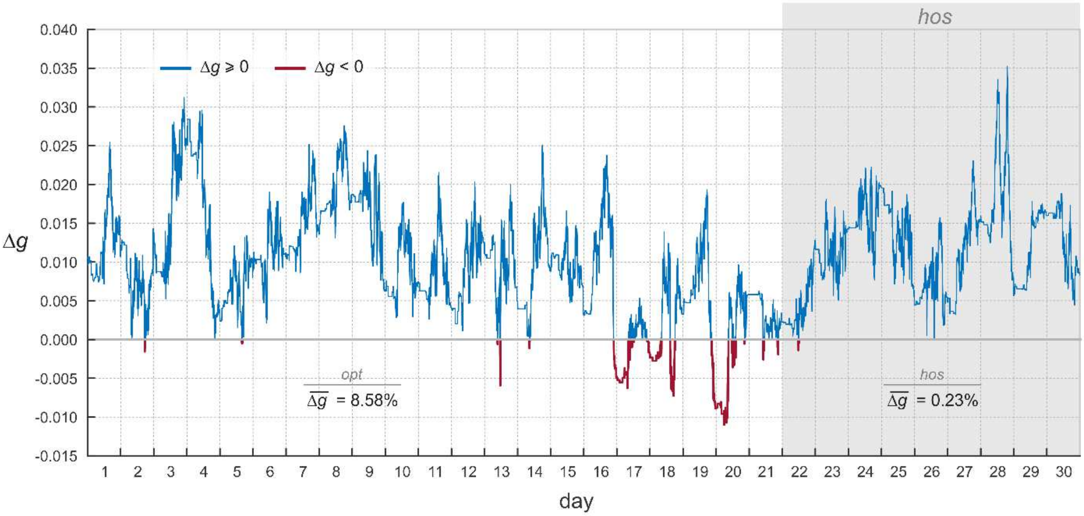

Fig. 14- Differences between the Gini index of a free-floating system and a mixed one of the chosen Pareto solution.

The final aim of the proposed model is to locate the stations and to define station-based sub-areas, in which it is mandatory to drop-off vehicles at stations. Starting from the chosen clusters of stations, the related station-based sub-areas are defined by superposition of buffers with radius $dlim$ centred at each station. In Figure 15 we show the stations and the station-based sub-areas of four significant Pareto front solutions named dem(max), i.e. the solution with the highest demand value, w(min), i.e. the solution with the lowest total of walking distances, g(min), i.e. the solution with the lowest Gini index value, and trade-off solution, previously defined.

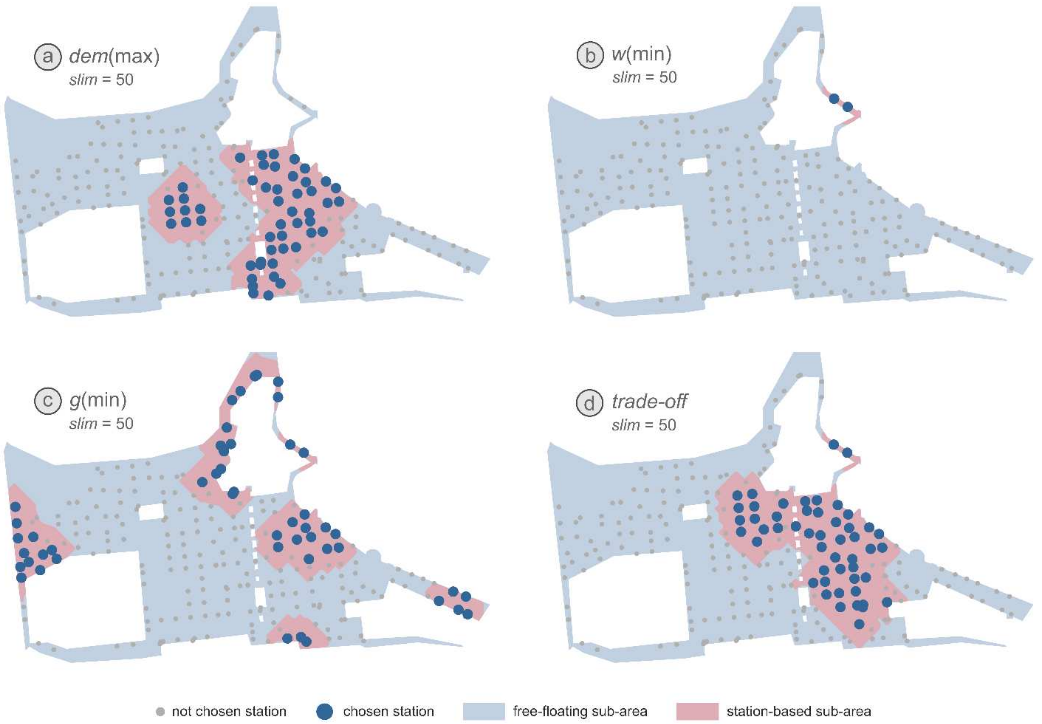

Fig. 15- Free-floating and station-based sub-areas of four Pareto front solutions with $slim$ = 50.

In general, we can see that the overlap of the buffers generates station-based continuous sub-areas with a jagged outline. This is due to the radius of the buffers defined according to Manhattan distances between the stations and the centroids of the micro-zones. The contours could be simplified by generating convex areas, for example, by accepting maximum user walking distances higher than $dlim$. The same applies to any sub-areas which are distinct but very close to each other (such as those at the top centre of Figure 15(c)) that could be merged together. Discontinuities between sub-areas can be also reduced by increasing the input values of c_min and cd_max.

The configuration with the maximum value of station demand, dem = 5606, (Figure 15(a)) shows two station-based sub-areas, with 50 stations, approximately corresponding to the service area with the greatest number of drop-offs (see Figure 8). However, this solution implies a value of the Gini index, g = 0.3762, higher than the free-floating one and one of the highest walking distances, as can be seen from Figure 13.

With a limited number of stations belonging to the choice set, to minimise the total of walking distances, the mixed system should have as few stations as possible, positioned where the minimum walking distances are longer in the free-floating system. Therefore, the solution in Figure 15(b), with w = 507528 metres, consists of a single small station-based sub-area with 2 stations located in an area with a very low number of drop-offs. This solution is very close to the free-floating system. In fact, the Gini index is equal to 0.3598 and the station demand is very low.

The fairest mixed system among Pareto front solutions (g = 0.3364) is made up of 6 station-based sub-areas, with 49 stations, located at the edges of the service area (Figure 15(c)). They are in population zones with a very low number of residents (see Figure 9), except for the sub-area on the left of the figure. This sub-area has a particular role in defining the Gini index. It mainly overlaps with population zone 22, which is one of the most populated areas and it is the only zone for which the mixed system level of service improves compared to that of the free-floating system ($los_{22} > 1$), as shown in bold in Table 3.

Table 3. Residents and level of service ratio los_q for each zone q of four Pareto front solutions with $slim$ = 50.

	q	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	pop_q	1718	1681	3100	1351	2783	1387	1004	551	1426	2	1119	464	565	225	441
los_q	dem(max)	0.81	0.81	0.80	0.82	0.72	0.52	0.67	0.78	0.57	0.77	0.54	0.80	0.51	0.82	0.81
	w(min)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.83	1.00	1.00	1.00	1.00	1.00
	g(min)	0.85	0.80	0.84	0.85	0.83	0.66	0.82	0.75	0.81	0.72	0.64	0.80	0.52	0.79	0.70
	trade-off	0.82	0.85	0.84	0.85	0.83	0.53	0.82	0.82	0.60	0.70	0.62	0.84	0.53	0.69	0.85

	q	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
	pop_q	850	148	2501	1577	1072	139	1839	1117	2929	1308	1353	364	982	1574	1370
los_q	dem(max)	0.58	0.77	0.56	0.80	0.83	0.80	0.83	0.53	0.68	0.77	0.74	0.83	0.59	0.81	0.63
	w(min)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	g(min)	0.59	0.68	0.82	0.84	0.87	0.84	1.01	0.58	0.84	0.82	0.75	0.79	0.65	0.79	0.60
	trade-off	0.60	0.81	0.70	0.84	0.87	0.84	0.86	0.53	0.81	0.81	0.76	0.82	0.68	0.84	0.64

The level of service ratio is mostly lower than 1 regardless of the Pareto front solution. There are exceptions for the w(min) solution where it is approximately equal to 1 in all zones but 10, corresponding to the only station-based sub-area. Despite the low number of drop-offs, los_{10} is equal to 0.83 and is not equal or greater than 1 because there are only 2 stations for micro-zones which extend over a narrow and long area compared to the position of the 2 stations. Another exception is that of zone 22 in the g(min) case, where the level of service ratio greater than one compensates for all the other los_q that are less than one, generating the minimum value of the Gini index overall.

The trade-off solution (Figure 15(d)) has two station-based sub-areas with 50 stations, and it is much the same as the dem(max) solution. In fact, as we can see from Figure 13(b) it has very similar dem and w function values, even if it has g = 0.3577, lower than that of the free-floating system.

To avoid confusing users, the sub-areas and their stations should remain the same for a long period of time. Therefore, it is necessary to verify that the solutions found can work well even after their implementation. Thus, to verify the effectiveness of the solutions found, some key indicators were also calculated for the hos period. In this case, the shape of the station-based sub-areas and the station position/capacity remains the same, but the trip data change because they relate to another period, i.e., from 22nd to 30th November. As can be seen from Table 4, the solutions found show very similar, if not the same, indicators both for opt and hos periods. In this table, in addition to the four solutions of the

Pareto front, the indicators relating to the case with the entire subset of 222 stations ($\boldsymbol{CK}$), named all stations, is shown. In this case, the system is almost entirely station-based, so the station demand is approximately equal to 98%. The rest of the drop-offs take place in a small free-floating sub-area where there is no possibility of implementing stations. For the same case and the hos period, the total number of stations (nst) is less than 222 because some of them are without demand and have not been counted.

