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A network based method to study urban sharing mobility: the case of Milan

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Abstract

Urban Mobility is a complex phenomenon with many actors involved that has been changing due to the diffusion of Sharing Mobility. This shifting is affecting individual habits and cities dynamics, which need to be considered by policy makers and operators for better programming services and incentives. This paper aims at improving the way sharing mobility is analyzed and monitored. We propose and test a methodology, based on the theory of networks, aimed at studying sharing mobility dynamics among the districts of a city. The method uses data tracking people's movements made with shared vehicles, developing a set of geo-localized measures with the potential to be suited to different purposes. Insights coming from this type of analysis, can be used as a support tool for decision-making processes in the mobility field. The methodology is applied to the city of Milan with data coming from BikeMi -Milan's bike sharing program- and Urbi, a platform that handles real-time data from car sharing providers such as Enjoy, Car2go and Share'nGo.

Keywords: Car sharing; bike sharing; network analysis; urban mobility; Milan

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1. Introduction

Access based consumption, better known as the less precise term *sharing*, is taking its momentum (Bardhi & Eckhardt, 2012). This concept has spread to several fields thanks to the facilitation of technological platforms that match demand and request in real time. New business models - most of them disruptive - based on sharing different type of goods have been successfully launched during the last years (e.g. Airbnb and Enjoy). This phenomenon has been addressed as the sharing economy revolution (Pilzare, 2012) and it is greatly affecting also mobility (Bardhi & Eckhardt, 2012). Shared mobility sector is in fact one of the fastest growing segments of the shared economy. Car sharing for instance is expanding at annual rate of 30% (Freese & Schönberg, 2014) and it is present approximately in 18 nations and 4 continents (S. A. Shaheen & Cohen, 2008). The consulting firm Roland Berger predicts that by 2020 the revenue of that market will be between 3.7 and 5.6 billion of euros (Berger, 2014). Similarly, bike sharing is getting more and more spread, currently there are over 7000 programmes in the world, involving over 800,000 bicycles in 855 cities (Fishman, 2016a).

Those two relatively recent mobility modes have been studied, especially from a qualitative point of view by researchers with the aim to assess, among others, benefits, user preferences, behaviours or service improvements tactics (Fishman, 2016; Efthymiou, Antoniou, & Waddell, 2013). Studies instead linking sharing mobility displacements with the territory are fewer and in any case focused mostly on service coverage and tend to be circumscribed to just a single mode (Saibene & Manzi, 2015). Quantitative studies with the territory as the unit of analysis have not been exhaustively explored. The diffusion of this type of services, provides nowadays a significant amount of data that can be employed to asses which are the influences of car and bike sharing on the territory and how do they connect and reshape the urban scene.

This paper proposes a methodology, rooted in the theory of networks, to analyse how the sharing mobility modes are linked to the urban territory. Modelling the phenomenon as a geographic network gives, besides the synthetic representation, a baseline to create a set of indicators suitable to specific needs. In the case of mobility those are the needs of the city stakeholders such as public administration, users and firms. The methodology implements geo-localized data about displacements to build a network whose nodes are urban districts. In this way the focus of the study becomes the districts, their role and their interconnection within the network created by how the people move around the city. With the traditional mobility paths and connections between areas are established by the available infrastructure. With free-floating systems trips are more tailored on people needs thus the intensity of connection between zones is not obvious and probably depends also on the modes used for the displacements. Geographic distance and intensity of connection are always correlated? Does the role of a district in the network change overtime? Is the current infrastructure of each district able to handle its traffic peaks?

A type of analysis like the one here proposed provides a tool able to answer those questions.
The paper is structured as follows. Section 2 comprises a literature review about the sharing mobility modes object of the study: car sharing and bike sharing. A particular emphasis will be given to studies that used geo-localised data. The methodology used to build the model and all the phases of project can be found in section 3, along with a description of the data used. Section 4 is about the model application to the city of Milan. It describes the principal results and discusses the scalability of the model itself.

