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Investigating Potential Electric Micromobility Demand in the city of Rome, Italy

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Abstract

Recent electric micromobility solutions can represent a sustainable transport alternative in urban environments. Indeed, these can be adopted as a substitute of car, especially for specific distance classes, as well as they can increase accessibility to transit services. Aiming to investigate the potential demand that can be moved from private cars to environment-friendly micromobility modes (e.g., e-scooters and e-bikes), a methodology based on exploiting data by probe vehicles is presented. To test its goodness, it is applied to the city of Rome (Italy) with challenging results.

Keywords: micromobility; probe vehicles; Floating Car Data; e-bikes; e-scooters.

1. Introduction

In recent years, the concept of sustainability of urban environments has become central (Eltis, 2019). Particularly, increasing attention is paid to micromobility systems such as bike-sharing and e-scooter-sharing, seen as favorable modes of transport due to emission mitigation, congestion reduction and improvements to users' health and lifestyle (Zhang and Zhang, 2018; Caggiani et al., 2020). Furthermore, they can provide flexible options to solve first and last-mile travel problems.

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However, although current trends suggest the growth of micromobility, there is little research investigating how cities can plan and implement these systems in a way that best suits their unique transportation, weather, and demographic markets. Most of the existing literature focuses on user surveys and system-use data analysis (DeMaio, 2009; Fishman et al., 2013; Lin et al., 2011), identifying features that can influence micromobility adoption. Only a few of them proposed methods for investigating new markets.

Existing studies are usually qualitative or based on survey data from which general trends in travel behavior and usage among a self-selected sample can be identified. For example, recent studies on bike sharing based on revealed preferences quantify the effects of environmental conditions and population demographics (Lazarus et al., 2020; Moran et al., 2020; Parkes et al., 2013). Others showed that demographic, built environment and transport-infrastructure statistics have a significant influence on shared bikes reallocation (Zhao et al., 2019). Additional studies investigated the factors affecting the bikeshare adoption using historical trip data (Noland et al., 2016; An et al., 2019) and demonstrating as also the weather has significant effects on bikeshare usage (El-Assi et al., 2015; Younes et al., 2020).

About the adoption of micromobility with respect to other modes, in particular with respect to private car (Fishman et al., 2015; Younes et al., 2019), research mainly tackled to the impact of travel times and costs, finding that the fuel price had a positive and significant impact on micromobility (Hamilton and Wichman, 2018; Wang and Zhou, 2017; He et al., 2020).

The use of micromobility to serve short-distance trips has showed great potential to help alleviate traffic congestion by reducing many trips made by private cars. From the report of Porsche Consulting (2019) on sharing mobility, e-scooters are mostly adopted for distances up to 3 km, while e-bikes up to 6 km. The National Household Travel Survey (NHTS) reported that nearly 60% of vehicle trips have less than six miles traveling distances (FHWA, 2017), while in Europe 50% of all car trips are shorter than 5 km. The convenience and affordability of micromobility has thus the potential to capture these short trips. Therefore, in this context, this study aims to fill a gap in the literature by empirically determining the potential demand that can be moved from private transport to (electric) micromobility services (e-bikes and e-scooters).

Usually, the potential for modal shift has been based on collecting revealed-preference household questionnaires. However, the ongoing development of telematics to automate and facilitate tracing data collection at microscopic level can open new challenges. For example, data by probe vehicles (i.e., floating car data – FCD) have been vastly used in literature for travel time and travel demand estimation with specific regard to private transport (Nigro et al., 2018; Cipriani et al., 2014; Eisenman and List, 2004; Ásmundsdóttir, 2008; Ásmundsdóttir et al., 2010).

The study aims to investigate urban private transport through floating car data (FCD) in order to identify the trip characteristics and infer which trips can be potentially interested to move to electric micromobility services, consequently facilitating the selection of policies to be implemented for pushing people to more environment-friendly transport services.

Paper is organized as follows. Section 2 presents the methodology developed to point out the potential demand of micromobility, while Section 3 reports its implementation to Rome. Conclusions and the further developments are reported in the last Section.

2. Methodology

This paper presents a new approach for extrapolating potential (electric) micromobility demand by selecting compatible trips from floating car data (FCD) based on travel characteristics and availability of suitable infrastructure for micromobility in the study area.

2.1. Analysis of the FCD dataset

FCD derive by probe vehicles equipped with an OnBoard Unit (OBU). The OBU records and stores several information of the vehicle (vehicle ID, the day and time of the trip, the speed and the state of the engine, the geo-referenced positions of the vehicle at regular detection intervals), tracking its position. Thus, information at high spatial coverage are collected, such as travel times of individual trips and route choice.

