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A multi-objective model to design shared e-kick scooters parking spaces in large urban areas

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ABSTRACT

In recent years, the micromobility and the usage of shared electric kick scooters (e-kscooters) have been constantly growing, especially for systematic and recreational trips in large urban areas. Micromobility might be seen as a well-suited last-mile solution by providing a flexible travel service connection with public transport and MaaS (Mobility as a Service), in general. However, there is a need for implementing adequate regulations regarding safety aspects and shared e-kscooter parking locations, but also for meeting the user requirements. The choice of optimal shared e-kscooter parking locations could help decision-makers to regulate unmanaged dockless shared e-kscooter parking spots that could generate issues for other road users. To this end, in this paper, a novel multi-objective Micromobility Maximal Coverage Parking Location model (M-MCPL) is developed. The model has been solved by applying an elitist Genetic Algorithm that returns the optimal shared e-kscooter parking locations based on the following objective functions: i) the maximization of the population coverage; ii) the maximization of multimodal accessibility coverage (i.e., bus, railway, and metro modes); iii) the maximization of the attraction coverage considering the most relevant points of interest for each corresponding zone in large urban areas. The proposed M-MCPL model has been applied to the case of Rome (Italy) and results suggest priorities for the shared e-kscooter parking locations design. Furthermore, the proposed model is flexible and can be considered as a decision support tool for decision-makers when planning dedicated services in different large urban areas. For that purpose, we conducted the sensitivity analysis by focusing on the single-objective model in which decision-makers might be interested in providing only high accessibility to transport services or maximizing potential demand.

1. Introduction

The spreading of shared mobility has led to the success of vehicles belonging to the so-called micromobility category. In particular, in the centers of the major European cities, e-kick scooter-sharing companies have imposed their presence, both autonomously and by participating in public tenders. The ease of driving, the agility in traffic, and the speed that can be achieved with minimal physical effort are features that make e-kick scooters a good alternative to private cars, especially in restricted traffic zones and for first/last mile connections (Ignaccolo et al., 2022), as well as in areas or time intervals in which there is a lack of public transport service. In addition, such an alternative can be considered a valid element of a MaaS system. However, most of the time, public administrations do not provide a clear regulation of these new forms of mobility, especially because e-kscooters (e-scooter from now on) are pre-eminently supplied as free-floating services (Caggiani et al., 2017; Zhou et al., 2019; Sun et al., 2019). Shared e-scooter services have been spreading only in the last few years; due to the novelty of this mode, few attempts have been made by scholars to design proper e-scooter infrastructures (Fazio et al., 2021). Especially in Italy, the COVID-19 pandemic triggered and boosted the e-scooters spreading. Moreover, city administrations have long left room for operators to decide on the management of the service, while academic studies generally focused on the relocation of the vehicles to satisfy operators' and users' needs, without considering the legitimacy of the choices. Furthermore, the problem with the regulation has led to the emergence of some important issues with e-scooter service, mainly related to their safety during circulation and the illegal parking performed by the users, who prefer to "abandon" the vehicles in a spot located as close as possible to their destination, neglecting the needs of other road users (James et al., 2019; Schellong et al., 2019; Jiao and Bai, 2020; Zakhem and Smith-Colin, 2021; Buehler et al., 2022). Therefore, the issues related to land use

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and the obstructions in road spaces and/or sidewalks generated by improper parking behavior cannot be disregarded. However, one should consider that, although usually equated to e-bikes, e-scooters have some specific features that should be taken into account when considering the planning and designing of parking locations/infrastructure, such as: i) *E*-scooters are a recent mode of transport which usage increased during the pandemic emergency. Also due to this reason, it is difficult to have trip data that faithfully reflect the potential demand for the service; ii) The shared e-scooter service is usually performed by several private companies operating in the same city, then a complete and homogeneous dataset on travel information is difficult to obtain; iii) the shared e-scooter services are smaller than bikes and they are generally used for shorter trips (in time and distance) (Chang et al., 2019). All this means that the space required for potential parking spaces is smaller than the one used for a bike-sharing service and that the capacity of the station can be considered a fuzzier factor; iv) *E*-scooters can be considered as a good solution for the first/last mile "extension" of public transport trips enhancing the capillarity of the transit service (they can often be taken aboard metro and regional trains, and, in the case of shared services, it is beneficial for users to have them available close to railway stations and bus stops).

Based on these premises, the objective of this paper is to provide a novel mathematical model for selecting parking locations dedicated to shared e-scooter vehicles. To this end, a novel multi-objective Micromobility Maximal Coverage Parking Location model (M-MCPL) is developed. The multi-objective M-MCPL model selects the shared e-scooter parking locations to satisfy the trade-off between the needs of the operators (to cover the transport demand and the accessibility of public transport) and those of users (to have shared e-scooters available in the places of interest), allowing administrations to avoid excessive and illegal land use by the users and improving the safety conditions of the service. Those aspects have been included in the objective functions of the proposed M-MCPL model which are related to: i) the maximization of the population coverage perceived as potential users of shared e-scooters; ii) the maximization of multimodal accessibility coverage considering bus, railway, and metro modes; iii) the maximization of attraction coverage considering several points of interest (POIs). Therefore, the proposed model is multi-objective and uses an elitist genetic algorithm to generate Pareto front of optimal solutions. The proposed model has been applied to the city center of Rome (Italy) which benefits from detailed territorial zoning to guarantee the coverage of population and availability of shared e-scooter service both from the aspects of public transport and POIs' accessibility. Furthermore, the sensitivity analysis has been carried out by considering separately each objective function, and by varying the distance coverage of e-scooters and different budget scenarios in terms of the number of parking locations. Consequently, this is especially beneficial for the specific goal of decision-makers and for investigating the opportunities for adopting e-scooter technology based on economic resources. The proposed model could be used to define optimal geofencing of the parking areas in order to reduce and control the improper/illegal parking of e-scooters.

The remainder of the paper is organized as follows: second section presents the state of the art on the topic; third section illustrates the proposed M-MCPL model; section four presents the case study and the results. Finally, conclusions are drawn in section five.

2. Literature review

The literature review on micromobility, and especially on shared e-scooters, has experienced recent expansion that has been mostly focused on policy implementation, analysis of micro-drivers' behavior, and the potential of substituting private trips with these new and more sustainable mobility solutions (Kazemzadeh and Sprei, 2022). Conversely, location models have been extensively used in the literature related to the transportation field; more in detail, the approach we propose in this study falls within location-allocation problems (which will be analyzed in depth in section 2.2). However, it is worth mentioning different approaches, such as location-routing optimization problems. Examples are those by He and Wang (2023) that propose a location-routing model to optimize the gathering site locations in the case of free-floating bike–sharing, and by Hulagu and Celikoglu (2020, 2021) which dealt with electric vehicle charging stations locations solving their location-routing problem, also considering energy consumption constraints and using Multiple Objective formulation (Hulagu and Çelikoglu, 2019). Therefore, we organized our literature overview as follows: the first section describes the recent findings regarding the e-scooter policy regulations, and precisely, the parking regulations and the studies related to the selection of e-scooter parking locations, and the factors that influence e-scooter driving behavior. The second part of the literature review regards on location-allocation models for shared-mobility stations, focusing on micromobility vehicles. Finally, in the third part, we describe the contributions of this work with the respect to the most recent related studies and the findings from the review.

2.1. Research on e-scooter users' behavior and regulation

The topic of shared e-scooter driver behavior has recently been addressed by scholars in literature in the last few years. For instance, the evidence of stated preference driver behavior has shown the potential for e-scooter implementation in five cities (Copenhagen, Munich, Barcelona, Tel Aviv, and Stockholm) by taking into account several issues that should be managed, e.g., the lack of regulations, mitigation of multimodal traffic, and the price dissatisfaction (Esztergár-Kiss et al., 2022). Similarly, Vallamsundar et al. (2022) analyzed the travel behavior and the geographical aspects of e-scooters based on a survey study conducted in the city of Austin. The survey results indicate that potential users attracted by e-scooters are younger individuals in the age group 26–45 years old. Furthermore, the authors determined the main factors that influence e-scooter usage such as trip distance, connectivity to transit, congestion, parking issues, and pollution reduction. Another study proposed by Mouratidis (2022) examined the profile of micromobility and Uber users which showed similar characteristics of e-scooter users such as younger age groups, less educated, without disabilities, and with residence in denser neighborhoods. Followed by the e-scooter user behavior patterns, other recent research findings showed the potential of e-scooters for replacing car trips (Wang et al., 2022). The research study carried out by Reck et al. (2022) pointed out trip distance as one of the fundamentals for micromobility mode choice considering the willingness of users to walk between around 60 to 200 m to access the parking location of e-scooters. Similarly, Guo and Zhang (2021) applied a mixed logit model for extracting significant factors that affect the car mode substitution with e-scooter; the results suggested that parking is the main motivation factor (i.e., users with parking issues have a 0.04 higher probability of choosing e-scooters). Moreover, Reck et al. (2021) developed a methodology used to analyze bivariate relationships between four different micromobility modes, i.e., dockless e-scooters, dockless e-bikes, docked e-bikes, and docked bikes, and estimate the mode choice models. From their analyses, the authors stated that users prefer docked e-bikes during peak hours and dockless e-scooters during off-peak hours. However, few studies in the literature investigated the interaction between shared e-scooters and public transport. Zuniga-Garcia et al. (2022) investigated the statistical relationship between e-scooter and bus transit services in university campus areas of the city of Austin, which indicated that 10% of transit trips increment might result in 2.5% of e-scooter trips increment. Furthermore, Weschke et al. (2022) used multinomial regression for analyzing the mode shift behavior of shared e-scooters in Germany which showed that public transport and walking can be substituted by >60% of e-scooter trips.

Recently, scholars have focused their interest on the e-scooter service operation limits by proposing methods to regulate their usage in urban areas, and by restricting their interaction with other traffic (Liazos et al., 2022; Prencipe et al., 2022). Similarly, the systematic review provided by Kazemzadeh et al. (2023) investigated e-scooter safety that suggested the necessity for operating e-scooters on sidewalks and bike lanes, wearing helmets, as well as speed regulation to decreasing the vulnerability of e-scooter drivers when interacting with other road users. Such policy regulations, for instance, in the city of Rome, include the maximum e-scooter speed limit of 20 km/h and the permission to circulate in pedestrian zones, reserved bicycle lanes, and zones with a speed limit of 30 km/h (D'Andreagiovanni et al., 2022). Differently, Brown (2021) investigated the U.S. cities' scooter parking regulations, where most of them are allowed to be parked at bike racks. Another study proposed by Zakhem and Smith-Colin (2021) analyzed the areas with high e-scooter parking demand that would eventually show indications for the future micromobility management policy implementation, e.g., use of GPS trajectories and penalizing high-speed streets (>35 mph) within the network. The aforementioned studies have shown the importance of e-scooter parking locations, both from regulation and safety points of view.

2.2. Research on location-allocation models for shared-mobility stations

The topic of shared-mobility station location has been addressed by scholars in literature, in particular in the case of electric vehicles with station-based service. Most of the studies, especially in the case of free-floating systems, focus on the problem of relocation of vehicles at the end (or beginning) of the service (e.g., You and Hsieh, 2014; Caggiani et al., 2018; Chen et al., 2018; Prencipe et al., 2022). However, this problem differs substantially from the one addressed in this study because in this case the relocation should not be carried out by the operator, but the users themselves are obliged to go to the provided parking spots that are similar to those of a station-based service, although certainly greater in number and with a capacity not limited by the presence of physical infrastructures. A similar problem to the one presented in this work is the location of virtual stations for free-floating bike-sharing services (FFBSS). In this respect, Caggiani et al. (2017) introduced the concept of dynamic virtual stations to ease the relocation problem in FFBSS by generating spatio-temporal clusters of the usage patterns of the available bikes in every zone of the city. Similarly, Zhou et al. (2019) developed a multi-objective planning model to obtain virtual FFBSS stations in a university campus minimizing the distance between the origin and the station and the total construction cost as the objective function. Sun et al. (2019) proposed a mixed-integer linear programming (MILP) model to locate virtual stations for FFBSS to maximize user demand during morning and evening rush hours. Zhang et al. (2019) proposed a location-allocation maximum coverage model to define a geo-fence that would protect users to park FFBSS vehicles at illegal spots. Hua et al. (2020) identified spatial candidates for virtual stations using the best clustering of FFBSS trip data in the city of Nanjing by using the spatio-temporal clustering technique. Similarly, Zhao and Ong (2021) proposed a procedure integrating the Density-Based Spatial Clustering of Applications with the Noise method and the k-means clustering algorithm to identify potential bicycle parking locations and establish their capacities for the city of Xiamen.

When it comes to e-scooters, most of the authors have dealt with the peculiarities of e-scooters when considering the location of charging/battery swapping stations (Carrese et al., 2021). An earlier study is the one by Wang (2007), who developed a model for the location of recharging stations for recreational e-scooters; the model, using an integer program, aims at minimizing the cost of locating the station at a candidate site considering the recharge time, fleet size, locating capacity and mean length of stay at destinations. The model is validated by applying it to the case study of Penghu County; results suggest that speedy recharge could significantly reduce the number of stations. Chen et al. (2018) used Multi-Objective Particle Swarm Optimization to determine the optimal location and number of stations, differentiating between charging stations and battery-swapping ones. Results have shown that both types of stations should be located in more dense areas while charging stations should be present in the outskirts of the low population density areas. Akova et al. (2021) presented a mixed-integer linear programming formulation for the location of the cost-optimal recharging stations for e-scooters; their model integrates a location model with an energy consumption model based on vehicle motion dynamics, in order to obtain an accurate calculation of the energy consumption. Results show a potential underestimation of recharge station requirements, with some e-scooters running out of battery before finishing their trips. A similar study is the one developed by Der Lin et al. (2021) that proposed a Monte Carlo simulation to predict the demand of stochastic battery swapping for e-scooters and to estimate different scenarios for battery swapping station locations, optimizing the cost of rentals, and covering users' demand. Sandoval et al. (2021) have proposed a clustering algorithm for establishing e-scooter parking locations based on the potential demand based on a dataset of trips from the city of Nashville (Tennessee, USA). Likewise, Zakhem and Smith-Colin (2021) used trip clustering method to identify parking zones for dockless e-scooters. Finally, Ayfantopoulou et al. (2022) conducted a data-driven analysis using the K-Means algorithm to select suitable locations for dock-based scooter-sharing service stations, based on trip data, road

Table 1
Relevant literature on location-allocation of e-scooter stations.