In the dem(max) solution, the station demand is very low compared to the total one (dem is about 53%). This is due mainly to the maximum number of stations that could be created ($slim$ = 50), which is relatively small compared to the service area, and to the relatively small user maximum walking distance ($dlim$ = 150) which does not allow station-based sub-areas to cover large zones. Indeed, the station-based sub-area percentage over service area (sba) is equal to 27.7%. There is no unsatisfied station demand for the opt period (due to compliance with constraint (4.3.b.17)) and is also null in the hos period. Therefore, the assumed δ = 2 is sufficient. If any increases in station demand are expected, it is necessary to increase δ.

Table 4. Key indicators of the four Pareto front solutions with $slim$ = 50 and a comparison with a station-based system.

	ΔT	dem	dem [%]	und	w [km]	g	$\overline{\Delta g}$	nst
all	opt	10281	98.3	0	691	0.37	62.9	222
stations	hos	3533	97.8	0	691	0.37	58.4	217
dem(max)	opt	5606	53.6	0	719	0.38	86.6	50
	hos	1914	53.0	0	719	0.38	90.5	50
w(min)	opt	32	0.3	0	508	0.36	39.2	2
	hos	11	0.3	0	507	0.36	24.3	2
g(min)	opt	3243	31.0	0	665	0.34	4.1	49
	hos	1042	28.8	0	665	0.34	5.3	47
trade-off	opt	5272	50.4	0	676	0.36	8.6	50
	hos	1779	49.3	0	676	0.36	0.2	50

	pav	psp	psp_1	psp_2	psp_3	sba [%]	$mwsb$ [m]	wsb [%]
all	12	221	80	87	54	89.0	51.68	-35.5
stations	12	209	80	80	49	89.0	51.68	-35.5
dem(max)	5	57	4	34	19	27.7	67.61	21.5
	5	52	4	32	16	27.7	67.61	21.5
w(min)	0	2	0	1	1	0.5	68.26	-28.0
	0	2	0	1	1	0.5	68.26	-28.0
g(min)	1	57	13	25	19	24.2	69.01	-11.8
	1	52	13	23	16	24.2	69.01	-11.8
trade-off	4	57	3	30	24	29.3	66.64	-0.3
	4	52	3	27	22	29.3	66.64	-0.3

The highest total of round-trip user walking distances belongs to the dem(max) solution, with a value that is higher than all stations case due to the limited number of stations.

The g(min) solution has the best Gini index and the lowest $\overline{\Delta g}$. The trade-off configuration also presents very good values. Instead, the other mixed system solutions do not bring an improvement in equality compared to the free-floating system since their medium-high $\overline{\Delta g}$ values.

The stations are implemented both on pavements and in place of parking spaces. The total number of stations on pavements (pav) is quite low, while most stations replace car parking places (psp) especially those with an hourly parking rate equal to 1 €/hour (psp_2).

Two other interesting indicators are the average user walking distances in station-based sub-areas ($mwsb$) and the percentage increase of this distance compared to that of the free-floating system in the same sub-areas (wsb). The average distance is always less than the limit one ($dlim$ = 150) and varies from a maximum of approximately 69 meters to a minimum of 51.68 meters. In the same sub-areas, we observe that there is always an improvement in the average distances travelled (wsb < 0) except in the dem(max) solution. However, it is worth noting that the improvement refers to the average distances in the station-based sub-areas and not in the total of the round-trip walking distances (w) for which there is always a diminishment except in population zone 22 as shown in Table 1.

In order to better understand the potential of the proposed model, further analyses were carried out changing some input parameters as described in the following Section 5.3.1

5.3.1. Sensitivity analysis

In this section two sensitivity analyses were carried out. In the first (Section 5.3.1.a), all input parameters remained unchanged, excluding the maximum number of stations that could be realized. Conversely, in the second broader and more general analysis (Section 5.3.1.b), most of the parameters were changed.

5.3.1a. Increase in the maximum number of stations

Model (4.3.b.1)-(4.3.b.17) was also solved for $slim$ = 150 and $slim$ = 222 (entire $\boldsymbol{CK}$ stations subset), leaving all other input parameters unchanged. A summary of all the Pareto solutions found (chosen station clusters from 27 in the Figure 12) is shown in Table 5. In this table, the number of times each cluster is chosen in all Pareto front solutions ($npar$) and whether it belongs to the four significant solutions, is shown. There are some station clusters that are chosen few times regardless of the value of $slim$ and they are, above all, clusters 9, 17 and 23. It can be noted that these clusters are adjacent to each other and are in a zone of the service area with very low drop-offs (see Figures 8 and 12). As the maximum number of stations increases, the number of chosen clusters for the dem(max) and trade-off solutions increases. This does not happen so noticeably for w(min) solutions, where the number of station clusters tends to remain very low to minimise walking distances, and for g(min) solutions where the number of clusters is between 7 and 11. In this case, the chosen clusters are repeated for the three $slim$ values. For example, clusters 4, 10,12 and 27 are always chosen. They are located at the edges of the service area, as seen for $slim$ = 50.

Table 5. Summary of all the Pareto solutions found

$slim$	k	1	2	3	4	5	6	7
50	$npar$	30	51	48	239	29	0	32
	dem(max)		x					
	w(min)				x			
	g(min)			x	x			
	trade-off		x		x			
150	$npar$	128	194	139	298	147	108	220
	dem(max)	x	x		x	x		x
	w(min)				x			
	g(min)		x		x	x		
	trade-off		x		x	x		x
222	$npar$	241	168	204	304	214	240	195
	dem(max)	x	x	x	x	x	x	x
	w(min)							
	g(min)		x		x	x		

	trade-off	x	x		x	x	x	x

$slim$	k	8	9	10	11	12	13	14
50	$npar$	0	12	190	108	139	170	6
	dem(max)							
	w(min)							
	g(min)			x	x	x		
	trade-off						x	
150	$npar$	89	55	323	151	220	183	116
	dem(max)	x	x	x			x	
	w(min)							
	g(min)			x		x		
	trade-off	x	x	x			x	
222	$npar$	87	47	367	160	238	219	240
	dem(max)	x	x	x	x	x	x	x
	w(min)							
	g(min)			x		x		
	trade-off	x	x	x	x	x	x	x

	k	15	16	17	18	19	20
50	$npar$	20	264	4	142	52	256
	dem(max)				x	x	
	w(min)						
	g(min)		x				
	trade-off				x		
150	$npar$	112	333	21	157	98	339
	dem(max)				x	x	x
	w(min)						
	g(min)		x		x		x
	trade-off		x		x	x	x
222	$npar$	243	356	42	157	98	372
	dem(max)	x	x	x	x	x	x
	w(min)		x				
	g(min)		x		x		x
	trade-off	x	x	x	x	x	x

	k	22	23	24	25	26	27
50	$npar$	142	0	27	15	73	161
	dem(max)					x	x
	w(min)						
	g(min)						x
	trade-off			x			x
150	$npar$	275	32	203	97	168	172
	dem(max)	x	x	x		x	x
	w(min)						
	g(min)			x		x	x
	trade-off	x	x	x		x	x
222	$npar$	252	37	177	97	142	173
	dem(max)	x	x	x	x	x	x
	w(min)	x					
	g(min)			x		x	x
	trade-off		x	x		x	x

Among these solutions we show the trade-offs in Figure 16. The number of chosen stations and the station-based sub-areas increase as $slim$ increases. In the $slim$ = 150 case, a part of the service area, with few drop-offs, remains uncovered. The $slim$ = 222 case differs from the all stations case we mentioned previously, since some stations remain unselected.

In Table 6 and Table 7, we show the key indicators for the significant solution with $slim$ = 150 and $slim$ = 222, respectively. Even in these cases we can see that the indicators for the opt and hos periods are consistent with each other. The station demand is on average higher and always satisfied. The walking distances are on average higher except for the case w(min) which, always involving few stations, remain approximately the same regardless of $slim$ value. The variation range of the Gini index is similar, with the g(min) solution proving to be the best in any case. The total number of car parking spaces to be converted into stations increases as $slim$ increases. In particular, dem(max), the solution for $slim$ = 222, coincides with the all station solution (see Table 2). The average walking distance $mwsb$ is very similar in both cases to those of $slim$ = 50 since the station density is quite uniform throughout the service area. In the same sub-areas, we observe that there is always an improvement in the average distances travelled (wsb).

Fig. 16- Free-floating and station-based sub-areas of trade-off solutions with $slim$ = 150 and $slim$ = 222.

Table 6. Key indicators of the four Pareto front solutions with $slim$ = 150.

	ΔT	dem	dem [%]	und	w [m]	g	$\overline{\Delta g}$	nst	pav
dem(max)	opt	9394	89.8	0	744462	0.3699	48.7	150	10
	hos	3257	90.2	0	744462	0.3699	48.8	148	10
w(min)	opt	32	0.3	0	507529	0.3598	39.2	2	0
	hos	11	0.3	0	507529	0.3598	24.3	2	0
g(min)	opt	6170	59.0	0	733405	0.3346	8.7	86	6
	hos	2143	59.3	0	733405	0.3346	2.7	85	6
trade-off	opt	9082	86.8	0	723461	0.3627	30.5	148	9
	hos	3124	86.5	0	723461	0.3627	30.5	145	9

	ΔT	psp	psp_1	psp_2	psp_3	sba [%]	$mwsb$ [m]	wsb [%]
dem(max)	opt	151	44	64	43	74.4	59.27	-22.3
	hos	144	44	61	39	74.4	59.27	-22.3
w(min)	opt	2	0	1	1	0.5	68.26	-28.0
	hos	2	0	1	1	0.5	68.26	-28.0
g(min)	opt	92	26	38	28	40.8	64.47	-6.8
	hos	87	26	35	26	40.8	64.47	-6.8
trade-off	opt	150	38	67	45	68.9	58.12	-23.0
	hos	142	38	63	41	68.9	58.12	-23.0

Table 7. Key indicators of the four Pareto front solutions with $slim$ = 222.