2. State of Art

This section is divided into two parts. In the first one the main objectives of the researches performed on sharing mobility are presented. The second part instead focuses on the quantitative approaches used to study mobility and underlines the fact that most of them have been implemented just with the traditional mobility modes (e.g. public transportation).

1.1. Sharing mobility modes

Sharing mobility modes, advocates the idea behind the Product Service Systems (PPS), which are basically systems that provide solutions to customers by the integration of products and services, satisfying user needs while improving resource consumption (Quet al., 2016). In this particular scheme, service providers tend to hold the ownership of products and provide users with different forms of services. The idea is simple: users can enjoy the privacy of potentially any type of car (or bike) without the commitment of a purchase, maintenance and insurance costs but basically paying for the use. The costs for the user are typically an inscription fee, a monthly fee and a cost of use (Efthymiou, Antoniou, & Waddell, 2013). Car sharing researches in the literature can be divided in the following group according to their aim: (a) user characteristics and behaviour, (b) environmental impact of car sharing, (c) demand analyses and forecast and (d) service optimization (Kang, Hwang, & Park, 2016). Similar objectives are also pursued by the studies concerning bike sharing as can be drawn from Fishman (Fishman, 2014)adding to these, the ones related to how certain factors, such as weather or topography, can influence the level of activity (Faghih-Imani, Eluru, El-Geneidy, Rabbat, & Haq, 2014; Frade & Ribeiro, 2014; Jurdak, 2013; Rudloff & Lackner, 2013).

1.2. New trends studying mobility

A rich amount of information containing individual's coordinates is routinely tracked each time a person travels using a public transport smart card, makes a call, sends an email or even uses a credit card. These data sources offer a unique opportunity to understand and characterize the patterns of human travel behaviour at a massive scale (Hasan et al., 2013). In the city of Harbin in China for example, GPS data were used to understand the travel taxi-pattern (Cui et al., 2016) of about 7 million of users. Nevertheless, GPS data so far is constrained just to some transportation medias and have a restricted availability. Other import sources, with similar characteristics are the data collected from Automated Fare Collection Systems used by (Nunes, Dias, Zegras, & e Cunha, 2016) and (Zhong, Arisona, Huang, Batty, & Schmitt, 2014), or by the smart subway fare card transactions (Hasan et al., 2013). In this last case information about the entire journeys of the users were completed by predicting visited locations using the popularity of places in the city as an interaction parameter between different individuals.

As mentioned, some other type of data, not directly related with the transportation has also been used to infer journeys behaviours. These other types of data tend to have a lower resolution or granularity and a possible bias to tackle but can embrace different modes and perceived mobility in a larger scale. (Hawelka et al., 2014) uses social media data, particularly twitter data to estimate the volume of international travels. Another method employs the dataset of mobile phone traces collected by mobile network operators. This type of data is usually known as CDR (Call detail record) data, which documents mainly the details of a telephone call or other communications transaction that passes through a facility or a device (Horak, 2007). Occasionally, the spatial granularly of the data is a disadvantage if is not treated correctly, but, compared to travel survey data, CDR data have lower collection cost, larger sample size, higher update frequency, broader spatial and temporal coverage (Calabrese et al., 2013). CDR data are used to: predict traffic zone - commercial or residential - division of a city (Dong et al., 2015), compute regular mobility analysis in terms of congestion of a road, and travel times for road segments (Toole et al., 2015), or understand the intra-urban variation of mobility and the non-vehicular component of overall mobility (Calabrese et al., 2013).

The potential of data driver studies has not been explored extensively with new transportation modes such as bike and car sharing. It remains a remarkable opportunity, especially since the introduction of new players, such as IT platforms that gather and match status information from different mobility providers in order to offer an integrated set of real-time alternatives to the user.