Reference	Model	Parameters	Case study
Wang (2007)	Integer programming	Recharge speed, length of stay, station capacity, cost	Penghu County
Chen et al. (2018)	Multi-Objective Particle Swarm Optimization	Distance from customers, land cost, station cost, station capacity	Synthetic
Akova et al. (2021)	Location Problem	Vehicle motion dynamics-based energy consumption	Ayazaga Campus (ITU, Instanbul)
Der Lin et al. (2021)	Allocation Model with Monte Carlo Simulation	Land cost, traffic flow, station cost, average travel distance	Central District of Taichung City, Taiwan
Sandoval et al. (2021)	Clustering algorithm with hyperparameter tuning	Scooter trips' end locations	Nashville, Tennessee, USA
Zakhem and Smith-Colin (2021)	Trip clustering	Scooter trips' origin and destination locations	City of Dallas, USA
Ayfantopoulou et al. (2022)	Facility location model with K-Means algorithm	Trips data, road geometric characteristics, and station capacity	Thessaloniki, Greece
Ayyildiz (2022)	Hybrid fuzzy MCDM	Almost 50 criteria	Instanbul, Turkey
Altintasi and Yalcinkaya (2022)	GIS-based Analytic Hierarchy Process	Distance to points of interest and public transportation stations, existence of bicycle infrastructure, population density, slope	Karsiyaka District in Izmir, Turkey
Deveci et al. (2023)	Hybrid fuzzy MCDM	12 criteria, concerning users, public authority, service operator, and urban livability	Synthetic
Altay et al. (2023)	BWM-MARCOS model	Economic, geographic, and socio-demographic criteria	Synthetic (University Campus)

Table 2
Relevant literature MCLP for shared vehicles' station location.

Reference	Vehicle	Model	Parameters
Frade et al., 2011	e-cars	MCLP	Demand
Wang and Lin (2013)	mixed stations	Tri-level model with stochastic RBF-based solution algorithms	Traffic flow, Travel time, recharging delay, tour utility, income, EV purchasing cost, station cost, government budget
Hu et al., 2019	bike-sharing	Potential Path Area and Capacitated CMCLP	Demand
Bayram et al., 2022	e-cars	MCLP (GIS solver)	Population and road traffic
Sun et al., 2020	e-cars	MCLP	Population, historical trips, station cost, recharging time, station capacity, and budget

geometric characteristics, and station capacity; they applied their method to the case of Thessaloniki.

As far as the authors' knowledge, the only studies found in the literature that consider a larger number of parameters, including socio-demographic ones, are those that apply multicriteria analysis methods, with the ultimate goal of providing a ranking of a few predetermined locations. In this respect, Ayyildiz (2022) presented a fuzzy multi-criteria method for e-scooter charging station location-selection considering several criteria weighted by experts. Altintasi and Yalcinkaya (2022) used a GIS-based Analytic Hierarchy Process to rank e-scooter charging station locations and applied the method in Karsiyaka District in Izmir, Turkey; the main criteria used for the location ranking are distance to points of interest and public transportation stations, the existence of bicycle infrastructure, population density, and slope. Altay et al. (2023) propose an integrated interval type-2 fuzzy best-worst method implemented with MARCOS to rank the shared e-scooter station locations inside a university campus. Similarly, Deveci et al. (2023) used a hybrid fuzzy MCDM model taking into account 12 criteria, concerning users, public authority, service operator, and urban liveability. Table 1 summarizes the relevant literature on location-allocation of e-scooter stations according to the models implemented, their parameters, and the case study.

Table 1 shows that existing literature related to optimization methods primarily emphasizes recharging issues and station costs as parameters for localization, while none of the approaches addresses mobility needs by considering socio-demographic parameters. The only articles that address such issues are the ones adopting MCDA approaches, which however acknowledge a series of few pre-established locations and employ a multicriteria method to furnish a ranking of the proposed localizations. In Table 1 one can see that several models and algorithms can be used for the location allocation of shared transport facilities. In our work we propose the utilization of a Maximum Coverage Location Problem (MCLP) approach; our choice falls on MCLP since it offers computational simplicity and flexibility compared to more complex models that would increase CPU time significantly. Although there are no studies that use MCLP for the localization of scooter stations specifically, scholars have applied it recently in the broader context of shared mobility stations. MCLP has been used by Hu et al. (2019) in the case of bike-sharing station locations. Moreover, different scholars used MCLP for the location of charging stations for electric vehicles (Frade

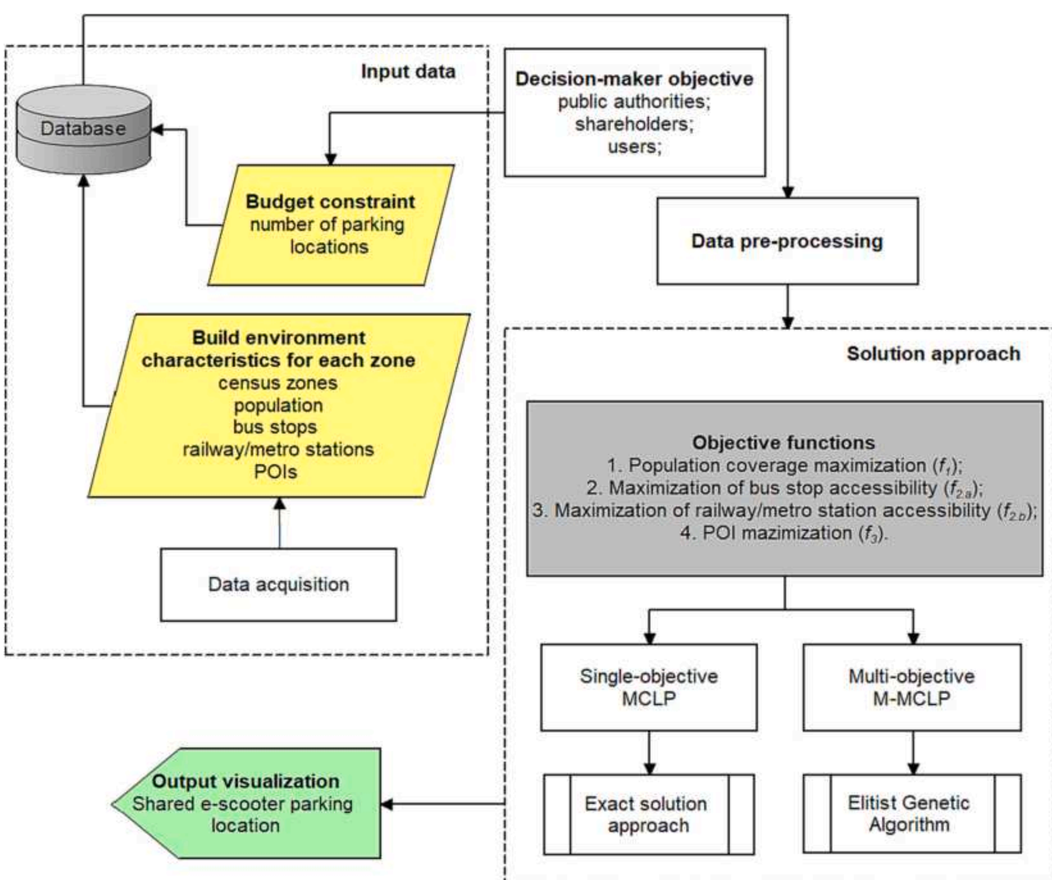

Fig. 1. Shared e-scooter parking location framework.

et al., 2011; Wang and Lin, 2013; Sun et al., 2020; Bayram et al., 2022. Table 2 summarizes relevant literature on the use of MCLP for the location of shared vehicle stations, proving its suitability in solving this type of problem.

2.3. Contributions

Motivated by the recent shared e-scooter management issues and the necessity for policy regulations, in this study, we focused on designing a shared e-scooter parking location model. The choice of the optimal shared e-scooter parking location requires different aspects to be considered for avoiding illegal parking and road infrastructure issues. To the best of the authors' knowledge, no scholars have dealt with the problem of locating parking stations for e-scooters, considering different aspects such as potential demand data, presence of attractive destinations, and the possibility to work as a proxy for first/last-mile connection with public transport. In this respect, this paper proposes a model that takes a step forward embedding the following issues: i) considering the peculiarities of e-scooter-sharing services; (ii) taking into account both data on potential demand and points of interest for the users; (iii) using a multi-objective model, i.e., able to obtain Pareto front optimal solutions guaranteeing high levels of achievement towards different objectives. In addition, the detailed contribution of the proposed model is described as follows:

- The novel M-MCPL problem aims at choosing the optimal areas for shared e-scooter parking locations by taking into account one of the main strategic issues of the shared e-scooter locations, such as providing a certain service to the users within a specified distance limit (i.e., service coverage), which has been scarcely tackled in the literature. The strategic planning of shared e-scooter parking locations is the first and one of the crucial steps that might further help cities in regulating nowadays issues of improper e-scooter usage.
- The proposed study examines different factors and aspects that can influence the usage of e-scooters and the selection of parking locations (e.g., as reported in the literature review provided by Vallamsundar et al. (2022)) for obtaining a comprehensive understanding of the shared e-scooter parking location problem. Consequently, we went further in quantitatively modeling those aspects into a multi-objective M-MCPL optimization problem.
- The proposed model embeds the accessibility of public transportation for reaching shared e-scooter parking locations which, based on the authors' research, has been investigated in the literature only from a statistical point of view and has never been considered in an e-scooter parking location optimization model.
- To the best of the authors' knowledge, this is the first study that proposed a novel version of the MCPL model for selecting shared e-scooter parking locations from a multi-objective perspective (maximizing public transport accessibility, demand, and points of interest).

3. Methodology

Shared e-scooters could indeed increase the opportunity for mode shifting from private cars, as well as reaching multimodal accessibility, especially in the case of restricted traffic zones (e.g., historical centers and pedestrian zones). However, the high number of injuries and unmanaged shared e-scooter parking locations have been pushing some cities to limit or ban the usage of this mode (see Eurocities, 2023). To meet these requirements, this study deals with finding the optimal areas for placing shared e-scooters' parking locations that mitigate those issues and help decision-makers regulate unmanaged dock-less shared e-scooter placement.

The selection of optimal areas for placing shared e-scooter parking locations should involve one or more goals of decision-makers (Macioszek et al., 2023). Thus, in this study, we focused on public authorities, shareholders, and users as the main decision-makers interested/involved in managing shared e-scooter parking locations, as depicted in the proposed methodological framework (Fig. 1). The first part of the proposed framework related to data acquisition comprises the detailed territorial zoning of considered study area (i.e., census zones, population, bus and railway/metro stations, and POIs). Then, we developed a novel multi-objective Micromobility Maximal Coverage Parking Location model (M-MCPL) that deals with positioning shared e-scooter locations considering multiple objective functions.

The proposed multi-objective M-MCPL model has been solved with a variant of elitist Genetic Algorithm, i.e., the Non-dominated Sorting Genetic Algorithm (NSGA-II). This is a well-used solution approach that shows good performance when dealing with multiple objectives and generating a well-grounded representation of Pareto front (Deb, 2001). In addition, we carried out a sensitivity analysis by focusing on each decision-making goal separately, which gave us the possibility to analyze the influence of different goals (i.e., population coverage maximization, maximization of bus stop accessibility, maximization of railway/metro station accessibility, POIs maximization) on the placement of shared e-scooter locations.

Table 3
The nomenclature of the proposed M-MCPL model.