	ΔT	dem	dem [%]	und	w [m]	g	$\overline{\Delta g}$	nst	pav
dem(max)	opt	10281	98.3	0	691086	0.3674	62.9	222	12
	hos	3533	97.8	0	691086	0.3674	58.4	217	12
w(min)	opt	357	3.4	0	507862	0.3637	70.4	12	0
	hos	97	2.7	0	507862	0.3637	77.2	9	0
g(min)	opt	6170	59.0	0	733405	0.3346	8.7	86	6
	hos	2143	59.3	0	733405	0.3346	2.7	85	6
trade-off	opt	9988	95.5	0	711969	0.3580	40.0	199	12
	hos	3453	95.6	0	711969	0.3580	40.3	197	12

	ΔT	psp	psp_1	psp_2	psp_3	sba [%]	$mwsb$ [m]	wsb [%]
dem(max)	opt	221	80	87	54	89.0	51.68	-35.5
	hos	209	80	80	49	89.0	51.68	-35.5
w(min)	opt	12	0	4	8	3.2	57.08	-44.0
	hos	9	0	3	6	3.2	57.08	-44.0
g(min)	opt	92	26	38	28	40.8	64.47	-6.8
	hos	87	26	35	26	40.8	64.47	-6.8
trade-off	opt	198	80	75	43	82.9	53.56	-31.1
	hos	190	80	70	40	82.9	53.56	-31.1

5.3.1b. Variation of several input parameters

This sensitivity analysis was performed considering the simultaneous variation of multiple input parameters. In addition to the three $slim$ values (50,150 and 222), different values of d_{lim}, in_{max}, and $clim_r$ were set. In particular, we set d_{lim} = in_{max} in a range from 150 to 450 metres at 50 metre intervals in order to analyse the results when the maximum distance that a user is forced to walk increases. Furthermore, in addition to $clim = 100$, the maximum number of car parking spaces to be removed was set equal to $clim = clim_1 = clim_2 = clim_3 = 50$. All the other case study inputs remained unchanged.

Optimisations with all combinations of the above parameters were carried out. The main statistics (minimum, mean, maximum and standard deviation values) on key indicators of four Pareto front solutions are shown in Table 8.

Table 8. Main statistics on key indicators of the four Pareto front solutions for all input parameter combinations.

	ΔT	dem	dem [%]	und	w [km]	g	$\overline{\Delta g}$	nst
dem(max) opt	min	5606	53.6	0	691.09	0.3554	36.5	16
	mean	9071	86.7	0	1614.68	0.3950	86.6	57
	max	10404	99.4	0	2927.50	0.4300	100	222
	st. d.	1274	12.2	0	635.71	0.0213	17.3	45
dem(max) hos	min	1914	53.0	0	691.09	0.3554	30.3	16
	mean	3121	86.4	0	1614.68	0.3950	85.9	57
	max	3593	99.5	0	2927.50	0.4300	100	217
	st. d.	448	12.4	0	635.71	0.0213	19.7	44
w(min) opt	min	32	0.3	0	507.53	0.3282	0.0	2
	mean	160	1.5	0	536.63	0.3467	25.5	4
	max	357	3.4	0	585.50	0.3637	70.4	12
	st. d.	70	0.7	0	25.70	0.0123	27.9	2
w(min) hos	min	11	0.3	0	507.53	0.3282	0.0	2
	mean	50	1.4	0	536.63	0.3467	17.3	4
	max	97	2.7	0	585.50	0.3637	77.2	9
	st. d.	22	0.6	0	25.70	0.0123	22.1	1

	ΔT	dem	dem [%]	und	w [km]	g	$\overline{\Delta g}$	nst
g(min) opt	min	389	3.7	0	571.26	0.3191	0.0	3
	mean	2397	22.9	0	778.51	0.3270	1.2	22
	max	6942	66.3	0	1363.28	0.3364	8.7	86
	st. d.	2422	23.1	0	232.59	0.0048	2.6	24
g(min) hos	min	130	3.6	0	571.26	0.3191	0.0	3
	mean	792	21.9	0	778.51	0.3270	0.5	21
	max	2372	65.7	0	1363.28	0.3364	5.3	85
	st. d.	821	22.7	0	232.59	0.0048	1.3	24
trade-off opt	min	5272	50.4	0	676.46	0.3257	0.0	16
	mean	6966	66.6	0	1329.70	0.3460	15.6	49
	max	9988	95.5	0	1876.96	0.3629	40.0	199
	st. d.	1224	11.7	0	394.70	0.0104	10.2	43
trade-off hos	min	1779	49.3	0	676.46	0.3257	0.0	16
	mean	2383	66.0	0	1329.70	0.3460	9.6	48
	max	3453	95.6	0	1876.96	0.3629	40.3	197
	st. d.	426	11.8	0	394.70	0.0104	8.0	42

	ΔT	pav	psp	psp_1	psp_2	psp_3	sba [%]	$mwsb$ [m]	wsb [%]
dem(max) opt	min	0	43	4	0	0	27.7	-35	51.7
	mean	1	78	55	18	5	74.2	69	130.9
	max	12	221	90	87	54	93.0	186	233.1
	st. d.	3	38	21	25	13	17.6	62	50.4
dem(max) hos	min	0	40	4	0	0	27.7	-35	51.7
	mean	1	73	52	17	4	74.2	69	130.9
	max	12	209	85	80	49	93.0	186	233.1
	st. d.	3	37	20	23	12	17.6	62	50.4
w(min) opt	min	0	2	0	0	0	0.5	-44	57.1
	mean	0	4	4	0	0	2.0	39	116.5
	max	0	12	6	4	8	4.4	102	175.8
	st. d.	0	2	2	1	1	1.2	53	38.1
w(min) hos	min	0	2	0	0	0	0.5	-44	57.1
	mean	0	4	3	0	0	2.0	39	116.5

	max	0	9	6	3	6	4.4	102	175.8
	st. d.	0	1	2	1	1	1.2	53	38.1
g(min) opt	min	0	6	5	0	0	4.0	-12	64.5
	mean	1	28	14	10	4	17.2	102	158.9
	max	6	92	45	38	28	50.2	378	334.6
	st. d.	2	27	12	14	9	15.9	123	86.8
g(min) hos	min	0	4	4	0	0	4.0	-12	64.5
	mean	1	25	13	9	3	17.2	102	158.9
	max	6	87	38	35	26	50.2	378	334.6
	st. d.	2	25	11	13	8	15.9	123	86.8
trade-off opt	min	0	33	3	0	0	29.3	-31	53.6
	mean	1	65	43	17	5	52.0	88	137.0
	max	12	198	80	75	45	86.3	217	220.3
	st. d.	3	38	16	23	13	15.5	82	54.8
trade-off hos	min	0	33	3	0	0	29.3	-31	53.6
	mean	1	60	40	16	5	52.0	88	137.0
	max	12	190	80	70	41	86.3	217	220.3
	st. d.	3	36	15	21	12	15.5	82	54.8

Analysing this table, it appears that as has already been found, the solutions of the hos period are approximately identical to the opt period, excluding the demand level which is clearly lower given that hos is shorter than opt. This shows that the 21 days on which the optimisation is based also well represent the remaining 9 days of the month of November. The station demand is always satisfied, and it is generally quite high for the dem(max) and trade-off solutions. Those of the trade-off solutions are very similar to the solution of the dem(max), given the hypotheses of their choice. Only its average value appears to be a little lower. Conversely, the station demand is on average low for g(min) and close to zero for w(min). The smallest value of the Gini index is equal to 0.3191 which was found, for the g(min) solution, in all cases with a $dlim$ = 300 m and $clim$ = 100. However, its largest value (0.43) corresponds to dem(max) for the same $dlim$ = 300 but with a lower value of available parking spaces ($clim$ = 50). In any case, the Gini index does not deviate much from its average value. The number of stations (nst) and the station-based sub-area percentage over service area (sba) statistics vary in line with the station demand. The average user walking distances in station-based sub-areas ($mwsb$) remain on average around 70 metres and exceed 300 metres only in some cases with the lowest values of the Gini index. To better analyse what happens as the maximum distance that a user is forced to walk increases, we report detailed results for all combinations and for some of the key indicators in Figure 17 and Figure 18.