3. Methodology

For the propose of the study, three macro-phases have been individuated: Data gathering and aggregation; Network construction and analysis; and Key performance indicators (KPIs) design. Figure 1 shows graphically these phases.

a. Data gathering and aggregation

The input and base of the model are two type of data: a dynamic one and a georeferenced one. The first category comprises data about the displacement made with the mobility modes object of the analysis (e.g. car sharing). What is needed are information, on a given period and for each mode, about the origin and destination coordinates of each trip, along with the starting and the ending time. These data can be gathered, according to the city of analysis, mostly in two ways: directly from the service provider – usually a private – or indirectly from a third part. In the case of Milan, data came both from direct and indirect sources. Clear Channel, unique bike sharing provider for the city during the period of analysis, provided data about bike trips while car sharing data were provided by Urbi, a urban mobility aggregator. Urbi provides to users, through a mobile application, real-time information about the availability of sharing mobility vehicles owned by the different providers in a specific area.

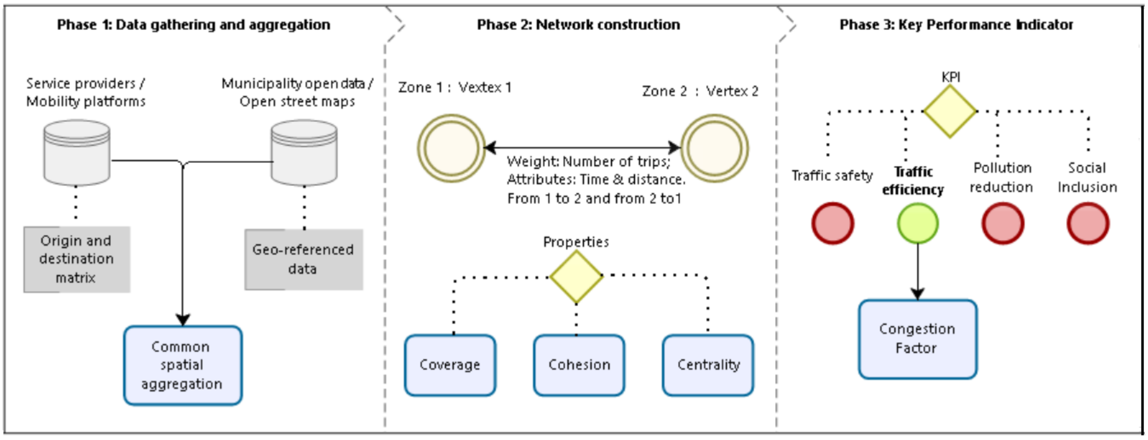

Fig. 1 Phases of the methodology

Regarding the time slot to consider, in general, for statistical reason, a bigger sample is always better than a small one, but of course gathering and managing data represents a cost (not only economic). The span of time to select depends on the scope and limitations (e.g. availability). For instance if the purpose is to analyse seasonality, the period should be larger.
The second category of data, that allows linking the dynamic layer to the territory, includes geo-spatial data describing the maps of the cities with their division in districts or neighbourhoods. Typically, those information are held by public administration and tend to be accessible online. Alternatively, other sources of geo-spatial data, such as Google Maps or OpenStreetMap can be used to gather those information.

Matching the two categories allows to represent origin and destination of each trip on a map. In the case of a free-floating car sharing system, reasonably several origins/destinations happen to be relatively close to each other to the point that, for the purpose of the analysis, they could be considered as just one location. In particular, when more than a mode is considered in the model a common unit of spatial aggregation is convenient. If one level of the administrative division of the city – zone, districts, neighbourhood – is detailed enough to not lose data consistency of the trips distribution, that one can be chose as level of aggregation. This way, other type of information – such as infrastructures, demographic and economic data - can be exploit. The level of aggregation used in the application of the model to Milan was represented by the 88 NIL – Nucleo di Identità Locale – of the city, that are the equivalent of districts.