Sets	
I	Set of zone centroid $i, i \in I$
J	Set of candidate sites for locating shared e-scooter $j, j \in J$
B	Set of bus stops node $b, b \in B$
R	Set of railway/metro stations access/egress nodes $r, r \in R$
Parameters	
d_{ij}	Distance between zone centroid i and the potential shared e-scooter location j
t_{ib}^{bus}	Approximated travel time between zone centroid i and bus stop b
t_{ir}^{rail}	Approximated travel time between zone centroid i and railway/metro access/egress nodes r
s	Fixed number of shared e-scooter locations to be selected
h_i	Population [no. residents] of the zone centroid i
D_c	Threshold for distance coverage
T_c	Threshold for time coverage
a_{ij}	Parameter a_{ij} equal to 1 if the distance between the zone centroid i and shared e-scooter location j is within the range $D_c, (d_{ij} \le D_c)$, i.e., within the subset $N_i \subseteq J$ where $N_i = \{j \in J \mid d_{ij} \le D_c\}$, 0 otherwise
a_{jb}^{bus}	Parameter a_{jb}^{bus} equal to 1 if the approximate travel time between the potential shared e-scooter location j, that corresponds to the zone centroid i, and bus stop node b is within the range $T_c, (t_{ib}^{bus} \le T_c)$, i.e., within the subset $N_i^{bus} \subseteq B$ where $N_i^{bus} = \{b \in B \mid t_{ib}^{bus} \le T_c\}$, 0 otherwise
a_{jr}^{rail}	Parameter a_{jr}^{rail} equal to 1 if the approximate travel time between the potential e-scooter j, that corresponds to the zone centroid i, and railway/metro ingress/egress station node r is within the range $T_c, (t_{ir}^{rail} \le T_c)$, i.e., within the subset $N_i^{rail} \subseteq R$ where $N_i^{rail} = \{r \in R \mid t_{ir}^{rail} \le T_c\}$, 0 otherwise
acc_i^{bus}	Parameter acc_i^{bus} related to the total bus accessibility measure of each zone centroid i
acc_i^{rail}	Parameter acc_r^{rail} related to the total railway/metro ingress/egress accessibility measure of each zone centroid i
p_i	The total number of points of interest associated with zone centroid i
Decision variables	
y_i	Binary decision variable related to the covering decisions, where y_i is equal to 1 if the zone centroid i is covered by chosen shared e-scooter location j, 0 otherwise
x_j	Binary decision variable related to the location decisions, where x_j is equal to 1 if the candidate shared e-scooter location j is chosen, 0 otherwise

3.1. Problem description

In this section, we describe the mathematical formulation of the novel multi-objective Micromobility Maximal Coverage Parking Location model (M-MCPL), developed as an extension of the maximal coverage location problem originally proposed by Church and ReVelle

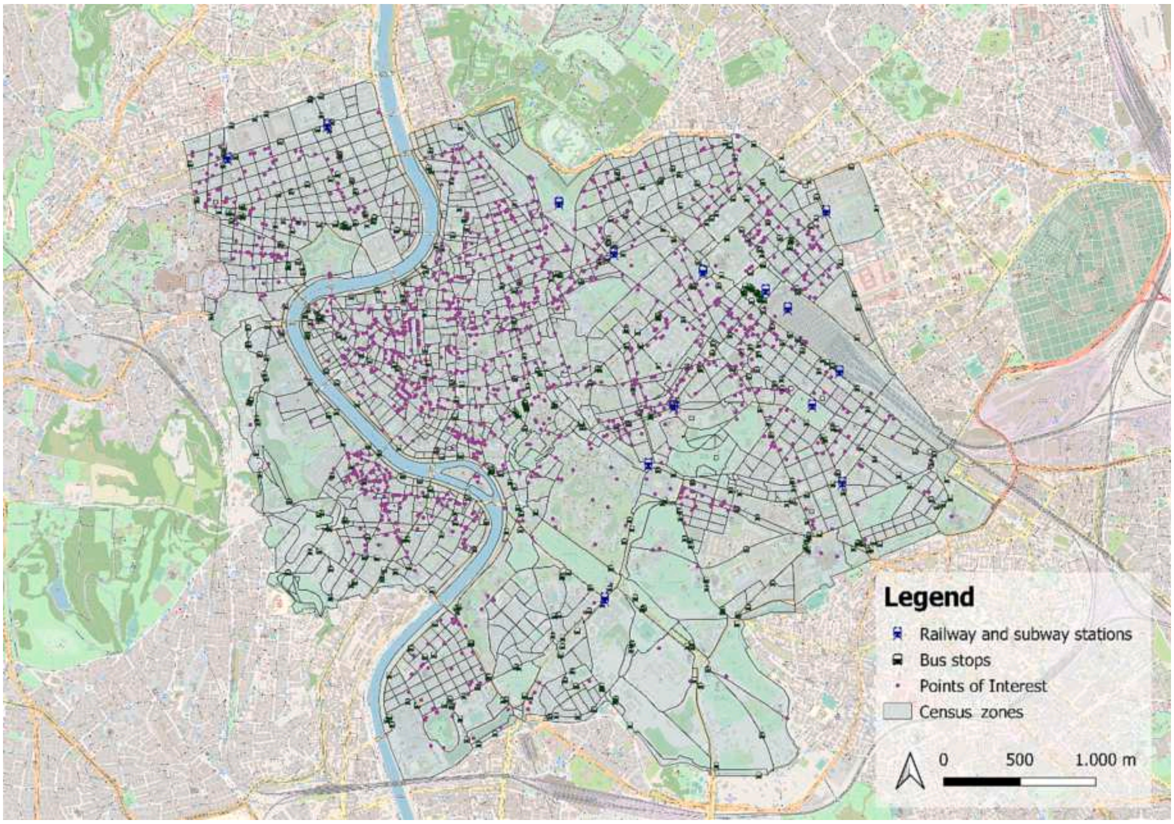

Fig. 2. Case study and data.

(1974), in which we focused on the shared e-scooters services since they are considered as one of the promising micromobility modes for decreasing the transport-related environmental impact in urban areas. Therefore, the goal of the proposed model is to find the optimal areas to determine the shared e-scooter parking locations that could meet the requirements of users and mobility service providers. The M-MCPL ensures that the coverage of the selected location is maximized considering three aspects: i) the maximization of the population coverage (hereinafter referred to as "residents"), perceived as potential users of shared e-scooters; ii) the maximization of multimodal accessibility coverage considering bus, railway and metro services; iii) the maximization of attraction coverage considering several POIs (e.g., touristic and historical attractions, education institutions, religious sites, green areas, and restaurants). The nomenclature adopted in the proposed M-MCPL model is reported in Table 3.

The mathematical formulation of the multi-objective M-MCPL model, expressed as Integer Linear Programming (ILP) model, is specified as follows:

$$maxf_1 = \sum_{i \in I} h_i \cdot y_i \tag{1}$$

$$maxf_{2.a} = \sum_{i \in I} acc_i^{bus} \cdot y_i \tag{2.a}$$

$$maxf_{2.b} = \sum_{i \in I} acc_i^{rail} \cdot y_i \tag{2.b}$$

$$maxf_3 = \sum_{i \in I} p_i \cdot y_i \tag{3}$$

s.t.

$$y_i \leq \sum_{j \in N_i} a_{ij} \cdot x_j, \forall i \in I \tag{4}$$

$$\sum_{j \in J} x_j = s \tag{5}$$

$$y_i, x_j \in \{0, 1\}, \forall i \in I, j \in J \tag{6}$$

The proposed multi-objective M-MCPL model aims at maximizing the coverage of the optimal parking locations of shared e-scooter parking places considering three objective functions. Objective function $f_1(y)$ (Eq. (1)) aims at maximizing the demand (population) coverage expressed as the number of residents h_i of each zone i. The second objective is related to the accessibility coverage of public transport; more in detail, we decided to distinguish between two sub-objectives related to urban connection; in this case, we considered bus stops ($f_{2.a}(y)$), and railway/metro ingress/egress stations ($f_{2.b}(y)$). In detail, each shared e-scooter parking location candidate j is associated with the corresponding zone centroid i. In this way, each zone contains one shared e-scoter location candidate. Furthermore, the considered accessibility measure is a traditional gravity-based measure as developed by Hansen (1959). The total bus accessibility measure of each zone i containing the corresponding shared e-scooter parking locations candidate j is expressed by the following formulation:

$$acc_i^{bus} = \sum_{b \in N_i^{bus}} e^{\left(-t_{ib}^{bus}\right)} \cdot a_{jb}^{bus} \forall i \in I, \forall j \in J, i = j \tag{7}$$

Similarly, the total railway accessibility measure of each zone i containing the corresponding shared e-scooter parking locations candidate j is expressed through the following formulation:

$$acc_i^{rail} = \sum_{r \in N_i^{rail}} e^{\left(-t_{ir}^{rail}\right)} \cdot a_{jr}^{rail} \forall i \in I, \forall j \in J, i = j \tag{8}$$

Third objective function $f_3(y)$ (Eq. (3)) aims at maximizing the coverage by taking into account the points of interest p_i.

Constraints (4) state that demand at node i cannot be covered unless

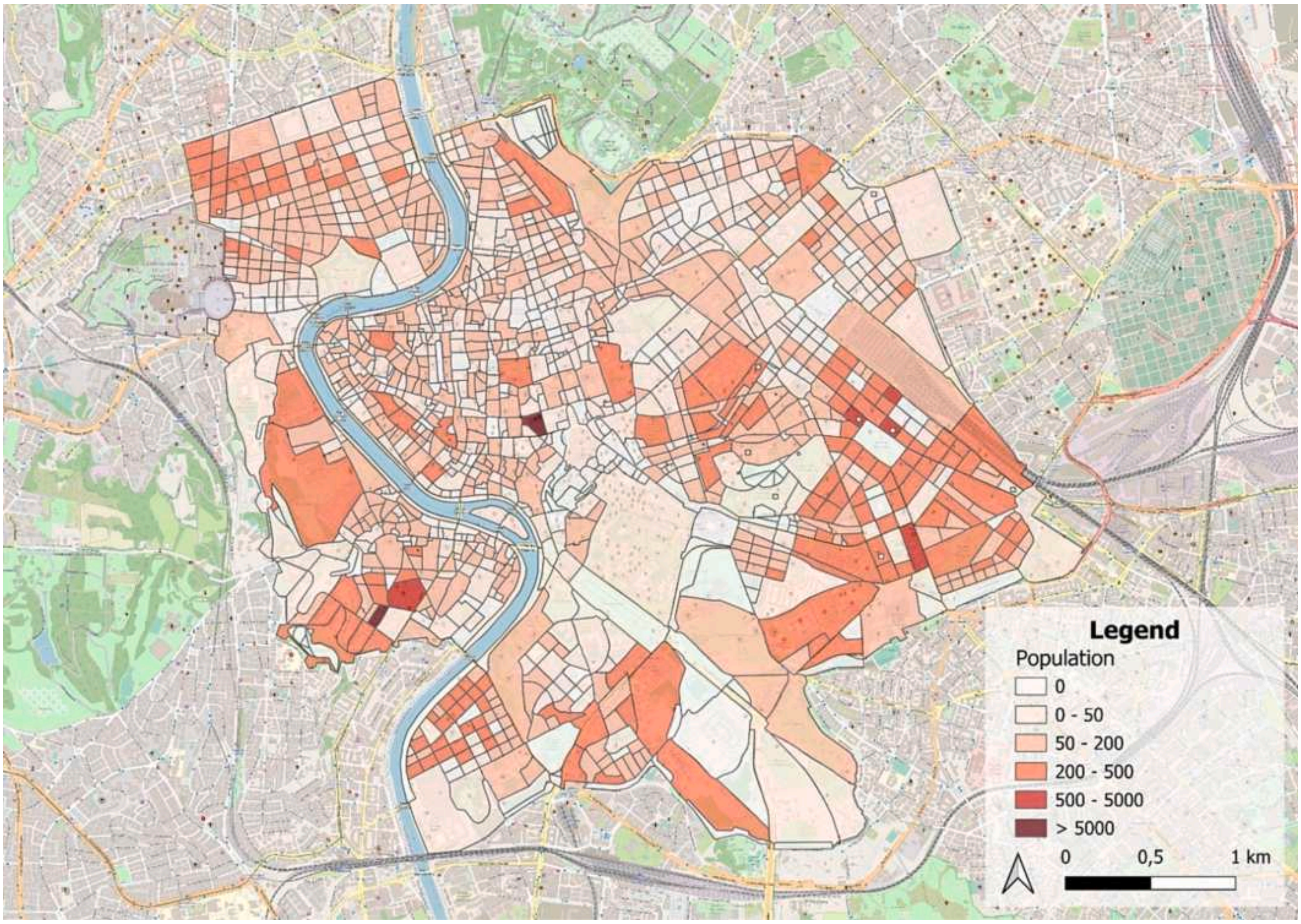

Fig. 3. Case study: population distribution per census zone.

at least one of the shared e-scooter location j is selected. Constraint (5) indicates that we cannot locate more than s shared e-scooter locations, which implies that the number s is known in advance according to the pre-fixed budget of the decision-makers. Constraints (6) are related to the binary nature of the variables x_j, y_i.

4. Case study

4.1. Territorial framework and data

The method has been applied to the case study of Rome. Rome is the capital city of Italy. It is well-known all around the world for its historical heritage and such touristic vocation has awakened the interest of several e-scooter sharing companies; these services are indeed often used by tourists for their trips, but also by younger residents to reach schools and universities (Laa and Leth, 2020; Klassen and Jödden, 2022). At present, there are 7 e-scooter-sharing operators in Rome, counting approximately 14,500 vehicles. The presence of such many operators and vehicles has led to the emergence of some issues with the service, especially related to illegal parking. In this respect, the administration is working to draft a new call for regulation according to which, from January 2023, the sharing operators will be reduced from the current 7 to 3 (Municipality of Rome, 2022). Consequently, this will reduce the number of e-scooters to a maximum of 9000, with 3000 units assigned to the central areas with the rest equally distributed among the other districts. The situation that the city of Rome is currently experiencing can be considered representative of many other Italian cities, which, for the same reasons, are issuing service regulations for specific shared e-scooters. Providing a novel model to regulate/manage the parking operations can be a good solution to reduce the problems related to parking; however, in order to guarantee the free-floating soul of the service, the location of the parking spots must be carefully evaluated to maintain as much as possible the capillary of the e-scooter service. For these reasons, the city of Rome was chosen as a case study for the application of the developed model in the paper. In particular, we decided to focus our attention on the heart of the city center; we chose this boundary since it physically encompasses the principal tourist attractions, the most relevant POIs, and the main railway/bus station of the city.