The raw data requires to be preprocessed to identify error sources and correct them. First, the dataset is subjected to a trip-concatenation process to filter out brief stops registered within a trip in order to assure its continuity and thus correctly identify the destination of the trip. For every trip, the first location where the engine of the vehicle is turned on is considered the origin O and the location where the engine is turned off is considered the destination D of the trip. However, stops can be registered due to temporary interruptions, loss of GPS signal, functionality issues of the vehicle engine etc, thus, all stops shorter than 10 minutes have been identified and filtered out. Then, trips whose distance is lower than the maximum pedestrian threshold have been removed, as well as trips whose duration is inexplicably long considering the area of our study. Removing error sources in the data brings to a 58% reduction of the initial FCD dataset; then, the trip-concatenation process generated an additional reduction of 28%.

The remaining data N_{OD} is further classified into home-based trips (HB) and not home-based trips (NHB): in the first case, the origin point (or the destination) of the trip is the home of the user. The classification is performed through a clustering of the destinations reached by each vehicle. The clustering follows a DBScan algorithm (Ester et al., 1996). DBSCAN parameters are: 1) the minimum number of points $minPoints$ that have to be in the neighborhood of a given point to start the development of a cluster and 2) the radius ε of said neighborhood, meaning that if the distance between two points is lower or equal to this value then the two points are considered neighbors and can belong to the same cluster. The radius ε was fixed to 120 meters and the $minPoints$ equal to one. Once generated the clusters, for each vehicle the one with the highest frequency of overnight stops was classified as the residence. Overnight stops derived by the analysis of the time windows of arrival and departure times of vehicles.

Lastly, the trips have been aggregated as a function of the temporal distribution of FCD demand on sample days in order to identify the on-peak demand and off-peak demand time intervals for both weekdays and weekends. Characterizing trips according to their temporal distribution as well as the HB/NHB classification can in fact be useful to determine the scope of the trip, which can help to identify the potential market segment for sharing electric micro-mobility services or for private e-scooters and e-bikes.

2.2. OD Compatibility Analysis

In accordance with the values from literature, in this study we propose to adopt two distance thresholds: up to 6 km, which represents the maximum e-bike trip length, and up to 3 km, which represents the maximum e-scooter trip length. The output dataset of the filtering and classification process described in Section 2.1 has thus been further classified according to the distance threshold sp^m_{max}, where m is the e-micromobility mode (e.g. e-bike or e-scooter). Then, for both home-based (HB) and not-home based (NHB) sets, the share of travel demand that could potentially be carried out through the e-micromobility mode m, only based on the average travelled distance, is calculated as:

$$N^{HB}_m = \frac{n^{HB}_m}{N_{OD}};\ N^{NHB}_m = \frac{n^{NHB}_m}{N_{OD}} \tag{1}$$

where n^{HB}_m and n^{NHB}_m are the number of home-based and not home-based trips, respectively, under the relative distance threshold sp^m_{max}.

2.3. Infrastructure Compatibility Analysis

In a second phase, the characteristics of the road infrastructures, where the selected trips take place, are considered, developing an index that we called Micromobility Compatibility Index (MCI). MCI could be used by transportation planners and e-micromobility operators to evaluate the capacity of specific road segments to accommodate e-bikes and e-scooters. The index takes into account the physical and operational characteristics of the links of the road network as obtained from Open Street Map (https://www.openstreetmap.org).

For each traffic zone z of the study area, the MCI is computed as the ratio between the total length of road infrastructures suitable for e-micro-mobility L^z_m (cycle ways, pedestrian streets and residential streets, secondary and tertiary roads with maximum one lane for travel direction, trails within parks and green areas with suitable paving) and for private cars L_c^z (motorways, primary, secondary, tertiary roads, and residential streets):

$$MCI^z = \frac{L_m^z}{L_c^z} \tag{2}$$

Then, for each trip k up to 6 km, the maximum distance threshold defined in this study, the micromobility compatibility index MCI_k of the trip is calculated as the weighted average of the indexes MCI^z of each zone z that the probe vehicle i within the trip k moves through, as depicted in Figure 1:

$$MCI_k = \frac{\sum_{z \in I^i} MCI^z \cdot l_k^z}{\sum_{z \in I^i} l_k^z} \tag{3}$$

where l_k^z is the length (in km) of the trip k in the zone z (Figure 1).