b. Network construction

The second phase of the model is the network construction. The established level of aggregation identifies the nodes or vertexes of the network. Those nodes represent origins and destinations of the trips. Any trip departing or arriving in a smaller geographical reference, needs to be aggregated to the chosen level. In this way trips star and end in zones and not in single geographical points.
Two nodes of the network, two areas, are connected with an edge if at least one trip between them occurred during the period of analysis. The intensity of the connection between two nodes is considered by adding a weight-equivalent to the number of trips in between - to the edge connecting them. Additionally, information regarding the time and the distance travelled are considered as attributes of each edge. Since each mode connects the city in a different way, two networks, one for bike sharing and one for car, were considered. The graph structure of a network and its properties allows to estimate the coverage of a mode, to identify the more demanding locations and to observed the possible isolated sections of the city given the trip distribution. All these geo-referenced measures are relevant for decisions related with mobility policies and infrastructure.

c. *Key performance indicators (KPIs) design*

For the third phase, a benchmark of the conventional transportation performance measures has been contemplated. The particular complexity of the transport field, where many goals need to be addressed such as traffic efficiency, traffic safety, pollution reduction and social inclusion, make performance based planning much more challenging(Kaparias et al., 2012). To limit the target and to show a possible development of the methodology here proposed, a geo-spatial indicator of traffic efficiency, which dives into the bottlenecks of the traffic systems, has been designed.

The Congestion Factor (from here CF) measures the factor by which the number of in-coming and out-coming vehicles increases during the peak times. This is measured per NIL and the specific peak time for each NIL is considered in the computation thus it represents the maximum variation of in/out-coming trips for each NIL. Considering the in-coming and the out-coming flow as different, two CF can be actually measured: inCF and outCF.

For the computation of both of them, the day has been divided into 24 time slots of one hour each. For inCF of a NIL i, the difference between the average number of incoming trips during a time slot t and the mean of incoming trips per time slot (hour) to the NIL i has been calculated. divided by the average number of incoming trips to that very NIL has been calculated. We refer to this value in the following way:

$$\Delta_{IN(i)}(t) = \frac{IN_{(t,i)} - \mu_{IN,i}}{\mu_{IN,i}} \tag{1}$$

Where,

$i \in \mathrm{NIL}$
$t = \text{time slot}$
$IN_{(t,i)} =$ average number of incoming trips for NIL i during time slot t
$\mu_{IN,i} =$ average number of incoming trips per hour for NIL i
For each NIL, the maximum value of $\Delta_{IN_i}(t)$ is selected .The *In-congestion Factor* is thus defined as follow:

$$INCF_i = \max\left[\Delta_{IN(i)}(t)\right] \tag{2}$$

An identical approach has been followed to calculate outCF:

$$OUTCF_i = \max\left[\Delta_{OUT(i)}(t)\right] \tag{3}$$

$$\Delta_{OUT(i)}(t) = \frac{OUT_{(t,i)} - \mu_{OUT,i}}{\mu_{OUT,i}} \tag{4}$$

Detecting where peaks in the demand have risen helps service providers to understand the criticalities of the system and to identify the geographic zones where congestion is more likely to occur. Besides the maximum variations, the information about the time slot when they occurred have been registered. This way the provider could find out in which period of the day a re-balance of the system has to be done to reduce the probability of vehicles stock out. For instance, if a NIL has a peak of outgoing travels from 11 to 12 a.m. is likely to happen that during or after that period none-or few vehicles would be found in that specific NIL. Moreover, the time information gives the possibility to roughly classify NILs in business/school and residential districts. A NIL with a peak of incoming travels deviation in the morning and of out coming travels in the evening probably belongs to the first category while a NIL with opposite characteristics is likely to be a residential zone. Opportunities in knowing that are many. Forecast mobility patterns helps service providers to better organize its fleet within the city in and public administration to decide where to invest in better infrastructures.