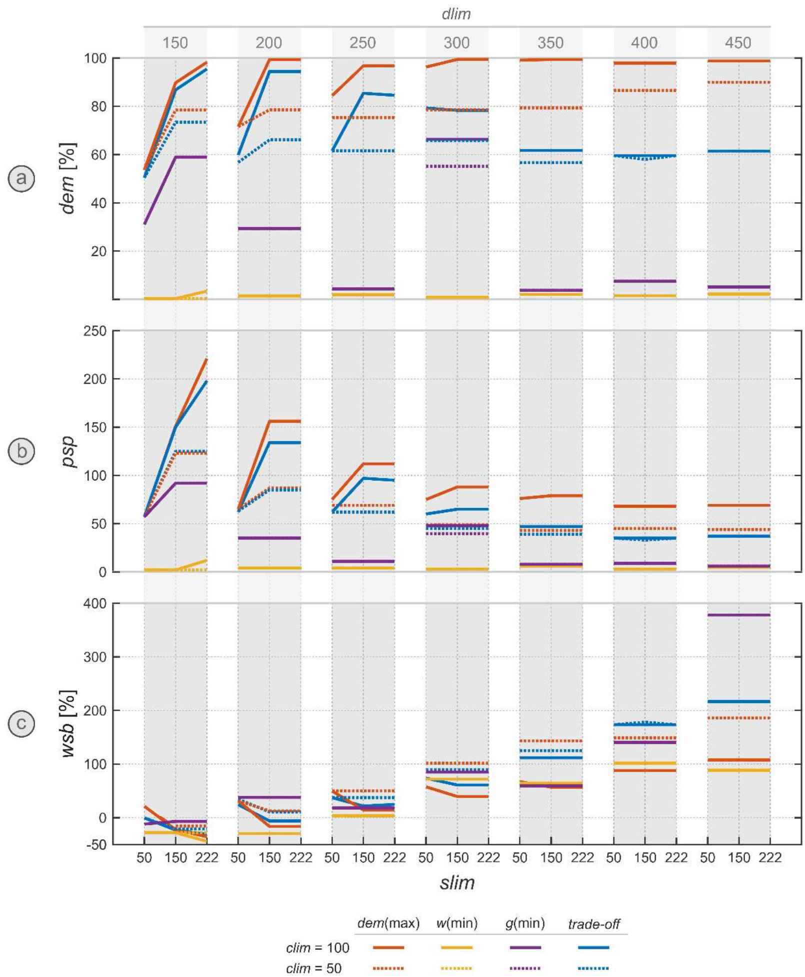

Fig. 17- Some key indicators for different $dlim$ and other input parameters

Figure 18(a) shows that, for dem(max) solutions the station demand (dem) increases, not only as $slim$, but also as the $dlim$ increases. If we do not place restrictive limits on car parking places ($clim$ = 100) we can achieve approximately 100% demand coverage starting from $dlim$ = 300 metres. In these cases, there is a complete conversion from free-floating to station-based systems. However, if we reduce the number of car parking places available for each hourly parking rate, this does not happen, but the station demand still remains around 80%. The trade-off solutions follow a similar trend to that of the dem(max) up to $dlim$ = 250 meters and then lead to a decrease in demand as $dlim$ increases. At the expense of one of the highest total walking distances (w = 1,363,276 metres), a good compromise g(min) solution between station demand level and minimisation of the Gini index is found in the case $dlim$ = 300 metres. In this case, the station demand is above 60% and the value of the Gini index is the lowest ever (g = 0.3191). Another good compromise, but which requires a higher number of car parking spaces to be replaced with stations, is the case of $dlim$ = 150 metres. For the other input combinations, dem takes on low values (around 30% for $dlim$ = 200 metres) or almost drops to zero, for the highest $dlim$, as happens in all w(min) cases.

The number of car parking spaces to be replaced with stations (psp) increases as $slim$ increases and decreases as $dlim$ increases (Figure 18(b)). This consideration is valid, on average, for all combinations. The lowest values of psp occur for w(min), given the very low number of stations necessary to keep the total walking distances low.

In Figure 18(c) the percentage increase in a user's average walking distance in station-based sub-areas compared to that of the free-floating system in the same sub-areas is shown. The negative percentages are worthy of note and belong largely to the case with $dlim$ = 150 and to a lesser extent to those with $dlim$ = 200. These are the cases in which a decrease in the average distances to be covered on foot in station-based sub-areas is evident. Indeed, for $dlim$ equal to 150 or 200 metres the station density is sufficiently high (in_max is equal to 150 or 200 metres, respectively) to be, on average, higher than that of the corresponding free-floating system sub-areas. For higher station density values ($dlim$ > 200 metres), the average walking distance in the station-based sub-areas increases up to a maximum of approximately 400% of the free-floating system, for g(min) solutions in the case of $dlim$ = 450 metres. The effect of $dlim$ and in_max on station-based sub-areas and station density can also be seen in Figure 19.

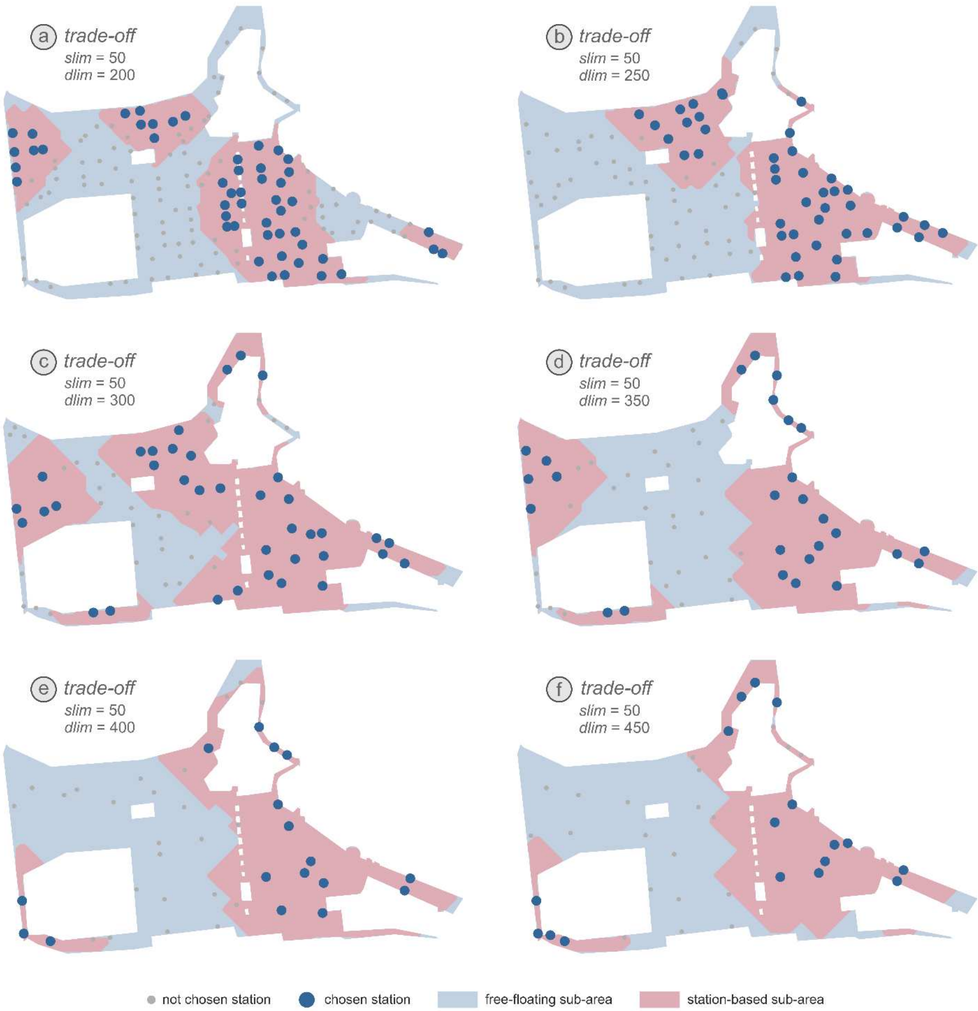

Fig. 18- Free-floating and station-based sub-areas of trade-off solutions with $slim$ = 50 and different $dlim$ values.

In this image we show the trade-off solutions for a maximum number of stations $slim$ = 50 and for cases with $dlim$ = in_max ≥ 200 metres. Given the increasing value of in_max, we see that the subset of stations ($\boldsymbol{CK}$) represented by the unchosen (in grey) and the chosen stations (in blue) is increasingly less dense, starting from Figure 18(a) up to Figure 18(f). Similarly, the station-based sub-areas have their boundaries increasingly distant from the chosen stations, given the increase in $dlim$. Furthermore, $dlim$ and in_max also influence the station demand for which the trade-off solutions show an increase up to $dlim$ = 250 meters (Figures 18(a), 18(b) and 18(c)), and a decrease in demand as $dlim$ increases (Figures 18(d), 18(e) and 18(f)), as seen in Figure 17(a).

Other interesting considerations can be made by observing the trends of Δg and $\overline{\Delta g}$ as the input parameters change (Figure 19).

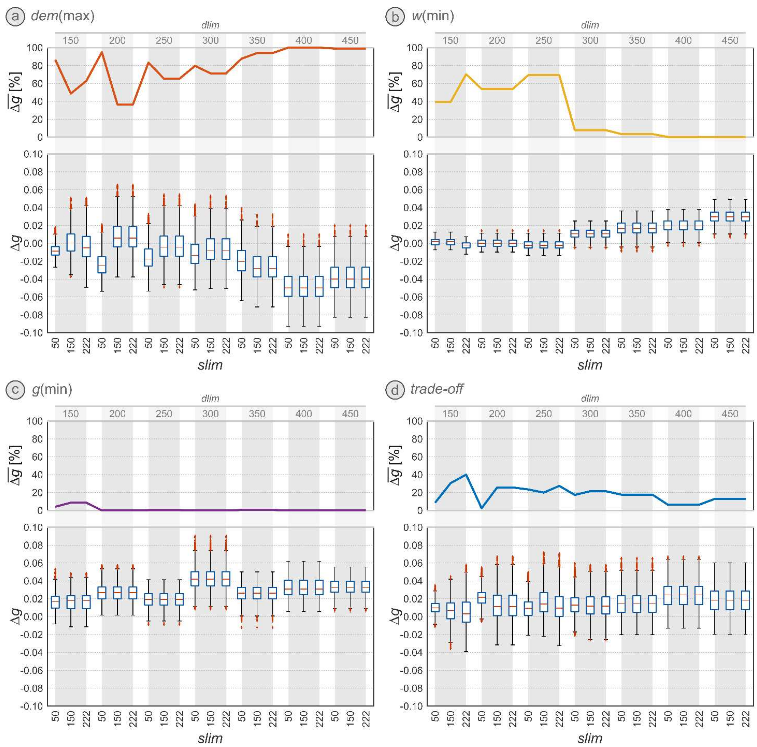

Fig. 19- Δg box plots and ($\overline{\Delta g}$) trends for different dlim and other input parameters

This figure represents, for $clim$ = 100 and for the opt period, the box plots of Δg, that is the difference between the free-floating and mixed system Gini index trend (every 2 minutes) and the $\overline{\Delta g}$ percentages for each of the $slim$ and $dlim$ inputs for the four significant Pareto front solutions. It is evident that the dem(max) solutions (Figure 19(a)) have a high $\overline{\Delta g}$ percentage, which even reaches 100% for the highest $dlim$ values. They also correspond to a greater range of Δg values shown by the long box plot whiskers. Even the w(min) solutions (Figure 19(b)) do not show good $\overline{\Delta g}$ for $dlim$ between 150 and 200 metres, even if the Δg ranges are smaller. In Figure 19(c), we observe that practically all g(min) solutions are desirable from the equality point of view, given that the $\overline{\Delta g}$ percentage is almost always zero and that all Δg values of the mixed system have a Gini index every 2 minutes almost always lower than that of the free-floating system. In fact, all box plots (including the whiskers) are mainly above Δg = 0. This confirms that reducing the complexity of the problem by considering a single g value for the opt period (through the mode of distances) almost always ensured a reduction in the Gini index every 2 minutes throughout the entire period. The trade-off solutions (Figure 19(d)) are good compromises between dem(max) and g(min) ones, as they have high $\overline{\Delta g}$ percentages only for $dlim$ = 150 but which are around 20% for all other cases.