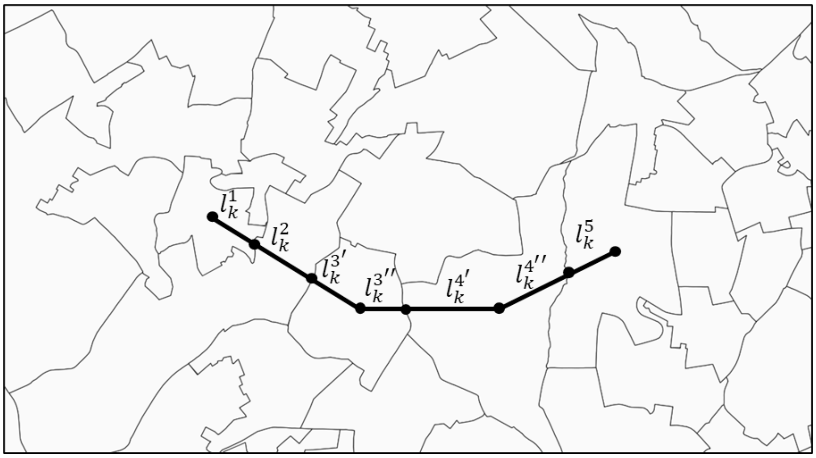

Fig. 1. Example of FCD track points and computation of travelled length in each zone.

Lastly, a compatibility threshold MCI^* is fixed and all the trips n_k^{HB} and n_k^{NHB} whose $MCI_k \leq MCI^*$ are removed from the potential travel demand calculated in (1), thus obtaining new fraction of travel demand N'^{HB}_m and N'^{NHB}_m compatible with e-micromobility that takes into account also road infrastructure compatibility.

3. Numerical results

The proposed approach has been used to assess the potential e-micromobility demand in the city of Rome, Italy, from a large FCD dataset containing 9 million recorded trips (post filtering process). The used FCD dataset belongs to the Octo Telematics company fleet and spans the entire metropolitan area of Rome through 243’784 vehicles (317 millions of records, 7% penetration rate) tracked during November 2015. The detection intervals of FCD vary according to the road infrastructure: when the vehicle is located along the motorway network or main roads of metropolitan areas the position is recorded every 30 seconds, whereas on remaining roads the position is recorded once every two kilometres.

The municipality area has been divided into 1’409 zones, posing as a compromise between the 13.656 census zones and the 155 census areas defined by the Italian Institute of Statistics. The average area of the zones is 86 ha, whereas the average population is of 1’900 inhabitants.

3.1 OD compatibility analysis

The filtered trip dataset has been first divided into weekdays and weekend trips and then into home-based trips (HB) and not home-based (NHB) trips. The number of suitable trips and resulting shares according to the two fixed thresholds of 3 km and 6 km are presented in Table 1.

Table 1. OD compatibility analysis results.

E-Scooters (≤3km)				E-Bikes (≤6km)			
		Number of trips	Share on total FCD trips [%]			Number of trips	Share on total FCD trips [%]
Weekdays	HB trips	1’296’129	14.1	Weekdays	HB trips	2’255’902	24.6
	NHB trips	937’572	10.2		NHB trips	1’704’123	18.6
	Total Weekdays	*2’233’701*	*24.3*		*Total Weekdays*	*3’960’025*	*43.2*
Weekends	HB trips	438’813	4.7	Weekends	HB trips	752’820	8.2
	NHB trips	244’963	2.6		NHB trips	438’568	4.8
	Total Weekend	*683’776*	*7.3*		*Total Weekend*	*1’191’388*	*13*
Total trips suitable for e-micromobility		2’917’477	31.6	Total trips suitable for e-micromobility		5'151’413	56.2

The 24.6% resulting share of potential e-bike demand (weekdays home-based trips) is quite high, however, further analyses on the zoning system of the Rome municipality show that most of these trips are generated from zones that cannot be considered micromobility-oriented. Thus, these results have highlighted the need for an infrastructure-based index that allows to select the trips moving along suitable road infrastructure that is able to accommodate e-micromobility services such as e-scooters and e-bikes.

3.2 Infrastructure Compatibility Analysis

The trips that are compatible by travelled distance are then filtered through an index that considers the configuration of the road infrastructure the vehicles move across, as explained in section 2.3.

In Figure 2 (a) the distribution of the MCI^z computed as seen in (2) for all the zones is shown. Then, for each of the compatible trips k (having travelled distances lower than 3 km and 6 km respectively), the MCI_k is computed as in (3).