The zoning of the study area has been conducted according to the one used by the Italian National Statistics Institute (ISTAT, 2022) for the general Census, with a total of 1364 census zones; the decision to use it is linked to the detailed level of information provided, with the densest areas of only $3m^2$; this allowed to retrieve also data on population from ISTAT, expressed as potential demand in the model. We represent the demand node as the centroid of each census zone. The locations of the main POIs of the city have been extracted from the OpenStreetMap database; the selected POIs are those related to touristic and historical attractions, education institutions, religious sites, green areas, and restaurants with a total number of 883 POIs. The same method has been used to extract the locations of bus stops and railway/metro stations with a total number of 477 and 14, respectively. Fig. 2 shows zoning, POIs, and public transport terminals for the selected case study. Additionally, Fig. 3 represents the population distribution for each census zone.

Table 4
Elitist NSGA-II parameter tuning of M-MCPL over 10 runs.

Obj. function	Maximum value	Minimum value	Best average value	Best Std. dev. value	Average CPU time [s]
			$Gen = 10; Pop = 25$		
$f_1(y)$	55,577.00	22,417.00	43,850.33	7105.97	146.52
$f_{2.a}(y)$	423.29	224.08	359.95	33.26	
$f_{2.b}(y)$	10.51	0.87	6.22	1.53	
$f_3(y)$	370.00	197.00	306.50	33.77	
			$Gen = 25; Pop = 50$		
Obj. function	Maximum value	Minimum value	Best average value	Best Std. dev. value	Average CPU time [s]
$f_1(y)$	56,656.00	16,900.00	39,499.59	9473.78	639.36
$f_{2.a}(y)$	433.11	182.14	341.75	47.63	
$f_{2.b}(y)$	10.46	1.34	6.23	1.92	
$f_3(y)$	381.00	191.00	295.53	40.08	
			$Gen = 50; Pop = 100$		
Obj. function	Maximum value	Minimum value	Best average value	Best Std. dev. value	Average CPU time [s]
$f_1(y)$	58,458.00	16,688.00	39,802.18	9857.69	2,619.00
$f_{2.a}(y)$	433.40	175.45	336.20	52.86	
$f_{2.b}(y)$	10.19	0.75	5.42	2.18	
$f_3(y)$	388.00	177.00	290.00	41.75	
			$Gen = 100; Pop = 200$		
Obj. function	Maximum value	Minimum value	Best average value	Best Std. dev. value	Average CPU time [s]
$f_1(y)$	60,942.00	12,544.00	40,043.23	9485.51	11,547.07
$f_{2.a}(y)$	436.48	136.07	343.61	55.81	
$f_{2.b}(y)$	11.15	0.51	5.18	2.47	
$f_3(y)$	403.00	126.00	286.03	45.99	

4.2. Application and results

The M-MCPL model has been run with a 13th Gen Intel(R) Core (TM) i9-13950HX CPU (5.5GHz) and 64GB of RAM, coded in Matlab R2022b, and applied to the case study of Rome. The presence of multiple objectives requires the generation of as many as possible sets of optimal solutions, known as Pareto-optimal solutions. Many optimization methods aim to solve this problem by converting multi-objective into a single-objective optimization problem for obtaining single Pareto-optimal solution (e.g., weighted-sum method). However, the generation of a Pareto front considering different Pareto-optimal solutions requires many simulation runs, and therefore higher computation time. For this reason, the best-

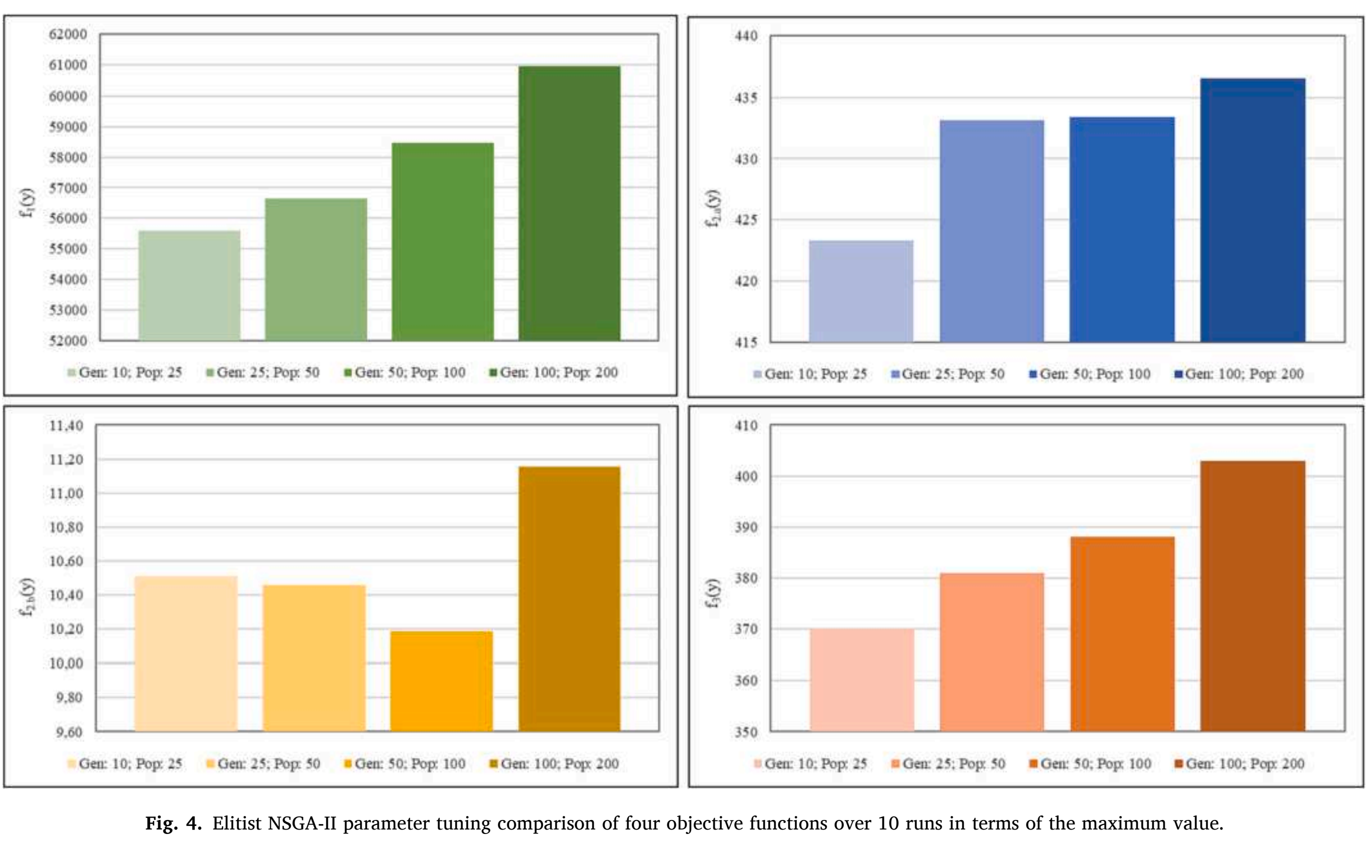

Fig. 4. Elitist NSGA-II parameter tuning comparison of four objective functions over 10 runs in terms of the maximum value.

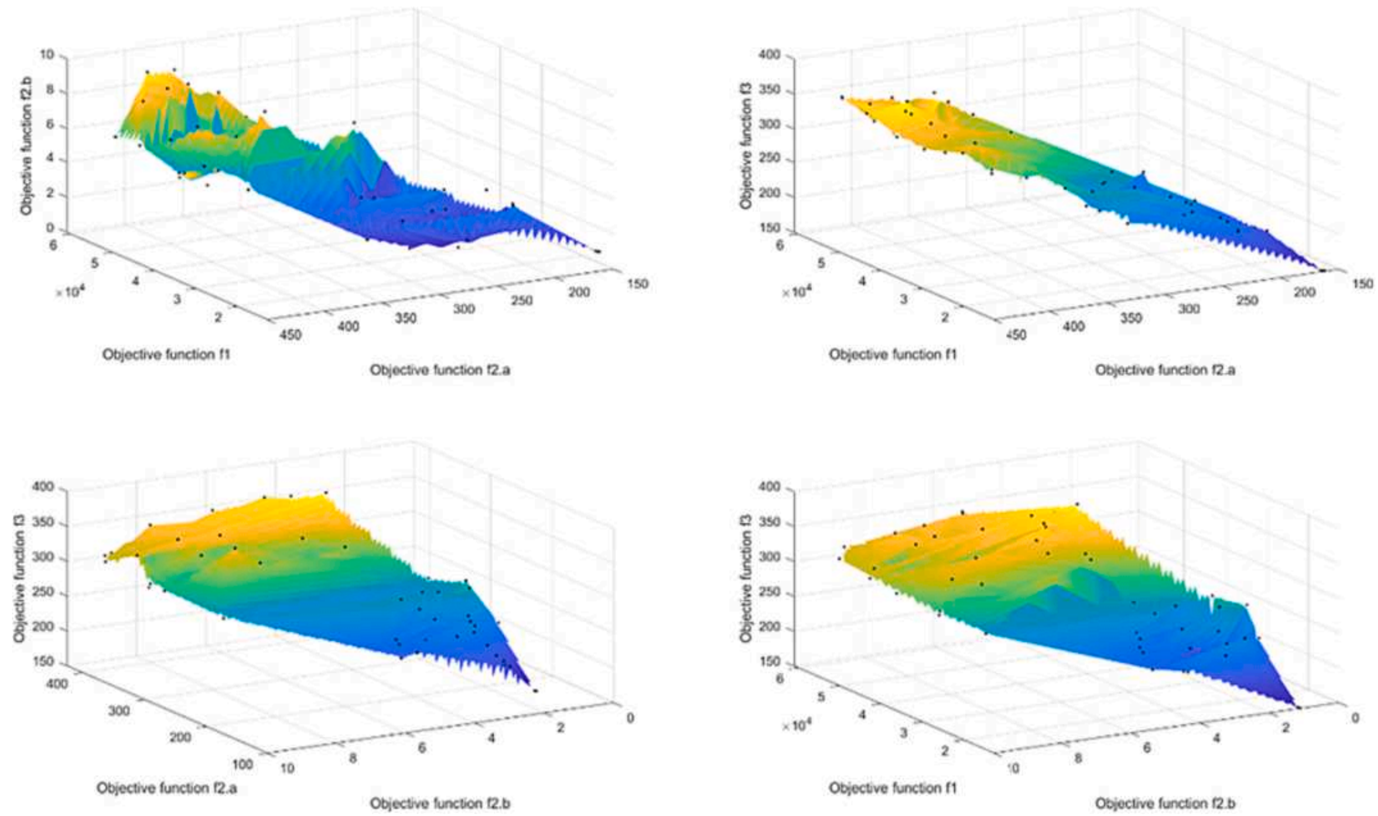

Fig. 5. The 3-dimensional representation of the Pareto front with the non-dominated solutions of the multi-objective optimization ($Gen = 100$ and $Pop = 200$).

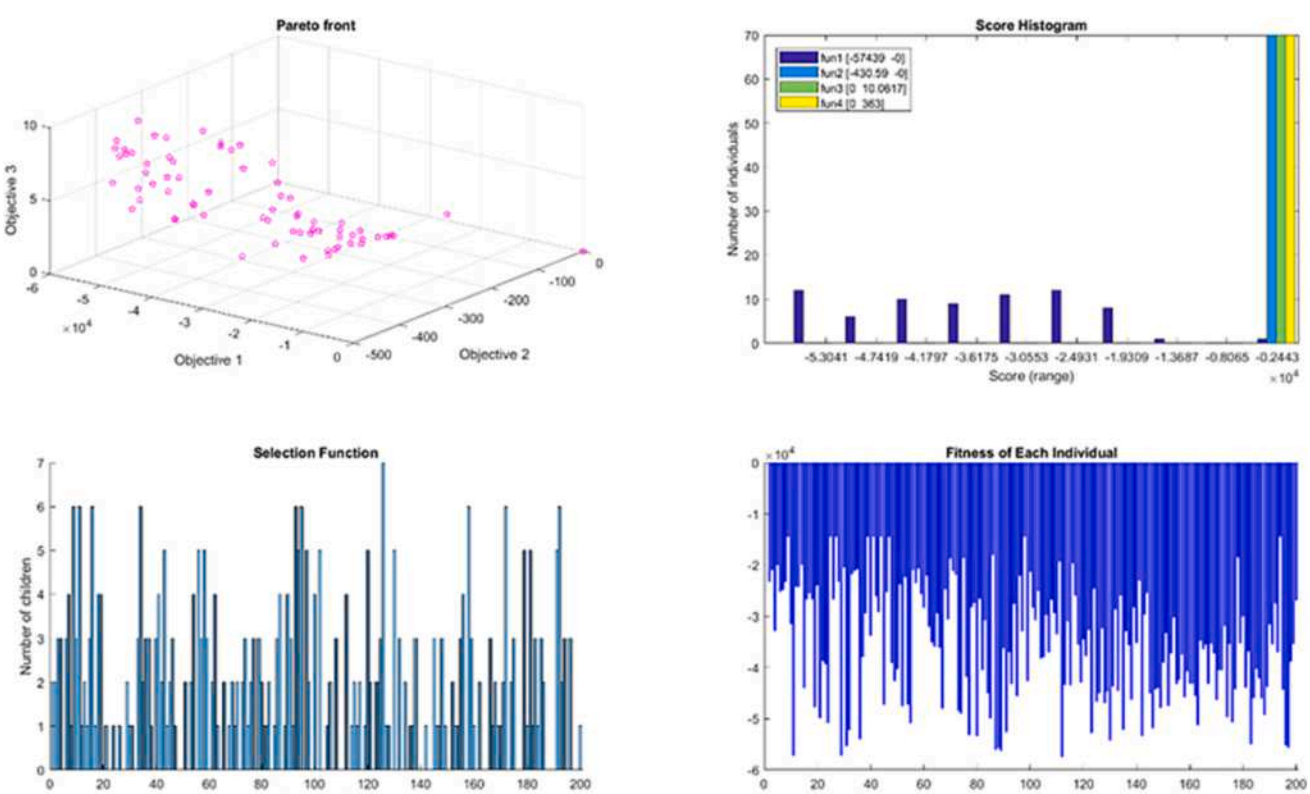

Fig. 6. Elitist NSGA-II performance of M-MCPL ($Gen = 100$ and $Pop = 200$).