The sensitivity analysis reported here can be of help for municipalities and operators in choosing a solution among those of the Pareto front, based on the importance that they place on one objective compared to the other two. If station demand is a priority (to address disorderly parking), one of the trade-off solutions could be chosen such as those with $dlim$ = 300 meters and $clim$ = 50 with one of the lowest g (0.3257). If they prefer to prioritise inequality minimisation among population zones, one of the g(min) solutions with $dlim$ = 300 could be chosen, as seen above. However, it is important to underline that forcing a user to walk a maximum of 300 meters to pick up or drop off a vehicle in station-based sub-areas may be excessive. In order not to lose users, this distance should be set less than or equal to a user's willingness to walk to pick up a vehicle, or to walk to their destination from the place where the shared vehicle has been dropped off. For example, the study of Kabra, Belavina and Girotra (2016) established that almost 80% of bike-sharing system users were willing to walk a maximum of 300 metres to reach a vehicle. This work is not related to e-scooter sharing, but in the absence of specific studies on these systems and in the city under consideration, we could still refer to this distance by analogy. Therefore, with a $dlim$ = 300 meters some users could leave the system and it could still be more advisable to choose solutions with $dlim$ between 150 and 200 metres.

6. CONCLUSIONS

Shared micromobility systems are an alternative to private modes of transport to cover urban short and medium distances and has a number of economic, environmental and social benefits. In particular, the most comfortable system is the free-floating one that allows users to pick up and drop off a vehicle anywhere in the service area at the nearest point to their origins/destinations, while still in line with the highway code. However, this high degree of parking freedom may easily generate unauthorised and irregular parking. Unauthorised drop-offs take place, for example, on pavements or cycle paths or on car lanes, obstructing pedestrians and other vehicle flows and so becoming a potential cause of accidents. On the other hand, irregular parking is mainly due to the high number of shared vehicles and the multiple user destinations, resulting in the deterioration of urban decorum.

To address these problems, operator-based processes and user-based regulations with mandatory or non-mandatory parking areas can be implemented. As for the former, vehicles reposition located in incorrect positions is carried out by the operators. To mitigate the problem without direct operator intervention, which cannot be continuous and simultaneous over the entire service area, stations can be created where vehicles can or must be released. The boundary of these parking areas or stations can easily be identified using geofence techniques, as well as with physical racks or dedicated spaces marked with paint.

To solve these issues, we proposed three decision support models for the redesign of free-floating micromobility systems, all applied to a real case study, the city of Bari (Apulia). The first model is an equity-based optimization model for location of stations in free-floating e-scooter sharing systems. In this case, users are obliged to drop off and pick up vehicles only to and from stations. However, the location of stations may create disadvantaged for one part of the population compared to another. For this reason, this model is 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 minimizing the total walking distances for each micro-zone, while the second objective function aims at maximising horizontal equity, i.e. minimizing 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 value of Pareto front.

The second model is an equity-based optimisation model for the location of parking areas in free-floating sharing systems. In this case, it is not mandatory to drop off vehicles in these zones, users are simply incentivised to do so. This model takes into consideration the minimisation of demand outside parking areas and the minimisation of inequality. Results showed the contrast between the minimisaton of drop offs outside stations and the minimisation of the Gini, due to the fact that the equity is higher when density of vehicles outside stations becomes greater. Pareto front solutions offer municipal councils and operators the possibility to find a compromise solution to better satisfy the two objective functions.

In literature, various methodologies and models for station locations have been proposed, which suggest the complete transformation of a free-floating system into a station-based one (with mandatory parking areas) or station implementation where it is recommended to release vehicles through app-based incentives for users to encourage them to park vehicles in those areas. What is innovative in our approach, differently from literature, is the concept of equity.

Municipal councils may want the entire conversion from free-floating to station-based to eliminate unauthorised and irregular parking. However, as this is also desirable to operators, this could be achieved with a very high number of stations to avoid making the system less attractive, with a loss of users due to the increased distances to be covered on foot in a station-based system. Usually, it is not possible to implement a very large number of stations so as to make the distances to be covered on foot similar to those of a free-floating system since it would be necessary to subtract a large quantity of space from other types of parking (such as that for private cars or mopeds) or from pavements. On the other hand, non-mandatory parking areas may be insufficient to address the problems related to free parking. In both cases, the presence of stations can make the system unequal for residents since a part of the population can be forced or encouraged to walk greater or shorter distances than the rest. A compromise solution to this problem is to convert a free-floating system into a mixed one with free-floating and station-based geofenced service sub-areas, also considering an equality objective, as proposed in the third model. To the best of our knowledge, such models are not proposed in literature. For these reasons, we suggest a multi-objective problem with the aim of finding a trade-off solution among the maximisation of drop-off station demand to minimise irregular parking, the minimisation of user walking distances, and the minimisation of inequality, in the accessibility of the system, among service area residents to ensure that there are no population zones that will be more affected by the walking distance changes due to the system conversion.

The proposed model was applied to a free-floating e-scooter sharing system in the city centre of Bari (Apulia, Italy). Nevertheless, the proposed model can also be used considering more than one system at the same time by aggregating the trip databases of all free-floating systems of the same type of micromobility vehicles. Furthermore, two sensitivity analyses were carried out starting with different input parameters. The entire available trip data (one month) was divided into two sub-intervals. The first sub-interval (three weeks) was used to solve the proposed problem. The other was used to validate model results. First, the key solution indicators of the first period are approximately identical to the second ones. This shows that the sub-interval chosen to solve the proposed problem well represents the subsequent period. Thus, it is recommended to select a time interval that is as representative as possible of average users' behaviour. The choice of a multi-objective is appropriate given that, as highlighted by the results, the three objectives are in contrast with each other, making it necessary to choose a compromise solution. It turned out that the free-floating system is unequal with inequality values, calculated with a Gini index, varying during the considered period. Therefore, it is important to choose a mixed configuration that maintains as much as possible over time lower inequalities compared to the starting ones, named trade-off solutions. In addition, three other significant Pareto solutions were analysed i.e., the configurations with the highest demand value (dem(max)), with the lowest total of walking distances (w(min)), and with the lowest Gini index value (g(min)). If on the one hand, the dem(max) solutions allow for a significant reduction in unauthorised and irregular parking, on the other hand they force users to cover large total distances on foot. However, there are trade-off mixed system solutions very close to the dem(max) ones which allow a reduction in inequity compared to the free-floating system. The w(min) Pareto solutions have a relatively low number of stations and therefore should be discarded a priori if the aim is to reduce free parking related problems significantly. Furthermore, these do not entail an appreciable decrease in inequity, given that they have a mixed configuration very close to the starting free-floating system. The g(min) solutions, despite having the lowest values of inequity, do not always represent a good compromise. In fact, they are related to a station demand that may be very low. However, there are cases in which the lowest value of the Gini index corresponds to a medium/high demand, such as those cases with the maximum distance, $dlim$, that a user is forced to walk to pick up or drop off a vehicle in station-based sub-areas (equal to 300 metres). However, it is necessary to pay attention to this value. Indeed, $dlim$ distances which are too high may discourage some users who might abandon the system; therefore, it could still be more advisable to choose solutions with lower $dlim$, for example equal to 150 metres. Investigations are underway to evaluate this distance based on e-scooter sharing user preferences. In any case, sensitivity analyses with different input parameters can be of help for municipalities and operators in choosing the solution among those of the Pareto front.

Our proposal is based on the analysis of a past trip database. The only parameter that takes into account any changes in future demand is the incremental factor δ. After the creation of station-based sub-areas, it is therefore necessary to cyclically monitor the demand to increase or decrease station capacity, if necessary. However, the sub-areas outline should remain the same over time to avoid user disorientation. Future work may concern the joint use of the proposed model with drop-off demand prediction models not only of shared micromobility vehicles but also of private ones to guarantee orderly parking for the latter as well.

To summarise, proposed models aim to increase the equity of free-floating systems, which should be equally accessible for the entire population. The solutions found are a trade-off between municipal council needs (to solve the illegal parking problem) and operator needs (to adopt systems with arbitrary parking, maximising the use of each vehicle).

Furthermore, further research may focus on the combined station location and network design of cycle lanes to improve station accessibility, may involve model parameters calibration (willingness to walk) through a survey for users. In the case of the third model it is possible to expand our proposal by considering the presence of stations also in the free-floating sub-area. In these stations, however, parking would not be mandatory, but encouraged through incentives. The value of the incentives could be dynamic over time depending on municipal administrations or operators' needs; this way more substantial rewards are provided during peak hours when unauthorised parking could cause a potential greater number of accidents.

ACKNOWLEDGEMENTS

This study is financed by the European Union—NextGenerationEU (National Sustainable Mobility Center CN00000023, Italian Ministry of University and Research Decree n. 1033-17/06/2022, Spoke 8. The authors would like to thank the BIT Mobility team for the shared e-scooters data.