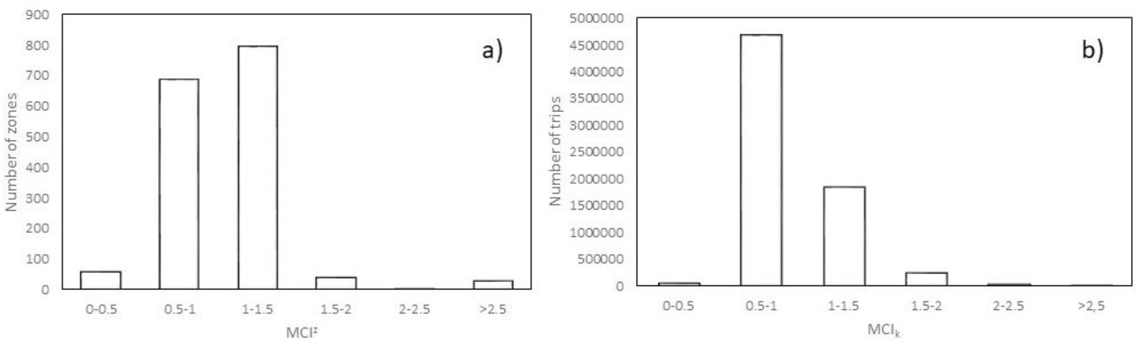

Fig. 2. (a) Distribution of MCI^z in Rome (b) Distribution of MCI_k in Rome

The MCI^z calculated for each zone of the city of Rome (Figure 2, a) is equal on average to 0.998 and to 1.006 in the 75° percentile. This means that the ratio between the infrastructures that can be adopted by e-micromobility and the infrastructures for cars is generally well-balanced. As for the MCI_k (Figure 2, b), its average value is equal to 0.948 with a standard deviation of 0.240.

If a threshold value MCI^* is considered, all those trips whose MCI_k is less than MCI^* are not considered compatible with micromobility due to the lack of suitable infrastructure. Therefore, these trips are removed from the demand shares presented previously in Section 3.1. In Table 2 we show that, as the MCI^* threshold becomes lower, the percentages of the demand shares decrease: if, for example, the MCI^* is set to 0.7 (equal to the difference between the mean MCI_k value and its standard deviation in the city of Rome), the demand shares decrease of approximately 1.1-1.8 percentage points for weekdays and 0.2-0.5 percentage points for weekends, compared to the shares computed with MCI^*equal to 0 (meaning the infrastructure compatibility is not taken into account).

If the MCI^* threshold is increased to 1.2 (equal to the mean MCI_k value plus its standard deviation), the demand shares strongly decrease to values lower than 2% for weekdays and lower than 1% for weekends.

Generally, MCI^* has not to be fixed a priori. It can be adopted as an objective function for the city planner involved in improving the street layout and road network characteristics.

Table 2. Impact of the MCI* threshold on the potential demand for weekdays and weekends, HB trips and NHB trips.

			Potential demand [%]								
			MCI^*								
			0	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4
Weekdays	HB	e-bikes	24.6	22.9	19.7	14.0	8.0	3.5	2.3	1.6	1.1
		e-scooters	14.1	13.0	11.4	8.3	5.0	2.1	1.4	1.0	0.8
	NHB	e-bikes	18.6	16.8	13.6	9.4	5.5	2.9	2.0	1.5	1.1
		e-scooters	10.2	9.1	7.4	5.3	3.2	1.6	1.1	0.9	0.7
Weekend	HB	e-bikes	8.2	7.6	6.6	4.7	2.7	1.2	0.8	0.5	0.4
		e-scooters	4.8	4.4	3.9	2.8	1.7	0.7	0.5	0.4	0.3
	NHB	e-bikes	4.8	4.3	3.5	2.4	1.4	0.8	0.5	0.4	0.3
		e-scooters	2.6	2.4	1.9	1.4	0.9	0.4	0.3	0.2	0.2

4. Conclusions and further developments

The paper tackles electric micromobility solutions, such as e-scooters and e-bikes, by developing a methodological framework to extrapolate the potential demand for e-micromobility from FCD trips. The proposed methodology is innovative in the data adopted, since FCD are usually used to evaluate the traffic network performances or to derive private demand. Moreover, the method is parametric: it means that it can be easily transferred to other contexts of study where FCD data are available.

The first step of the method is based only on travelled distances (OD compatibility analysis), whereas the second step moves a step forward through the definition of an index evaluating the compatibility of the network infrastructure with respect to micromobility. This index can be easily computed through the accessible Open Street Map open database.

The method has been applied to the city of Rome (Italy) where the potential demand for e-micromobility ranges between 24.6% and 2.60% of the FCD sample, respectively for Home-based trips during weekdays carried through e-bikes (up to 6 km) and for Not Home-based trips during weekends carried through e-scooters (up to 3 km). Since these percentages are based on travelled distances only, their values are quite high; however, when the infrastructure compatibility analysis is performed, the percentages decrease to respectively 2.3% and 0.3% for a micromobility compatibility index equal to 1.2.

Further developments will focus on refining the methodological process, the identification of home-based round trips as well as to validate the representativeness of the findings and its expansion procedure from FCD to the entire population of Rome. Furthermore, the aim is also to identify those trips that can be shifted from car to a multimodal solution based on mass transit service and on micromobility for the access and egress phase to and from the stations. Lastly, a standard behavioral approach can be considered based on random utility models, thus calibrating a modal shift model able to represent the choice between private mobility and sustainable mobility options such as e-micromobility for single trips or for multimodal trips by public transport.

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