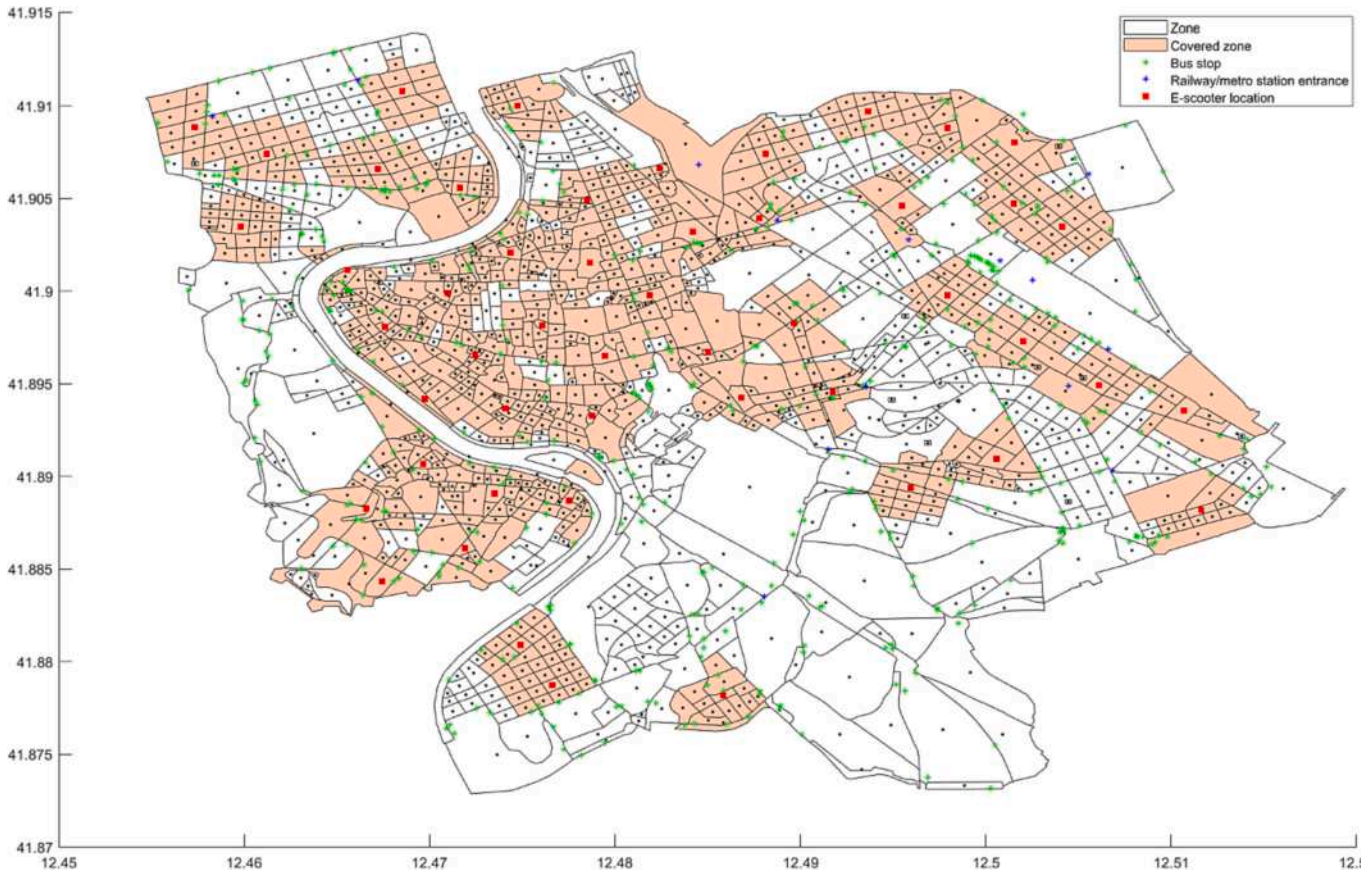

Fig. 7. One of the Pareto-optimal solutions of the multi-objective optimization with $s = 50$, $D_c = 200m$.

found solutions of the multi-objective optimization were obtained by applying an elitist Genetic Algorithm (GA), originally provided by Deb and Goldberg (1989), that has a feature of finding multiple Pareto-optimal solutions in one single simulation run. It has been noted in the literature that Elitist GA shows high performance in solving multi-objective optimization problems, and better convergence characteristics than non-elitist multi-objective evolutionary algorithms (Deb and Goel, 2001). In specific, we applied the elitist Non-dominated Sorting Genetic Algorithm (NSGA-II), proposed by Deb (2001), that outperforms other solution approaches in terms of convergence and computational complexity. The applied NSGA-II algorithm uses an elite-preserving mechanism and fast non-dominated sorting procedure. For more details, see Deb (2001) and Deb et al. (2002).

The Pareto-optimal solutions were generated by solving the multi-objective optimization model with four different objective functions $(f_1(y), f_{2.a}(y), f_{2.b}(y), f_3(y))$, as reported in Section 3. The number of shared e-scooter locations has been set as $s = 50$. In addition, parameter T_c referred to the time to walk a distance coverage D_c (i.e., the average distance needed for reaching a shared e-scooter parking location from the centroid of each zone by walking). The parameter D_c is considered as an on-the-fly distance that can be considered as a value of 200 m and 400 m, as it can be found in the literature for similar services (Cohen, 2016; Schoner and Levinson, 2013). Consequently, parameter T_c is the threshold of time coverage calculated as D_c divided by average walking speed set as 1 m/s.

Furthermore, parameter tuning of elitist NSGA-II is needed for obtaining high-quality Pareto-optimal solutions related to the maximization of population coverage, bus stop accessibility, railway/metro station accessibility, and POIs. Since there is no single way to find the best parameter configuration due to the problem size and complexity, the number of generations *Gen* and size of population *Pop* are considered as the most effective in obtaining good quality solutions (Mosayebi and Sodhi, 2020). For those reasons, we considered common values related to crossover fraction equal to 0.8, Pareto fraction equal to 0.35, and stopping criteria as the maximum number of *Gen* (Mohamed et al., 2022). Consequently, Table 4 reports descriptive statistics (best maximum, minimum, average, and std. dev. values) and average CPU time obtained over 10 runs for different size of *Gen* and *Pop*. In specific, we considered a proportional increasing of number $Gen = \{10, 25, 50, 100\}$ and $Pop = \{25, 50, 100, 200\}$ to obtain the insight of different representation of Pareto-optimal solutions. It is worth to notice that the increase of *Gen* and *Pop* results in higher average CPU time, on the one side, but on the other side, in the relevant improvement of all four objective functions, as observed in Fig. 4. The better-quality solutions are obtained by increasing the number of *Gen* and *Pop*, but for obtaining acceptable optimization results in a reasonable CPU time, we fixed the maximum *Gen* and *Pop* equal to 100 and 200, respectively. For instance, the best average percentage values of objective functions $f_1(y), f_{2.a}(y), f_{2.b}(y), f_3(y)$ over 10 runs, for $Gen = 10$ and $Pop = 25$ are $f_1(y) = 46.52\%$, $f_{2.a}(y) = 36.90\%$, $f_{2.b}(y) = 50.10\%$, $f_3(y) = 37.60\%$, while for $Gen = 100$ and $Pop = 200$ are $f_1(y) = 48.94\%$, $f_{2.a}(y) = 44.43\%$, $f_{2.b}(y) = 53.59\%$, $f_3(y) = 41.45\%$. Additionally, standard deviation values resulted in the highest dispersion for the objective function $f_1(y)$, due to the significant variations among all covered zones expressed in number of residents. For further insight into the descriptive statistics of each run see Appendix A.

Table 5a
Results of the Pareto-optimal solution (covered population $f_1(y)$ and land zones).

s	D_c	Covered population $f_1(y)$		Covered land zones		
No.	$[m]$	[*no.residents*]	[%]	[%]	*No.*	$[km^2]$
50	200	57,439	48.94	40.32	550	8.33

Table 5b
Results of the Pareto-optimal solution ($f_{2.a}(y)$, $f_{2.b}(y)$, $f_3(y)$).

s	D_c	Bus accessibility $f_{2.a}(y)$		Railway/metro accessibility $f_{2.b}(y)$		POIs coverage $f_3(y)$	
No.	$[m]$	–	[%]	–	[%]	*No.*	[%]
50	200	377.49	38.95	6.70	34.56	331	37.49

Based on the parameter tuning, the best values are obtained with $Gen = 100$ and $Pop = 200$. Consequently, Fig. 5 represents the Pareto front considering the best obtained set of non-dominated solutions; the 3-dimensional representation shows all combinations of the obtained Pareto-optimal set by considering the four objective functions when $G = 100$, and $Pop = 200$.

In addition, Fig. 6 depicts the elitist NSGA-II performance in terms of selection function, score, and fitness of each individual.

Fig. 7 shows one of the Pareto-optimal solutions by representing the spatial distribution of the shared e-scooter parking locations obtained as the output of the multi-objective optimization model with $D_c = 200m$ and $s = 50$. In detail, for the considered solution, in Table 5a and Table 5b, we report results in terms of values of objective functions, population and land zones. Additionally, for simplicity, we express those results in percentages.

The solution obtained from the model allows to optimize the four chosen objectives at the same time. Nevertheless, the proposed multi-objective M-MCPL model can be applied by considering three/two objective functions and their corresponding combinations, as reported in Appendix B. However, in section 4.3, we focused on each single objective function to match the specific goal of decision-makers, and therefore, obtained a comprehensive analysis and comparison between multiple and single targets on shared e-scooter parking locations and their performance.

4.3. Sensitivity analysis

The Pareto-optimal solutions of the multi-objective optimization provide a sparse coverage and accessibility distribution of the shared e-scooter locations. However, public administrations or transport operators might be interested in obtaining the maximization of the shared e-scooter service coverage by giving a higher priority to only one aspect (i.e., objective function). For this reason, we carried out a sensitivity analysis by splitting the multi-objective M-MCPL model into four different single-objective problems that could be adapted to a specific goal of micromobility stakeholders (i.e., public authorities, shared e-scooter mobility companies, etc.).

The MCPL model has been run with a 13th Gen Intel(R) Core (TM) i9-13950HX CPU (5.5GHz) and 64GB of RAM, coded in Matlab R2022b. The optimality of the solution is reached in reasonable computation time by using the Branch-and-Bound exact solution approach. For each single-objective optimization model, we obtained optimal solutions by varying the number of the shared e-scooter locations until obtaining full coverage; this is done to consider potential different budget resources dedicated to micromobility services, expressed in the number of shared e-scooter locations s. Therefore, for each one of the proposed cases, we reported the results for $s = \{5, 25, 50, 75, 100\}$.

Finally, we set the distance coverage as $D_c = \{200, 400\}$ to approximate the walking distance to reach the shared e-scooter parking location from each centroid. Therefore, we distinguish four different cases:

- Case 1 with the objective function $f_1(y)$;
- Case 2 with the objective function $f_{2.a}(y)$;
- Case 3 with the objective function $f_{2.b}(y)$;
- Case 4 with the objective function $f_3(y)$.

For each Case, we evaluated the following performance indicators:

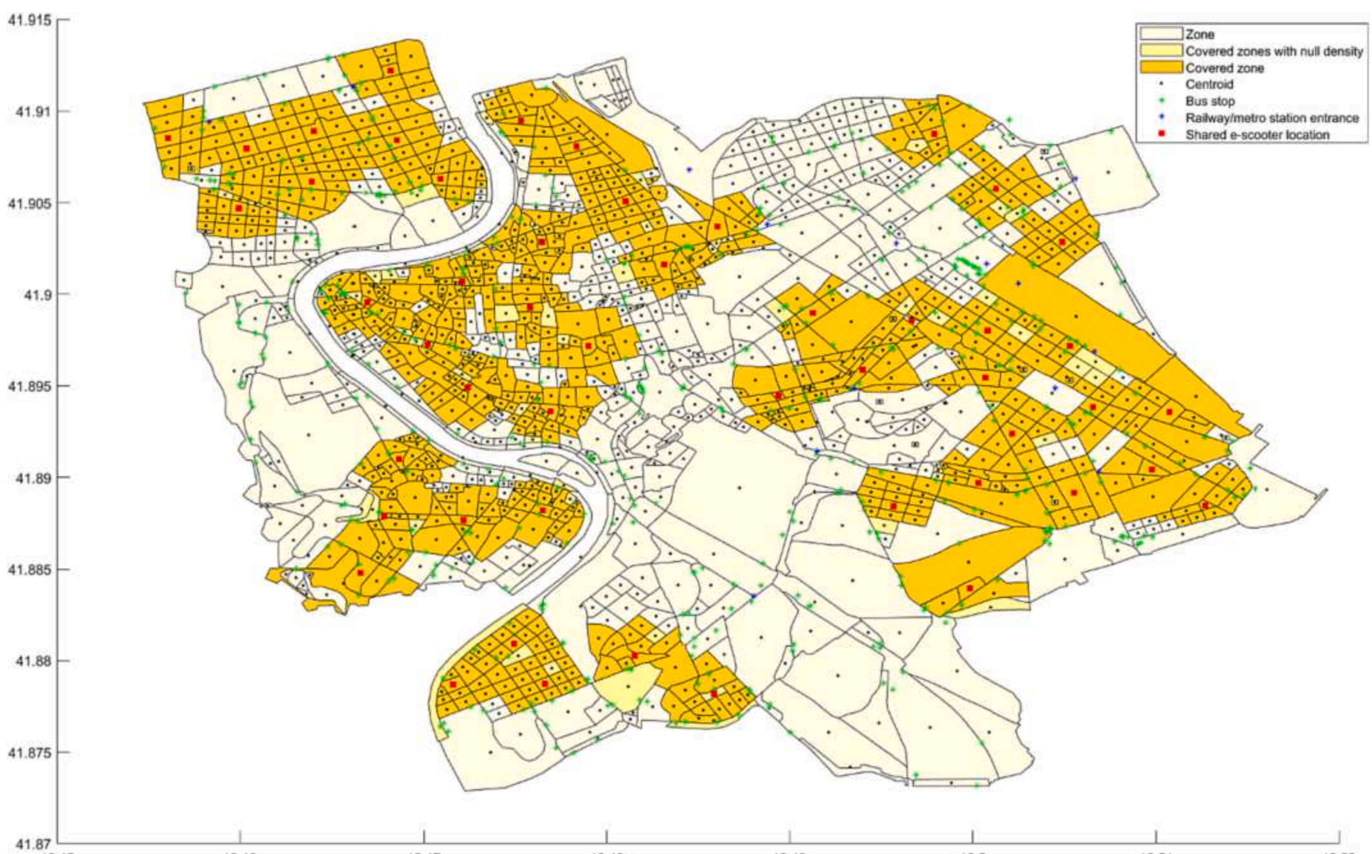

Fig. 8. The result of Case 1 - obj. Function $f_1(y)$ with $s = 50$ and $D_c = 200m$.