LIST OF FIGURES

Fig. 1- Proposed framework flowchart 28
Fig. 2- Lorenz curve and Gini index 35
Fig. 3 - E-scooter sharing operating area with zones and hypothetical stations. 39
Fig. 4 - Pareto front for each $slim$ value... 40
Fig. 5 - E-scooter parking areas for $slim$=100....................................... 43
Fig. 6- Pareto front for each maximum number of chosen stations ($slim$) 44
Fig. 7- Two Pareto solutions with 50 stations ($dem\ min, gmin$) 47
Fig. 8- Service area with a summary of system database 49
Fig. 9- Service area with resident micro-zones and population zone 50
Fig. 10- Gini index of the free-floating system every 2 minutes in the opt period.. 51
Fig. 11- Station choice sets and road network map............................... 52
Fig. 12- Subset of stations ($\boldsymbol{CK}$) and the choice set of 27 clusters. 54
Fig. 13- Pareto front solutions in a three-dimensional (a) and two-dimensional (b) space…………………………………………………………………………….55
Fig. 14- Differences between the Gini index of a free-floating system and a mixed one of the chosen Pareto solution. 56
Fig. 15- Free-floating and station-based sub-areas of four Pareto front solutions with $slim$ = 50. 57
Fig. 16- Free-floating and station-based sub-areas of trade-off solutions with slim = 150 and slim = 222. 66
Fig. 17- Some key indicators for different $dlim$ and other input parameters 71
Fig. 18- Free-floating and station-based sub-areas of trade-off solutions with $slim$ = 50 and different $dlim$ values. 73
Fig. 19- Δg box plots and (Δg) trends for different dlim and other input parameters 74

LIST OF TABLES

Table 1. Main results. 41
Table 2. Main results. 45
Table 3. Residents and level of service ratio $losq$ for each zone q of four Pareto front solutions with $slim$ = 50. 58
Table 4. Key indicators of the four Pareto front solutions with $slim$ = 50 and a comparison with a station-based system. 61
Table 5. Summary of all the Pareto solutions found 63
Table 6. Key indicators of the four Pareto front solutions with $slim$ = 150. 66
Table 7. Key indicators of the four Pareto front solutions with $slim$ = 222 67
Table 8. Main statistics on key indicators of the four Pareto front solutions for all input parameter combinations. 68

BIBLIOGRAPHY

Amarilies, H. S., Kamil, A. P., Adzkia, H. F., 2020. Maximum Coverage Distance Problem for Dockless Bike Sharing System: A Case Study of the Dockless Bike Sharing System in Jakarta. Proceedings of the 2020 the 3rd International Conference on Computers in Management and Business, 2020, pp. 306–309. DOI: 10.1145/3383845.3383893

Arif, A., Margellos, K., 2022. Locating Parking Hubs in Free-Floating Ride Share Systems via Data-Driven Optimization. IEEE Transactions on Intelligent Transportation Systems, Vol. 23, No. 8. http://dx.doi.org/10.1109/TITS.2021.3105579

AuX Platform, 2020. Distance decay: How far are you willing to travel to your destinations? Available online at: https://axuplatform.medium.com/distance-decay-6a47b98d57ee (accessed on April 2024)

Beairsto, J., Tian, Y., Zheng, L., Zhao, Q., Hong, J., 2022. Identifying locations for new bike-sharing stations in Glasgow: an analysis of spatial equity and demand factors. Annals of GIS, 28:2, 111-126, doi: 10.1080/19475683.2021.1936172

Bencekri, M., Lee, D., Kim, S., Shin, S., Lee, S., 2023. Equity-Based Allocation of Mobility Hubs in Seoul. Chemical engineering transactions 106, 265-270. DOI: 10.3303/CET23106045

Berke, A., Truitt, W., Larson, K., 2024. Is access to public bike-share networks equitable? A multiyear spatial analysis across 5 U.S. Cities. Journal of Transport Geography 114, 103759.

Bird, 2020. Encouraging Better Scooter Parking in Paris Through Design and Incentives. Available at: https://www.bird.co/sv/blog/encouraging-better-scooter-parking-in-paris-through-design-and-incentives/ (Accessed on February 2024).

Blanco, V., Gazquez, R., 2023. Fairness in maximal covering location problems. Computers and Operations Research 157, 106287. https://doi.org/10.1016/j.cor.2023.106287

Blanco, V., Marin, A., Puerto, J., 2022. Intra-facility equity in discrete and continuous p-facility location problems. Computers & Operations Research 162, 106487. https://doi.org/10.1016/j.cor.2023.106487

Brown, A., 2021. Micromobility, Macro Goals: Aligning scooter parking policy with broader city objectives. Transportation Research Interdisciplinary Perspectives 12, 100508. https://doi.org/10.1016/j.trip.2021.100508

Brown, A., Klein, N. J., Thigpen, C., Williams, N., 2020. Impeding access: The frequency and characteristics of improper scooter, bike, and car parking. Transportation Research Interdisciplinary Perspectives 4, 100099. https://doi.org/10.1016/j.trip.2020.100099

Caggiani, L., Colovic, A., Ottomanelli, M., 2020. An equality-based model for bike-sharing stations location in bicycle-public transport multimodal mobility. Transportation Research Part A: Policy and Practice. 140, 251-265. https://doi.org/10.1016/j.tra.2020.08.015

Cai, Y., Ong, G. P., Meng, Q., 2023. Bicycle sharing station planning: From free-floating to geo-fencing. Transportation Research Part C: Emerging Technologies, 147, 103990. DOI: 10.1016/j.trc.2022.103990

Carrese, S., D'Andreagiovani, F., Giacchetti, T., Nardin, A., Zamberlan, L., 2020. Night makes you beautiful: an optimization approach to overnight joint beautification and relocation in e-scooter sharing. 3rd Symposium on Management of Future Motorway and Urban Traffic Systems (MFTS2020), Jul 2020, Luxembourg, Luxembourg. hal- 03053339

Carrese, S., D'Andreagiovanni, F., Giacchetti, T., Nardin, A., Zamberlan, L., 2021a. A Beautiful Fleet: Optimal Repositioning in E-Scooter Sharing Systems for Urban Decorum. Transportation Research Procedia 52, 581-588. https://doi.org/10.1016/j.trpro.2021.01.069

Carrese, S., D'Andreagiovanni, F., Nardin, A., Giacchetti, T., Zamberlan, L., 2021b. Seek & Beautify: integrating UAVs in the optimal beautification of e-scooter sharing fleets. Proceedings of the 2021 7th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (IEEE MT-ITS). doi: 10.1109/MT- ITS49943.2021.9529312, 2021.

Chen, Y., Cheng, C., Li, S., Yu, C., 2018. Location optimization for multiple types of charging stations of electric scooters. Applied Soft Computing 67, 519-528. https://doi.org/10.1016/j.asoc.2018.02.038

Cheng, M., Wei, W., 2020. An AHP-DEA Approach of the Bike-Sharing Spots Selection Problem in the Free-Floating Bike-Sharing System. Discrete Dynamics in Nature and Society, Vol. 2020, Article ID 7823971, https://doi.org/10.1155/2020/7823971.

Cintrano, C., Chicano, F., Alba, E., 2020. Using metaheuristics for the location of bicycle stations. Expert Systems with Applications 161, 113684. https://doi.org/10.1016/j.eswa.2020.113684

Cintrano, C., Chicano, F., Stützle, T., Alba, E., 2018. Studying Solutions of the p-Median Problem for the Location of Public Bike Stations. Lecture Notes in Computer Science, Springer, Berlin, Germany, pp. 198–208, Article ID 11160. DOI: 10.1007/978-3-030-00374-6_19

Colovic, A., Prencipe, L. P., Giuffrida, N., Ottomanelli, M., 2024. A multi-objective model to design shared e-kick scooters parking spaces in large urban areas. Journal of Transport Geography 116, 103823. https://doi.org/10.1016/j.jtrangeo.2024.103823

Dawson, E., Rashed, M. A., Abdelfatah, W., Noureldin, A., 2022. Radar-Based Multisensor Fusion for Uninterrupted Reliable Positioning in GNSS-Denied Environments. IEEE Transactions on intelligent transportation systems, Vol. 23, NO. 12. doi: 10.1109/TITS.2022.3202139

Deb, K., 2001. Multiobjective Optimization Using Evolutionary Algorithms, New York, NY,USA,Wiley

Deveci, M., Gokasar, I., Pamucar, D., Chen, Y., Coffman, D., 2023. Sustainable E-scooter parking operation in urban areas using fuzzy Dombi based RAFSI model. Sustainable Cities and Society 91, 104426. https://doi.org/10.1016/j.scs.2023.104426

Désidéri, J. A., Fournier, L., Lanteri, S., Marco, N., Mantel, B., Périaux, J., Wang, J. F., 2000. Parallel multigrid solution and optimization in compressible flow simulation and design. Parallel Computational Fluid Dynamics 1999.

Editor(s): D. Keyes, A. Ecer, J. Periaux, N. Satofuka, P. Fox, Parallel Computational Fluid Dynamics 1999, North- Holland, 2000, pp. 3-15, ISBN 9780444828514, https://doi.org/10.1016/B978-044482851-4.50005-0.

Dinas, S., Banon, J. M., 2014. A REVIEW ON DELAUNAY TRIANGULATION WITH APPLICATION ON COMPUTER VISION. International Academy of Science, Engineering and Technology, Vol 3, Issue 2.

Eurocities, 2020. Playing by the Rules. Report on E-Scooter Operators and Fleets in Cities - a Survey of City Approaches and Options to Optimise Regulations. Report. Available at: https://eurocities.eu/wp- content/uploads/2020/07/Playing-by-the-r ules-A-report-on-e-scooter-operators-and-fleets-in-cities.pdf. (Accessed on February 2024).