Table 6
Results of Case 1 (obj. Function $f_1(y)$).

s	D_c	Covered population		Covered land zones			n_s	CPU time
No.	[m]	No.	[%]	No.	$[km^2]$	[%]	No.	[s]
5	200	29,192	24.87	75	0.60	3.96	8	1.78
5	400	52,807	44.99	292	2.14	14.16	15	2.28
25	200	70,580	60.14	383	3.40	22.47	4	1.71
25	400	114,288	97.38	1018	9.89	65.32	6	25.67
50	200	100,415	85.56	771	6.20	40.95	3	2.21
50	400	117,364	100	1096	12.75	84.23	3	10.69
75	200	113,784	96.95	965	8.83	58.34	2	14.11
75	400	117,364	100	1096	12.75	84.23	2	1.87
100	200	117,118	99.79	1061	11.17	73.79	2	14.12
100	400	117,364	100	1096	12.75	84.23	2	1.47

two general and one specific for each single-objective function. General indicators for all the cases are the covered population and the covered land zones. The specific indicators, i.e., bus and railway/metro accessibility and POIs coverage, are indicated in the following description of the results. The optimal solution for Case 1, with the objective function $f_1(y)$, $s = 50$, and $D_c = 200m$ is depicted in Fig. 8. As reported in Table 6, the percentage of the covered population when $s = 50$ is around 85%, while with $s = 25 > 60\%$ of residents in the considered zone is covered. We can observe that with $s = 100$ the selected shared e-scooter locations are positioned in the zones with a higher population coverage which results in the maximum land coverage of 73.79%, leaving uncovered only poorly populated and unpopulated zones. However, when $D_c = 400m$, we can reach full population coverage with $s = 50$.

Furthermore, according to Kamphuis and van Schagen (2020), we estimated the number of shared e-scooters per parking location required to satisfy the covered population. Specifically, the authors estimated

Fig. 9. The result of Case 2 with obj. Function $f_{2.a}(y)$ with $D_c = 400m$ and $s = 25$.

Table 7
Results of Case 2 (obj. Function $f_{2.a}(y)$).

s	D_c	Covered population		Covered land zones			Accessibility measure $f_{2.a}(y)$		n_s	CPU time
No.	[m]	No.	[%]	No.	$[km^2]$	[%]	–	[%]	No.	[s]
5	200	8334	7.10	120	0.69	4.42	165.17	17.04	2	1.38
5	400	32,526	27.71	386	2.39	15.77	361.74	37.32	9	2.19
25	200	41,853	35.66	528	3.05	20.14	530.19	54.70	2	1.40
25	400	111,068	94.64	1252	10.84	71.59	936.58	96.62	6	89.24
50	200	67,442	57.46	848	6.31	41.67	780.51	80.53	2	7.10
50	400	117,364	100	1364	15.14	100	969.23	100	3	2.46
75	200	102,070	86.96	1143	9.16	60.51	914.29	94.33	2	22.23
75	400	117,364	100	1364	15.14	100	969.23	100	2	1.51
100	200	112,428	95.79	1281	11.58	76.35	959.16	98.96	2	214.23
100	400	117,364	100	1364	15.14	100	969.23	100	2	1.59

Table 8
Results of Case 3 (obj. Function $f_{2.b}(y)$).

s	D_c	Covered population		Covered land zones			Accessibility measure $f_{2.b}(y)$		n_s	CPU time
No.	$[m]$	*No.*	[%]	*No.*	$[km^2]$	[%]	–	[%]	*No.*	$[s]$
5	200	9963	8.49	70	0.74	4.90	10.48	54.03	3	1.39
5	400	21,142	18.01	200	2.14	14.14	15.41	79.43	6	1.51
25	200	31,919	27.20	284	3.24	21.41	18.87	97.27	2	1.37
25	400	39,971	34.06	378	4.84	31.98	19.40	100	2	1.64
50	200	39,840	33.95	377	4.83	31.93	19.40	99.99	1	1.57
50	400	39,971	34.06	378	4.84	31.98	19.40	100	1	1.35
75	200	39,971	34.06	378	4.84	31.98	19.40	100	1	1.36
75	400	39,971	34.06	378	4.84	31.98	19.40	100	1	1.54
100	200	39,971	34.06	378	4.84	31.98	19.40	100	1	1.40
100	400	39,971	34.06	378	4.84	31.98	19.40	100	1	1.38

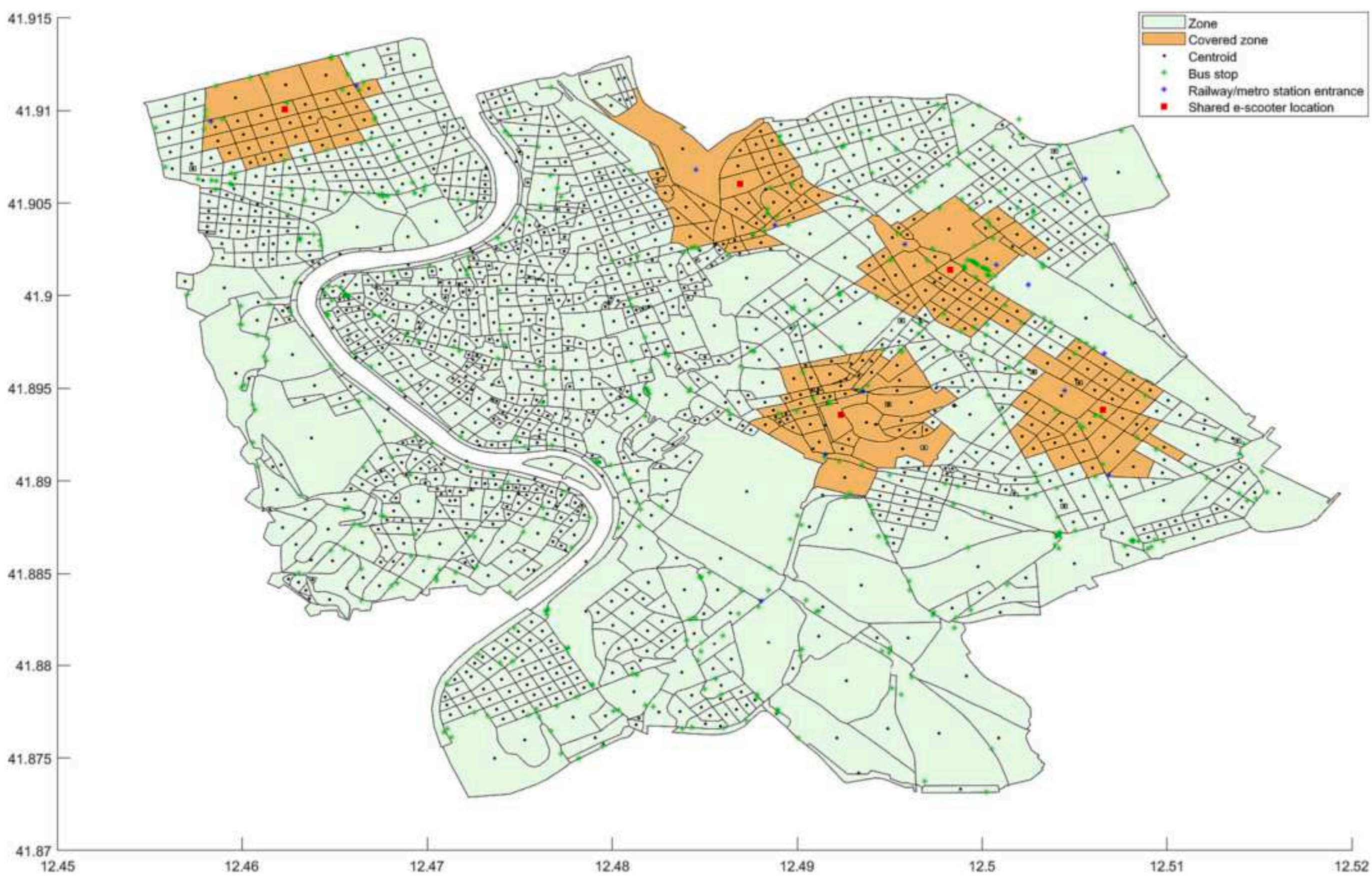

Fig. 10. The result of Case 3 with obj. Function $f_{2.b}(y)$ with $D_c = 400m$ and $s = 5$.

around 0.0006 e-scooters per resident in Germany. Proportionally, we estimated the ratio as 0.0014 per resident for covering the total population of 117,364 residents in the case study. Therefore, the total number of shared e-scooters is estimated as $no.e-\ scooter\ locations = 165$. Consequently, the approximate no. e-scooters n_s per e-scooter parking location s is calculated as $n_s = \left(\frac{covered\ population\ [\%] \times no.e-scooters}{no.e-scooter\ locations\ s}\right)$, as reported in Table 6.

The optimal solution of Case 2 with the objective function $f_{2.a}(y)$, and $s = 25$ is presented in Fig. 9, while Table 7 reports the results. It is observed that we can cover 100% of the population with 50 shared e-scooter locations, and almost 30% of the population with only 5 shared e-scooter locations when the distance coverage $D_c = 400m$. Accessibility has been used as a specific indicator for Case 2. However, the percentage of the population coverage as well as the bus accessibility measure is almost twice lower when the distance coverage $D_c = 200m$. This highlights the importance of investigating the willingness of users to walk for reaching the shared e-scooter location.

Table 8 shows the results of Case 3 with the objective function $f_{2.b}(y)$, while Fig. 10 depicts the results of the model for $D_c = 400m$, and $s = 5$. Again, accessibility has been used as a specific indicator. In Case 3, we observe that we can achieve total accessibility measure coverage with 50 shared e-scooter parking locations (see Table 8), and thus, there is no need for installing more locations, since we obtain no increase in population and accessibility coverage improvement.

The optimal solution of Case 4, with the objective function $f_3(y)$ and $s = 50$, is presented in Fig. 11. In this case, we observe similar results regarding the covered population and land zone with distance coverage $D_c = 200m$ and $D_c = 400m$. However, we achieved the maximum percentage of the POIs coverage for $s = \{50, 75\}$, respectively, which resulted in a percentage of the covered population of around 65%, as reported in Table 9.

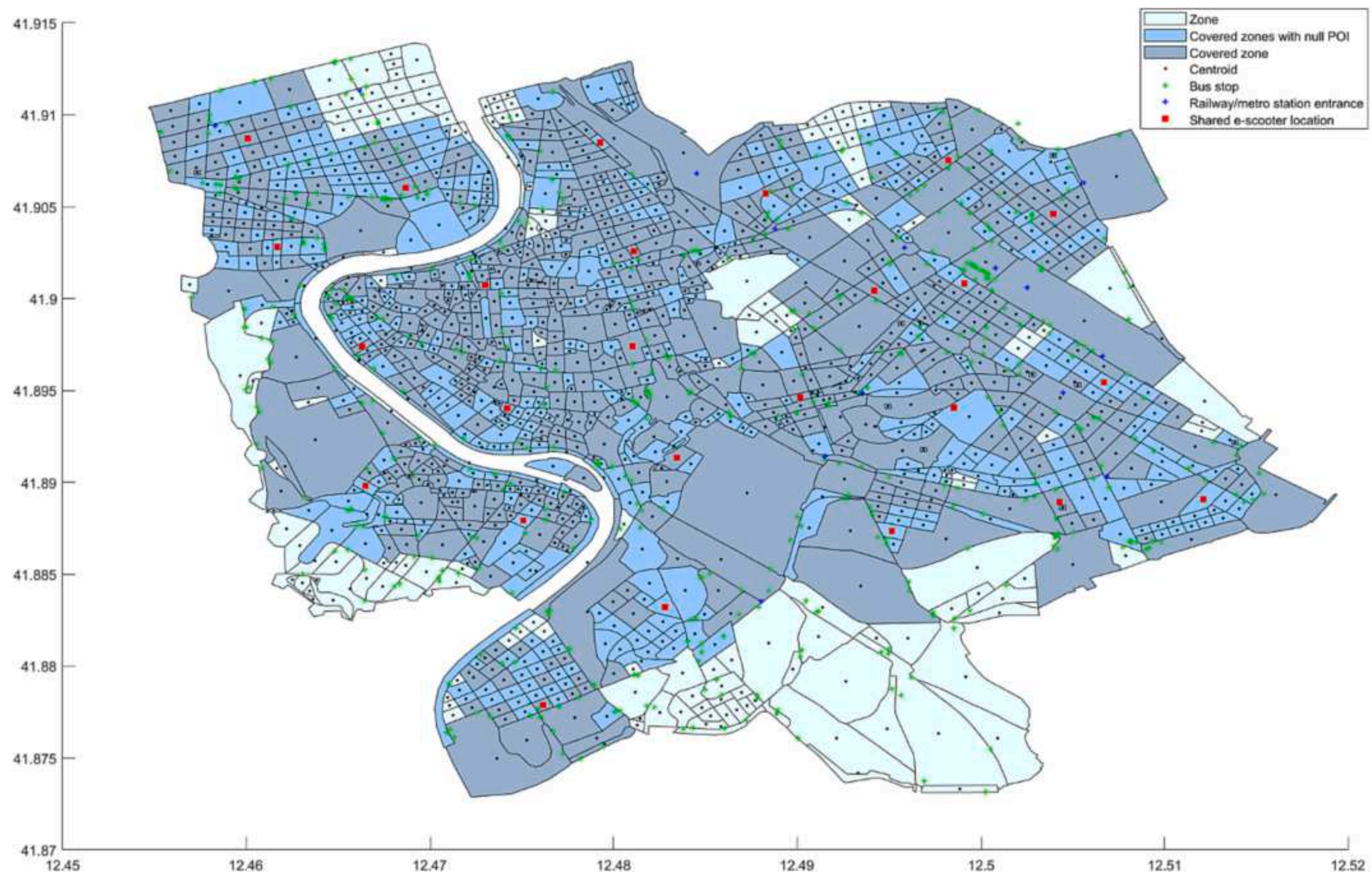

Fig. 11. The result of Case 4 with obj. Function $f_3(y)$ with $D_c = 400m$ and $s = 25$.

Table 9
Results of Case 4 (obj. Function $f_3(y)$).

s	D_c	Covered population		Covered land zones			POIs $f_3(y)$		n_s	CPU time
No.	$[m]$	*No.*	[%]	*No.*	$[km^2]$	[%]	*No.*	[%]	*No.*	$[s]$
5	200	5699	4.85	96	0.57	3.74	138	15.63	2	1.42
5	400	26,335	22.44	266	1.90	12.57	354	40.09	7	1.77
25	200	33,245	28.33	364	2.84	18.76	485	54.93	2	1.41
25	400	69,472	59.19	649	8.34	55.08	853	96.60	4	8.59
50	200	54,231	46.21	535	5.28	34.87	708	80.18	2	2.64
50	400	76,522	65.20	674	9.14	60.39	883	100	2	1.80
75	200	72,072	61.41	634	7.32	48.33	829	93.88	1	4.17
75	400	76,522	65.20	674	9.14	60.39	883	100	1	2.29
100	200	76,413	65.11	671	9.11	60.16	880	99.66	1	16.27
100	400	76,522	65.20	674	9.14	60.39	883	100	1	1.50

4.4. Discussion of results

The analysis of the results shows that, in the case of single-objective optimization, Case 2 achieves the best performance regarding population, land, and accessibility measure coverage with the lower number of shared e-scooter locations, although not covering all the POIs. Furthermore, the percentage of the covered population in Case 3, resulting in around 34% when $s = 50$ is significantly lower than in Case 2 in which the total population coverage can be satisfied. This result is correlated with the total number of investigated bus stops and railway/metro stations; the lower presence of railway/metro stations significantly affects the covered population decrease. Also, the value of distance coverage D_c has a relevant impact on the bus and railway/metro accessibility measure, and therefore, on the percentage of the covered population in the Case 2 and Case 3 if compared to Case 1. Based on these, we can observe that the distance coverage D_c in Case 2 has a large influence on the bus stations' accessibility measure and demand coverage, which is coherent to practical situations. These results show that the proposed model can be used as a first-step analysis in the decision-making process regarding the planning of shared e-scooter parking locations.

Results coming from the multi-objective M-MCPL model might be used to provide priority areas to locate e-scooter parking spots when all four objectives are considered equally important by the different actors in the decision-making process. Single-objective models can be used to refine the choice of location, according to the priorities assigned by the different stakeholders. For example, public authorities might be interested in providing high accessibility to transport services to promote multimodal trips by residents and tourists: hence, they could opt to refine location by adopting Case 2 ($f_{2.a}(y)$) and Case 3 ($f_{2.b}(y)$). Conversely, shared e-scooter providers are generally interested in maximizing service profits and, therefore, in maximizing potential demand (of residents and tourists) as reported in Case 1 ($f_1(y)$) and Case 4 ($f_3(y)$).

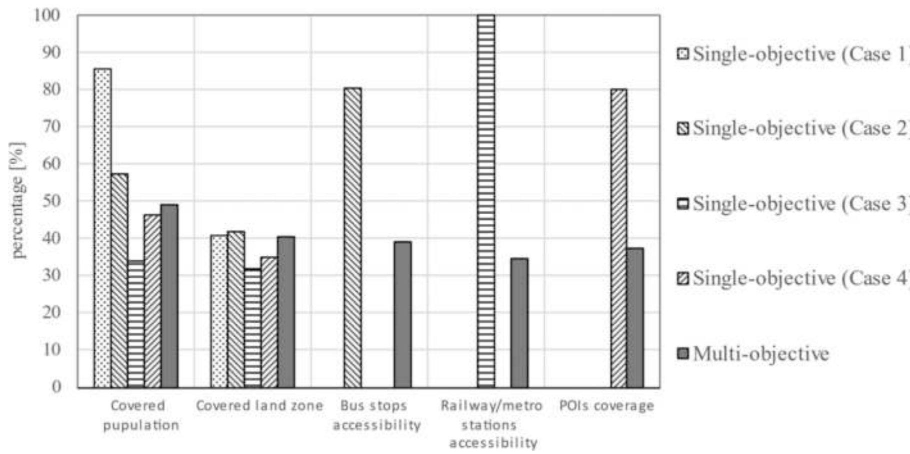

Fig. 12. The comparison of general and specific indicators among multi-objective (M-MCPL) and single-objective (MCPL) model results with $D_c = 200m$ and $s = 50$.

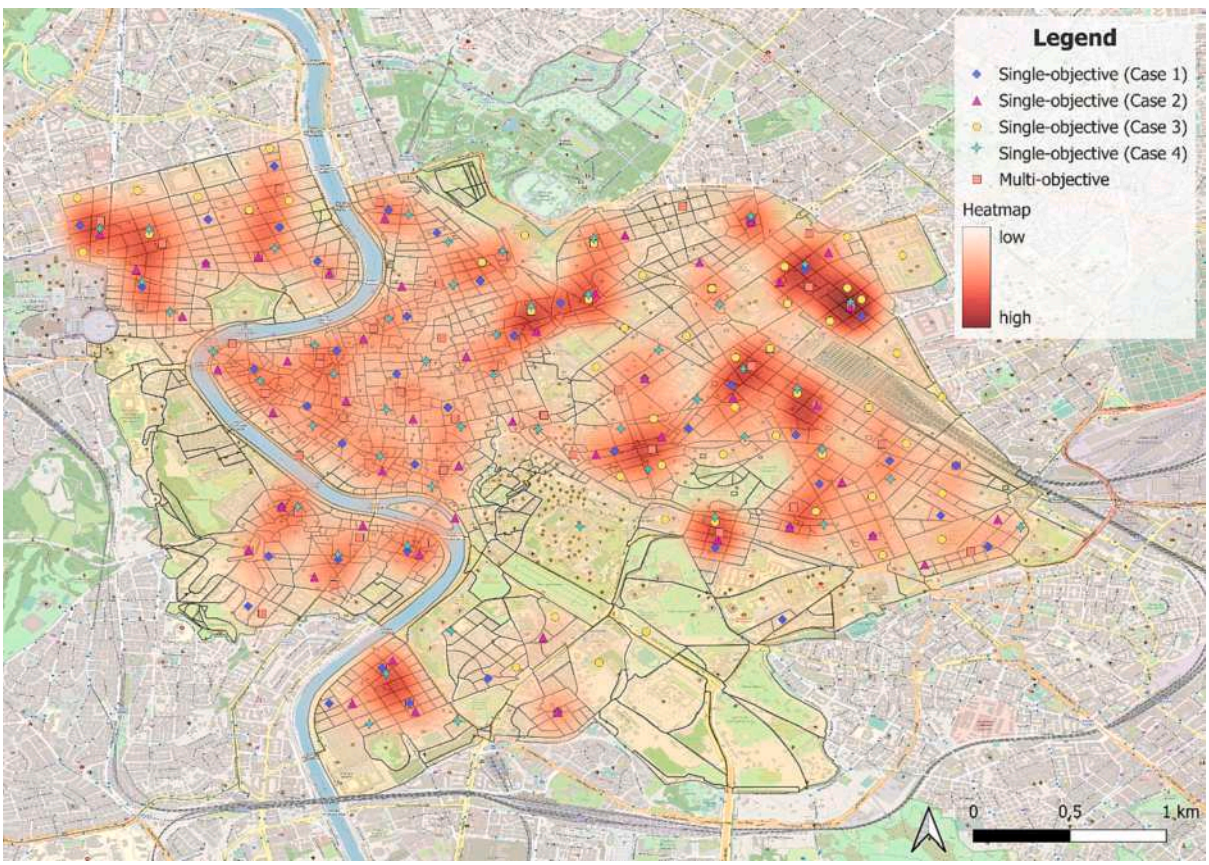

Fig. 13. Heatmap and geographical representation of shared e-scooter locations of multi-objective (M-MCPL) and single-objective (MCPL) results with $D_c = 200m$ and $s = 50$.

The comparison between multi-objective and single-objective results considering distance coverage $D_c = 200m$ and number of parking locations $s = 50$, is depicted in Fig. 12. In addition, results are compared considering two general indicators (covered land zones and covered population) which are common for both multi and single objective cases. Therefore, specific indicators in Case 2, Case 3, and Case 4 can be compared only with multi-objective model results. Even though all single-objective models tend to maximize their corresponding objective functions, it is worth noticing that the general indicator of land zone coverage is within the similar range between 30% and 40%. This means that MCPL models tend to place shared e-scooter parking locations in the most populated census zones. In addition, we can notice that the distance range coverage D_c plays a key role in terms of the difference between land coverage and the maximization of their corresponding objective functions, as observed in the sensitivity analysis (section 4.3). However, the proposed multi-objective M-MCPL model tends to maximize all objectives at the same time returning a similar percentage between all indicators (i.e., between 40% and 50%).

Finally, Fig. 13 depicts the geographical representation of obtained shared e-scooter locations considering M-MCPL and 4 cases of MCPL model with $D_c = 200m$ and $s = 50$. Considering the frequency of obtained shared e-scooter locations in census zones, results show that only

1 zone is considered optimal for locating the shared e-scooter parking spots in 4 out of 5 of the different models; more in general, only 175 zones are considered optimal in at least one of the 5 models, while 1189 zones result as unsuitable. This analysis also shows an overlapping of the resulting zones of about 30%, i.e., 75 over 250 shared e-scooter parking locations are common among at least two models. The heatmap in Fig. 13 shows that the density of shared e-scooter parking locations is higher in the northeast and in the northwest, while areas located in the south show a lower density. This proves the performability of the model to guarantee the coverage of main POIs of the city in line with the mapping of Fig. 2, which depicts that in these northern areas one can find the main amenities of the city, including the central railway station "Roma Termini" (in the northeast). The lower density of southern areas is compliant with a lower population distribution per census zone as one can see in Fig. 3, which is mainly occupied by historical venues and parks; an exemption is the southwestern neighborhood named "Testaccio", with a denser road network plenty of facilities and residential venues. The outcome of this analysis reflects the importance of investigating different criteria for placing shared e-scooter locations which can contribute to the decision-making process.

5. Conclusions

This study presented a novel multi-objective Micromobility Maximal Coverage Parking Location model (M-MCPL) to design parking locations for shared e-scooter services. The model returns optimal locations by satisfying four different objective functions related to population coverage, accessibility to public transport, and POIs attractiveness. The model has been applied to the central area of Rome: results show that the multi-objective model achieves coverage of around 39% (considering the average coverage value of obtained Pareto-optimal solutions) when all objectives have the same importance for the decision-makers. However, a decision-maker might opt to select one or a combination of four objective functions (e.g., in small towns where public transport is not present). This flexibility might be useful for decision-makers in the case of planning dedicated services (e.g., to tourists or for regular transit users) or applying the model in different contexts (e.g., small towns, and rural areas). Therefore, those aspects have been investigated through a sensitivity analysis in which we distinguished four cases with a single objective function. Results of Case 1, with the objective function $f_1(y)$, showed that we could achieve coverage of around 70% in terms of population, land density, and accessibility with the number of parking locations $s = 25$. However, in other cases, the model might obtain a more convenient achievement of full coverage. For example, in Case 2 and Case 3 with objective functions $f_{2.a}(y)$ and $f_{2.b}(y)$, we can achieve full coverage when the number of shared e-scooter parking locations $s = 50$.