Fan, Z., Harper, C. D., Taking a multimodal approach to equitable bike share station siting. Journal of Transport Geography, 115, 103814. https://doi.org/10.1016/j.jtrangeo.2024.103814

Fazio, M., Giuffrida, N., Le Pira, M., Inturri, G., Ignaccolo, M., 2021. Bike oriented development: Selecting locations for cycle stations through a spatial approach. Research in Transportation Business & Management, 40, 100576. https://doi.org/10.1016/j.rtbm.2020.100576

Frondel, M., Vance, C., 2017. Cycling on the extensive and intensive margin: the role of paths and prices. Transportation Research Part A: Policy and Practice, 104, 21-31. https://doi.org/10.1016/j.tra.2017.06.018

Fu, J., Shi, Y., Hu, Y., Ming, Y., Zou, B., 2023. Location optimization of on-campus bicycle-sharing electronic fences. Management System Engineering, 2,11. https://doi.org/10.1007/s44176-023-00020-9

Fu, L., Chen, W., Li, J., Arshad, A., Song, C., 2020. Spatio-temporal Clustering-based Parking Area Division of Dockless Shared Bicycles. 2020 International Conference on Artificial Intelligence and Computer Engineering (ICAICE), pp. 234-240, doi: 10.1109/ICAICE51518.2020.00051.

Fukushige, T., Fitch, D. T., Handy, S., 2022. Can an Incentive-Based approach to rebalancing a Dock-less Bike-share system Work? Evidence from Sacramento, California. Transportation Research Part A: Policy and Practise, 163, 181-194.

Gao, K., Yang, Y., Li, A., Qu, X., 2020. Spatial heterogeneity in distance decay of using bike sharing: An empirical large-scale analysis in Shanghai. Transportation Research Part D: Transport and Environment, 94(9):102814.

Gao, L., Ji, Y., Yan, X., Fan, Y., Guo, W., 2021. Incentive measures to avoid the illegal parking of dockless shared bikes: the relationships among incentive forms, intensity and policy compliance. Transportation 48, 1033–1060 (2021). https://doi.org/10.1007/s11116-020-10088-x

García-Palomares, J., Gutierrez, J., Latorre, M. 2012. Optimizing the location of stations in bike-sharing programs: A GIS approach. Applied Geography, 35, 235-246. https://doi.org/10.1016/j.apgeog.2012.07.002

Gini, CW., 1912. Variability and Mutability, Contribution to the Study of Statistical Distributions and Relations., Studi Economico-Giuridici della Regia Facoltà di Giurisprudenza di Cagliari, Università di Cagliari. Vol. III, Part II.

Giuffrida, N., Pilla, F., Carroll, P., 2023. The social sustainability of cycling: Assessing equity in the accessibility of bike-sharing services. Journal of Transport Geography, 106, 103490.

Gossling, S., 2020. Integrating e-scooters in urban transportation: Problems, policies, and the prospect of system change. Transportation Research Part D: Transport and Environment 79, 102230.

Hamidi, Z., Camporeale, R., Caggiani, L., 2019. Inequalities in access to bike-and-ride opportunities: Findings for the city of Malmö. Transportation Research Part A: Policy and Practice 130, 673-688.

Hemphill, R., MacArthur, J., Longenecker, P., Desai, G., Nie, L., Ibarra, A., Dill, J., 2022. Congested sidewalks: The effects of the built environment on e-scooter parking compliance. Journal of Transport and Land Use, 15(1), 481–495. https://doi.org/10.5198/jtlu.2022.2110

Iravani, H., 2022. A multicriteria GIS-based decision-making approach for locating electric vehicle charging stations. Transportation Engineering 9, 100135. https://doi.org/10.1016/j.treng.2022.100135

Istat, 2024. Basi territoriali e variabili censuarie. Available online at: https://www.istat.it/it/archivio/104317 (accessed on April 2024)

James, O., Swiderski, J. I., Hicks, J., Teoman, D., Buehler, R., 2019. Pedestrians and E-Scooters: An Initial Look at E-Scooter Parking and Perceptions by Riders and Non-Riders. Sustainability 2019, 11, 5591. https://doi.org/10.3390/su11205591

Kabra, A., Belavina, E., Girotra, K., 2016. Bike-Share Systems: Accessibility and Availability. Working Paper, Chicago Booth Research Paper No 15-04. 2016. Available online: https://ssrn.com/abstract=2555671 (accessed on April 2024).

Karner, A., Pereira, R. H. M., Farber, S., 2024. Advances and pitfalls in measuring transportation equity. Transportation. https://doi.org/10.1007/s11116-023-10460-7

Kaur, M., Kaur, U., 2013. Comparison between k-means and hierarchical algorithm using query redirection. Int. J. Adv. Res. Comput. Sci. Softw. Eng. 3 (7), 1454–1459.

Krause, E.F., 1973. Taxicab geometry. Math. Teacher 66 (8), 695–706.

Liazos, A., Iliopoulou, C., Kepaptsoglou, K., Bakogiannis, E., 2022. Geofence planning for electric scooters. Transportation Research Part D: Transport and Environment. 102, 103149. https://doi.org/10.1016/j.trd.2021.103149

Lime, 2020. Lime Introduces New Geofencing Technology, Setting Industry Standards For Scooters. Available on- line at: https://www.li.me/blog/lime-introduces-new-geofencing-technology-setting-industry-standards-for-scooters (Accessed on February 2024).

Lime, 2024. About us. Available on-line at: https://www.li.me/about (Accessed on February 2024).

LINK, 2020. Good (Geo)Fences Make Good Neighbors. Available on-line at: https://link-city.medium.com/good-geo-fences-make-good-neighbors-5af63b6a2843 (Accessed on February 2024).

Mahmoodian, V., Zhang, Y., Charkhgard, H., 2022. Hybrid rebalancing with dynamic hubbing for free-floating bike sharing systems. International Journal of Transportation Science and Technology, Vol. 11, Issue 3, p. 636-652.

Mangold, M., Zhao, P., Haitao, H., Mansourian, A., 2022. Geo-fence planning for dockless bike-sharing systems: a GIS-based multi-criteria decision analysis framework. Urban Informatics, 1, 17. https://doi.org/10.1007/s44212-022-00013-1

Meng, S., Brown, A., 2021. Docked vs. dockless equity: Comparing three micromobility service geographies. Journal of Transport Geography 96, 103185.

Moran, M. E., (2021). Drawing the map: The creation and regulation of geographic constraints on shared bikes and e-scooters in San Francisco, CA. Journal of Transport and Land Use, 14(1), 197-218. https://doi.org/10.5198/jtlu.2021.1816

Moran, M. E., Laa, B., Emberger, G., (2020). Six scooter operators, six maps: Spatial coverage and regulation of micromobility in Vienna, Austria. Case Studies on Transport Policy, 8(2), 658-671. https://doi.org/10.1016/j.cstp.2020.03.001

NACTO, 2018. The Bikeshare Planning Guide. Institute for Transportation & Development Policy. Available online at: https://itdp.org/publication/the-bikeshare-planning-guide/ (Accessed on July 2024)

Park, C., Shon, S. Y., 2017. An Optimization Approach for the Placement of Bicycle-sharing stations to Reduce Short Car Trips: An Application to the City of Seoul. Transportation Research Part A: Policy and Practice. 105, 154-166.

Roig-Costa, O., Miralles-Guasch, C., Marquet, O., 2024. Shared bikes vs. private e-scooters. Understanding patterns of use and demand in a policy-constrained micromobility environment. Transport Policy 146, 116-125.

Rojas, C., Linfati, R., Scherer, R. F., Pradenas, L., 2023. Using Geopandas for locating virtual stations in a free- floating bike sharing system. Heliyon, 9, e12749.

Sandoval, R., Geffen, C. V., Wilbur, M., Hall, B., Dubey, A., Barbour, W., Work, D. B., 2021. Data driven methods for effective micromobility parking. Transportation Research Interdisciplinary Perspectives 10, 100368.

Segway, 2022. The Bluetooth Parking Beacon – Micromobility's Revolutionary Parking Solution. Available on-line at: https://b2b.segway.com/blog/the-bluetooth-parking-beacon-micromobilitys-revolutionary-parking-solution/ (Accessed on February 2024).

Shi, X., Liang, Z., Seng, D., 2022. An Electric Fence-Planning Framework for a Dockless Bike-Sharing System Based on a Land Parcel Subdivision and Regional Coverage Maximization. IEEE Intelligent Transportation Systems Magazine, doi: 10.1109/MITS.2022.3181578.

Su, D., Wang, Y., Yang, N., Wang, X., 2020. Promoting considerate parking behavior in dockless bike-sharing: An experimental study. Transportation Research Part A: Policy and Practice. 140, 153-165.

Sun, Z., Li, Y., Zuo, Y., 2019. Optimizing the Location of Virtual Stations in Free-Floating Bike-Sharing Systems with the User Demand during Morning and

Evening Rush Hours. Journal of Advanced Transportation, Vol. 2019, Article ID 4308509, 11 pages.

The MathWorks Inc. (2022). MATLAB version: 9.13.0 (R2022b), Natick, Massachusetts: The MathWorks Inc. https://www.mathworks.com

Theil, H., 1967. Economics and Information Theory. Rand Mcnally and Company, Chicago.

TØI rapport, 2021. Available online at: https://www.toi.no/getfile.php?mmfileid=55176 (accessed on February 2024)

Voi Technology, 2024a. About us. Available online at: https://www.voi.com/voi-technology (accessed on February 2024)

Voi Technology, 2024b. How can I report a wrongly parked scooter? Available online at: https://help.voi.com/en_gb/how-can-i-report-a-wrongly-parked-scooter-HyEb1a0JF (accessed on February 2024)

Xanthopoulos, S., Tuin, M. V. D., Azadeh, S. S., Almeida Correia, G. H., Oort, N. V., Snelder, M., 2024. Optimization of the location and capacity of shared multimodal mobility hubs to maximize travel utility in urban areas. Transportation Research Part A: Policy and Practice 179.