However, the obtained locations do not consider a high-level land-use knowledge and the presence of areas that fall under private property, areas of archaeological interest, exclusively pedestrian areas, and areas where vehicle parking is risky or physically impossible. Moreover, the considered areas could depend on peculiar facts that cannot be verified if not by an on-field survey (e.g., the presence of obstacles, and lack of suitable spaces). Precisely for these reasons, it was considered appropriate to use the census zoning which has a fairly high level of detail and provides accurate data on the potential demand, rather than denser geometric zoning. Future research should certainly address this issue, e.g., by designing a geofencing model which might be used to exclude areas that have location constraints already known by the decision-makers or avoid unwanted areas. Also, in the presence of appropriate data, the model could be extended considering other or different objectives, for example optimizing the location in the zones with high environmental pollution or traffic congestion. Nonetheless, the proposed model can be also used as a general framework applicable to other micromobility solutions (e-bikes, bikes, cargo bikes, scooters, etc.).

CRediT authorship contribution statement

Aleksandra Colovic: Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Luigi Pio Prencipe:** Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Nadia Giuffrida:** Writing – original draft, Writing – review & editing. **Michele Ottomanelli:** Funding acquisition, Supervision, Writing – review & editing.

Data availability

Data will be made available on request.

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Appendix A. Descriptive statistics of the Elitist NSGA-II parameter tuning for each run of M-MCPL model with $s = 50$, and $D_c = 200m$.

No runs	Obj. Fun.	Gen = 10; Pop = 25 Max	Min	Avg	Std. dev.	CPU time [s]	Gen = 25; Pop = 50 Max	Min	Avg	Std. dev.	CPU time [s]
1	$f_1(y)$	52,541.00	24,130.00	37,562.00	9979.52	184.12	55,677.00	19,934.00	36,760.58	11,405.67	635.56
	$f_{2.a}(y)$	406.55	252.35	338.81	56.17		433.11	229.39	320.77	65.61	
	$f_{2.b}(y)$	7.09	2.64	4.93	1.53		10.08	1.72	4.97	2.68	
	$f_3(y)$	352.00	232.00	293.63	42.16		364.00	206.00	281.74	53.08	
2	$f_1(y)$	55,577.00	25,149.00	37,661.89	10,073.68	145.62	54,096.00	16,900.00	34,372.12	12,488.82	648.33
	$f_{2.a}(y)$	403.11	224.08	322.16	71.05		415.92	198.79	310.98	70.18	
	$f_{2.b}(y)$	8.80	2.60	5.02	2.08		10.04	1.83	4.66	2.61	
	$f_3(y)$	366.00	208.00	284.11	57.82		362.00	208.00	278.65	50.69	
3	$f_1(y)$	55,121.00	22,417.00	41,046.70	12,206.51	129.00	56,656.00	22,068.00	38,250.21	11,196.28	657.25
	$f_{2.a}(y)$	411.59	273.66	348.52	46.03		414.87	214.35	328.28	70.03	
	$f_{2.b}(y)$	9.29	1.72	6.22	2.57		9.33	1.35	4.81	2.18	
	$f_3(y)$	359.00	250.00	306.50	34.61		381.00	216.00	288.00	51.38	
4	$f_1(y)$	53,042.00	24,859.00	38,102.25	9594.68	152.33	56,365.00	21,539.00	37,434.37	11,555.73	619.21
	$f_{2.a}(y)$	418.37	246.55	335.83	57.13		422.41	244.30	341.75	60.50	
	$f_{2.b}(y)$	9.00	2.74	5.27	2.32		9.72	1.90	5.22	2.37	
	$f_3(y)$	357.00	244.00	293.75	36.60		367.00	234.00	293.16	44.45	
5	$f_1(y)$	55,264.00	26,168.00	41,796.40	9479.83	154.78	56,020.00	22,078.00	38,697.11	11,964.66	661.24
	$f_{2.a}(y)$	407.36	239.23	352.93	62.45		417.85	221.64	325.39	67.33	
	$f_{2.b}(y)$	9.27	2.70	6.10	2.07		10.46	1.69	5.15	2.44	

(continued on next page)

(*continued*)

No runs	Obj. Fun.	Gen = 10; Pop = 25 Max	Min	Avg	Std. dev.	CPU time [s]	Gen = 25; Pop = 50 Max	Min	Avg	Std. dev.	CPU time [s]
	$f_3(y)$	368.00	197.00	301.00	53.11		356.00	191.00	281.37	56.69	
6	$f_1(y)$	52,839.00	24,334.00	37,954.83	9821.49	128.32	55,993.00	25,326.00	39,499.59	9473.78	617.88
	$f_{2.a}(y)$	408.86	270.08	338.00	46.37		417.26	231.84	341.36	59.34	
	$f_{2.b}(y)$	8.37	1.60	4.85	2.37		10.08	1.88	5.29	2.38	
	$f_3(y)$	359.00	244.00	295.58	35.15		365.00	217.00	295.53	45.10	
7	$f_1(y)$	52,153.00	22,629.00	38,420.58	8364.29	141.62	54,104.00	23,409.00	37,566.24	11,337.73	632.87
	$f_{2.a}(y)$	423.29	257.21	342.06	51.77		424.89	182.14	307.70	86.36	
	$f_{2.b}(y)$	10.51	2.40	5.63	2.62		10.22	1.64	4.91	2.74	
	$f_3(y)$	367.00	204.00	293.17	46.79		370.00	198.00	274.06	53.39	
8	$f_1(y)$	54,603.00	29,153.00	40,759.89	9627.35	158.00	56,214.00	23,517.00	38,341.47	9890.85	637.22
	$f_{2.a}(y)$	410.03	258.71	339.24	56.25		429.94	259.05	339.89	47.63	
	$f_{2.b}(y)$	9.72	0.87	5.19	2.89		10.33	1.78	6.23	2.81	
	$f_3(y)$	349.00	236.00	302.00	43.47		377.00	220.00	285.32	41.23	
9	$f_1(y)$	55,569.00	35,627.00	43,850.33	7105.97	139.94	55,824.00	19,816.00	36,502.00	10,515.41	637.32
	$f_{2.a}(y)$	414.83	309.05	359.95	33.26		417.26	211.47	337.97	61.35	
	$f_{2.b}(y)$	8.07	2.04	5.03	2.27		9.24	1.34	5.08	2.57	
	$f_3(y)$	370.00	257.00	303.67	38.75		363.00	201.00	279.63	40.08	
10	$f_1(y)$	54,167.00	24,723.00	40,300.67	9440.83	131.49	55,033.00	22,790.00	37,213.88	10,335.38	646.73
	$f_{2.a}(y)$	401.47	278.97	347.73	45.35		417.07	257.83	333.17	55.74	
	$f_{2.b}(y)$	8.84	1.56	5.17	2.55		7.93	1.40	4.42	1.92	
	$f_3(y)$	353.00	243.00	302.44	33.77		360.00	220.00	282.82	42.91	

No runs	Obj. Fun.	Gen = 50; Pop = 100 Max	Min	Avg	Std. dev.	CPU time [s]	Gen = 100; Pop = 200 Max	Min	Avg	Std. dev.	CPU time [s]
1	$f_1(y)$	57,205.00	20,291.00	38,514.44	11,575.76	2755.52	57,439.00	14,521.00	37,377.29	11,377.24	10,966.83
	$f_{2.a}(y)$	428.15	198.68	323.33	71.81		430.59	136.07	323.15	68.84	
	$f_{2.b}(y)$	9.77	0.98	5.04	2.81		10.40	0.72	4.75	2.65	
	$f_3(y)$	385.00	194.00	281.32	57.40		366.00	126.00	271.49	56.03	
2	$f_1(y)$	56,599.00	20,533.00	39,802.18	11,713.95	2598.74	60,942.00	12,544.00	36,082.46	12,590.81	10,948.86
	$f_{2.a}(y)$	420.90	240.46	336.20	56.75		424.69	162.60	305.50	79.47	
	$f_{2.b}(y)$	9.63	0.99	4.66	2.31		9.44	0.83	4.23	2.50	
	$f_3(y)$	378.00	208.00	289.15	48.55		369.00	151.00	266.23	58.45	
3	$f_1(y)$	56,814.00	21,650.00	38,302.03	10,720.89	2538.35	59,091.00	14,664.00	35,686.12	12,375.66	10,217.80
	$f_{2.a}(y)$	431.33	237.99	335.17	52.86		429.39	161.57	319.58	73.03	
	$f_{2.b}(y)$	9.79	1.24	4.87	2.50		9.72	0.62	4.65	2.75	
	$f_3(y)$	365.00	222.00	285.76	42.54		376.00	181.00	272.68	55.00	
4	$f_1(y)$	57,067.00	19,858.00	38,656.03	10,709.78	2575.86	58,071.00	21,694.00	38,906.07	10,756.24	10,227.91
	$f_{2.a}(y)$	429.86	214.55	333.73	57.09		430.98	220.58	336.54	59.31	
	$f_{2.b}(y)$	10.04	0.87	5.08	2.58		10.18	0.89	4.84	2.51	
	$f_3(y)$	388.00	210.00	290.00	46.16		371.00	200.00	280.09	47.58	
5	$f_1(y)$	57,715.00	19,402.00	36,692.13	11,010.83	2615.77	57,969.00	15,442.00	35,134.38	11,877.99	10,031.71
	$f_{2.a}(y)$	427.06	175.45	309.18	72.78		436.48	178.67	314.34	72.24	
	$f_{2.b}(y)$	9.36	0.75	4.03	2.58		10.33	0.57	4.34	2.52	
	$f_3(y)$	362.00	192.00	272.39	49.04		403.00	138.00	266.74	65.48	
6	$f_1(y)$	56,507.00	21,154.00	37,244.24	11,143.57	2613.05	56,627.00	20,302.00	35,917.28	11,269.27	16,291.47
	$f_{2.a}(y)$	422.16	222.51	330.15	62.43		430.73	171.02	312.48	75.64	
	$f_{2.b}(y)$	9.54	0.85	5.04	2.46		11.15	0.68	4.63	3.00	
	$f_3(y)$	362.00	183.00	282.12	51.01		375.00	172.00	267.38	57.17	
7	$f_1(y)$	57,405.00	19,283.00	37,888.56	11,527.57	2665.62	57,941.00	24,036.00	40,043.23	9485.51	12,484.33
	$f_{2.a}(y)$	433.40	213.92	335.90	63.85		425.28	225.53	343.61	55.81	
	$f_{2.b}(y)$	10.19	1.54	5.42	2.68		9.11	0.83	4.76	2.47	
	$f_3(y)$	377.00	209.00	286.85	49.12		373.00	201.00	286.03	45.99	
8	$f_1(y)$	56,006.00	22,704.00	38,510.68	10,360.17	2605.44	57,676.00	20,785.00	37,821.00	10,342.20	13,213.05
	$f_{2.a}(y)$	421.42	229.51	328.68	54.30		426.56	218.63	323.98	65.21	
	$f_{2.b}(y)$	9.45	0.93	4.62	2.33		9.92	0.51	4.34	2.68	
	$f_3(y)$	367.00	195.00	283.29	41.75		379.00	181.00	277.45	50.25	
9	$f_1(y)$	56,999.00	22,498.00	38,092.45	9857.69	2618.18	57,884.00	19,843.00	38,495.71	10,674.31	10,558.53
	$f_{2.a}(y)$	419.42	235.73	331.98	55.18		430.37	206.15	333.06	62.33	
	$f_{2.b}(y)$	8.37	1.22	4.44	2.18		10.42	0.93	5.18	2.64	
	$f_3(y)$	362.00	212.00	286.11	43.10		376.00	200.00	282.94	50.96	
10	$f_1(y)$	58,458.00	16,688.00	35,528.88	12,210.93	2603.51	56,514.00	20,186.00	37,816.28	10,698.64	10,530.20
	$f_{2.a}(y)$	424.92	194.59	323.31	63.62		433.42	216.68	330.54	63.53	
	$f_{2.b}(y)$	9.77	1.20	4.88	2.72		10.03	1.07	4.71	2.58	
	$f_3(y)$	373.00	177.00	282.68	51.95		391.00	196.00	282.19	49.75	

Appendix B. The results of all combination between two and three objectives of the M-MCPL model with $s = 50$, $D_c = 200m$, $Gen = 100$, and $Pop = 200$.

Obj. functions	Maximum value $f_1(y)$		Maximum value $f_{2.a}(y)$		Maximum value $f_{2.b}(y)$		Maximum value $f_3(y)$		Average CPU time
	Value	[%]	Value	[%]	Value	[%]	Value	[%]	[s]
$f_1(y),f_{2.a}(y)$	58,474	49.83	427.56	44.11	–	–	–	–	10,445.63
$f_1(y),f_{2.b}(y)$	58,225	49.61	–	–	10.80	55.67	–	–	10,779.36
$f_1(y),f_3(y)$	56,657	48.27	–	–	–	–	389	44.05	10,648.53
$f_{2.a}(y),f_{2.b}(y)$	–	–	434.63	43.78	10.93	56.37	–	–	10,662.43
$f_{2.a}(y),f_3(y)$	–	–	424.90	43.84	–	–	383	43.37	10,836.86
$f_{2.b}(y),f_3(y)$	–	–	–	–	10.76	50.52	382	43.26	9573.44
$f_1(y),f_{2.a}(y),f_{2.b}(y)$	58,739	50.05	424.95	43.84	8.74	45.05	–	–	12,677.66
$f_1(y),f_{2.b}(y),f_3(y)$	57,318	48.84	428.58	44.22	–	–	357	40.43	12,454.58
$f_{2.a}(y)f_{2.b}(y),f_3(y)$	–	–	429.00	44.26	11.25	58.01	358	40.54	12,965.09

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