Yanocha, D., Allan, M., 2019. The Electric Assist: Leveraging E-bikes and E-scooters for More Livable Cities. Available at: https://www.itdp.org/publication/electric-assist/ (accessed on May 2024)

Zafar, U., Bayram, I. S., Bayhan, S., 2021. A GIS-based Optimal Facility Location Framework for Fast Electric Vehicle Charging Stations, 2021 IEEE 30th

International Symposium on Industrial Electronics (ISIE), pp. 1-5, doi: 10.1109/ISIE45552.2021.9576448.

Zakhem, M., Smith-Colin, J., 2021. Micromobility implementation challenges and opportunities: Analysis of e-scooter parking and high-use corridors. Transportation Research Part D: Transport and Environment, 101, 103082.

Zhang, C., Du, B., Zheng, Z., Shen, J., 2023. Space sharing between pedestrians and micro-mobility vehicles: A systematic review. Transportation Research Part D: Transport and Environment, 116, 103629. https://doi.org/10.1016/j.trd.2023.103629

Zhang, Y., Lin, D., Mi, Z., 2019. Electric fence planning for dockless bike-sharing services. Journal of Cleaner Production 206, 383-393.

Zhao, D., Ong, G. P., 2021. Geo-fenced parking spaces identification for free-floating bicycle sharing system. Transportation Research Part A, 148, 49-63.

Zhou, B., Gu, Z., Gu, F., Wu, P., Yang, C., Lie, X., Li, L., Li, Y., Li, Q., 2022. DeepVIP: Deep Learning-Based Vehicle Indoor Positioning Using Smartphones. IEEE Transactions on intelligent transportation systems, Vol. 71, NO. 12., pp. 13299-13309. doi: 10.1109/TVT.2022.3199507

CURRICULUM

SIMONA
DE BARTOLOMEO

Curriculum Vitae

Informazioni personali

Indirizzo	Strada Vicinale Vassallo 3/a, Bari
Telefono	+39 3388796432
E-mail	simona.debartolomeo@gmail.com simona.debartolomeo@poliba.it
Nazionalità	Italiana
Data di nascita	08/03/1998

Istruzione

MATURITÀ SCIENTIFICA
2016
Liceo Scientifico Enrico Fermi, Bari
Voto diploma: 97/100
Tipo Diploma: diploma italiano

LAUREA TRIENNALE
2016 - 2019
Politecnico di Bari
Dipartimento di Ingegneria Civile, Ambientale, del Territorio, Edile e di Chimica
Corso di Laurea Triennale in Ingegneria Civile e Ambientale

L-7- Laurea in Ingegneria Civile e Ambientale
Età di conseguimento del titolo: 21; Durata ufficiale del corso di studio: 3 anni
Votazione: 106/110; Data di conseguimento: 24/07/2021

LAUREA MAGISTRALE
2019 - 2021
Politecnico di Bari
Dipartimento di Ingegneria Civile, Ambientale, del Territorio, Edile e di Chimica
Corso di Laurea Magistrale in Ingegneria Civile
LM-23- Laurea Magistrale in Ingegneria Civile
Titolo della tesi: Efficienza dei servizi di mobilità condivisa. Il caso di studio di un sistema di Scooter Sharing della città di Bari.
Materia: Gestione ed esercizio dei sistemi di trasporto; Relatore: Leonardo Caggiani;
Età al conseguimento del titolo: 23; Durata ufficiale del corso di studi: 2 anni
Votazione finale: 110/110 con lode; Data di conseguimento: 05/10/2021

PERIODO ALL’ESTERO DEL DOTTORATO DI RICERCA
2024
Universidad de Cantabria
SUM+LAB Sustainable Mobility & Railways Engineering
Periodo: 23 Aprile 2024 – 23 Maggio 2024

DOTTORATO
Politecnico di Bari
Dottorato in Rischio e Sviluppo Ambientale, Territoriale ed Edilizio
Dipartimento di Ingegneria Civile, Ambientale, del Territorio, Edile e di Chimica
In corso

Premi e riconoscimenti

Borsa di studio anno accademico 2020/2021 per la tesi della Laurea Magistrale in Ingegneria Civile (curriculum trasporti) dal titolo “Efficienza dei servizi di mobilità condivisa. Il caso di studio di un sistema di scooter-sharing della città di Bari” (Città di Bari, Assessorato Politiche Giovanili, Educative e Città Universitaria).

Vincitrice del premio PHD AWARD 2024 conferito da Stefano Carrese, al convegno SIDT 2024 per la tesi di dottorato dal titolo: Decision support models and methods for the fair redesign and management of free-floating micromobility systems.

Trivector Award 2024 for Innovation and Sustainability per il paper dal titolo “A resilience indicator for sustainable tourism in urban road network” presentato durante la conferenza EWGT 2024 (Euro Working Group on Transportation; 4-6 Settembre, Lund, Svezia)

Best Young Researcher Award at TIS ROMA 2024 per il paper dal titolo “An equity parking area location model for the transition from free-floating to station-based shared micromobility systems” presentato durante la conferenza TIS ROMA 2024 (19-20 Settembre, Roma, Italia).

Articoli su rivista

Morgese, F., De Bartolomeo, S., Binetti, M., Caggiani, L., 2024. A tourism accessibility indicator for multimodal bike-public transport trips in a metropolitan area. European Transport 97(1), 1825-3997. https://doi.org/10.48295/ET.2024.97.1.

Atti di convegno

Prencipe, L. P., Colovic, A., De Bartolomeo, S., Caggiani, L., Ottomanelli, M., 2022. An efficiency indicator for micromobility safety assessment. 2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), pp. 1-6, doi: 10.1109/EEEIC/ICPSEurope54979.2022.9854627.

De Bartolomeo, S., Caggiani, L., Ottomanelli, M., 2023. An equity indicator for free-floating electric vehicle-sharing systems. Transportation Research Procedia 69, 115-122. https://doi.org/10.1016/j.trpro.2023.02.152.

Morgese, F., De Bartolomeo, S., Binetti, M., Caggiani, L., 2024. A Cycling Indicator for Tourism Accessibility Evaluation in Urban Areas. In: Tira, M., Tiboni, M., Pezzagno, M., Maternini, G. (eds) New Challenges for Sustainable Urban Mobility: Volume I. ECOOP 1987. Springer, Cham. https://doi.org/10.1007/978-3-031-62248-9_18

Morgese, F., De Bartolomeo, S., Binetti, M., Caggiani, L., 2024. A resilience indicator for sustainable tourism in urban road network. Transportation Research Procedia **, (Accettato in attesa di pubblicazione)

Presentazioni a convegno

Simona De Bartolomeo, Leonardo Caggiani, Michele Ottomanelli. An equity indicator for free- floating electric vehicle-sharing systems.
Conferenza: TIS ROMA 2022

Luigi Pio Prencipe, Simona De Bartolomeo, Leonardo Caggiani, Michele Ottomanelli, An artificial neural network-based technique for the evaluation of priority areas for micromobility accident risk mitigation.
Conferenza: Euro Working Group Transportation 2023 (EWGT 2023)

Presentation della tesi di dottorato dal titolo: “ Decision support models and methods for the fair redesign and management of free-floating micromobility systems.”
Conferenza: XXVI Scientific Seminar. The sustainable future of mobility: policies, applications, behavior, innovations. (SIDT 2024)

Fulvio Morgese, Simona De Bartolomeo, Mario Binetti, Leonardo Caggiani, Evaluation of tourist accessibility through multimodal cycling-public transport in the metropolitan area.
Conferenza: XXVI Scientific Seminar. The sustainable future of mobility: policies, applications, behavior, innovations. (SIDT 2024)

Simona De Bartolomeo, Michele Ottomanelli, Leonardo Caggiani. An equity-based optimisation model for location of parking areas in free-floating e-scooter sharing systems.
Conferenza: Euro Working Group Transportation 2024 (EWGT 2024)

Simona De Bartolomeo, Michele Ottomanelli, Leonardo Caggiani. An equity parking area location model for the transition from free- floating to station-based shared micromobility systems.
Conferenza: TIS ROMA 2024

Poster

Simona De Bartolomeo, Leonardo Caggiani, Michele Ottomanelli. An equity indicator for vehicle relocation in shared micromobility systems.
Convegno: SIDT 2024, XXVI Seminario Scientifico. The sustainable future of mobility: policies, applications, behavior, innovations.

Altre attività

CORRELATRICE

Politecnico di Bari
Tesi di Laurea Magistrale in Ingegneria Civile

Titolo della tesi: Una metodologia per la definizione delle aree di Geofencing per la sosta dei veicoli di un sistema di monopattini condivisi nella città di Bari.
Materia: Gestione ed esercizio dei sistemi di trasporto

Politecnico di Bari
Tesi di Laurea Magistrale in Ingegneria Civile
Titolo della tesi: Un metodo di progettazione delle piste ciclabili per l'ottimizzazione delle consegne in ambito urbano mediante cargo-bike.
Materia: Trasporti e logistica

Politecnico di Bari
Tesi di Laurea Magistrale in Ingegneria Civile
Titolo della tesi: Ottimizzazione delle consegne in ambito urbano mediante cargo bike.
Materia: Trasporti e logistica

MEMBRO DEL COMITATO DEI REVISORI

Membro del comitato dei revisori per la conferenza **TIS 2022**

Membro del comitato dei revisori per la conferenza **TIS 2024**

Revisore per le seguenti riviste:

- Research in Transportation Business & Management

Competenze

COMPETENZE INFORMATICHE

Excel: Avanzato
Word: Avanzato
Power Point: Avanzato

SOFTWARE APPLICATIVI

Autocad: Avanzato
QGis: Avanzato
Matlab: Intermedio

LINGUA INGLESE

Livello: Avanzato