4. Results

In the following section the described methodology has been applied to the city of Milan. In this case, six weeks of data tracking users' movements within the city, from the 25th of January of 2016 to the 7th of March, have been collected from BikeMi, Milan's bike sharing program (BSP) and the user-centred digital platform Urbi that handles real-time information of car sharing companies such as Enjoy, Car2go and Share'nGo.

In the BSP 350.093 trips connecting 263 stations of the city were performed and recorded in that period. Contemporaneously, 254.833 car-trips were performed and registered by Urbi: 108.067 trips coming from Car2go, 104.772 from Enjoy and 41.994 from Share'nGo. In the case of car sharing program (CSP) data, the travelled distance was not explicit but only the departure and arrival coordinates and the travelled time were provided. Those data were also comprehensive of rebalance trips - trips performed by service operators to maintain a reasonable spatial distribution of the vehicles – that should not be considered in our analysis. To identify them, we used the variation of the fuel level, feature provided for each trip. In particular, 0-delta-fuel trip lasting a considerably long period of time, was classified as a rebalance.

Geographic data was accessible through the Comune di Milano platform: "dati.comune.milano.it", that allowed us to extract the zone division of Milan by NILs and the location of most of the bike stations in a shapefile (SHP) format which stores information and geometry of spatial features. Departures and destination of the trips, originally given by a pair of geographic coordinates, were aggregated to the NILs. This means that from now on trips, in our analysis, do not start or end from single points but rather from districts. As mentioned this aggregation was needed to compare different modes. In fact bike sharing service works with fixed docking station while free-floating car sharing systems allow the user to pick-up and drop a vehicle everywhere.Sharing modes networks

A NIL in Milan is connected on average with 32 others (out of 88) by bike and with 63 others by car, meaning that the coverage of the car sharing network is significantly larger than bike sharing's one. Despite this, bike sharing trips are more frequent considering the zones covered by the service, on average 8,9 trips by bike are made for every single car sharing trip of the free floating providers analysed. Consequently, the density of the bike network, reflecting the fraction of edges or links that are actually present, is of 85% while is only of 74% for car. These and other details are summarized in the table 1.

Table 1 Networks properties

Features	Bike Sharing	Car Sharing
NIL coverage- Vertices	39 out of 88	86 out of 88
Average degree	32	63
Maximum number of edges*	1521	7396
Number of connections / edges (directed)	1290 NIL connections	5443 NIL connections
Density of the network	85%	74%
Average trip volume inside a NIL (vertex strength)	12109 trips	2529 trips
Average trip volume by connection (edges)	271 trips	20 trips

The strength of a vertex, which refers to all the trips arriving and departing to and from the specific spot, highlights the concentration of the bike sharing mode in just a few city locations. In particular, by far, the larger number of trips are performed in the Duomo NIL (18% of the entire translations), and the rest 41% are allocated in just 7 other areas (Buenos Aires – Venezia, Brera, Magenta - S. Vittore, Guastalla, Centrale, Sarpi and Pagano). To reach the same relative amount of trip volumes of car sharing (59%), 28 NILS are required and in this case, the NIL with the highest concentration of trips (Buenos Aires) accounts only for 5% of the entire volume. Thus the car sharing network has a smoother trip distribution compared to bike's one even if the displacement are still more frequent in the central zones (Buenos Aires, Duomo, Brera and Centrale).

Beside the strength by NIL, the figure 2 also displays that the farthest vertices (in terms of number of edges to cross), called the network diameter, are not associated with an apparent geographical distance. The CSP exhibits frequent trips connecting the city centre to the suburbs, for this reason the two NIL with the yellow dot,

* The maximum number of edges has been calculated considering a directed graph with self-loops, using n^2 where n is the number of nodes.

geographically close, represent the farthest vertices of the network. The BSP instead are preferred for trips connecting close NILs, probably also due to the first-30-minutes free usage promoted by the service provider.

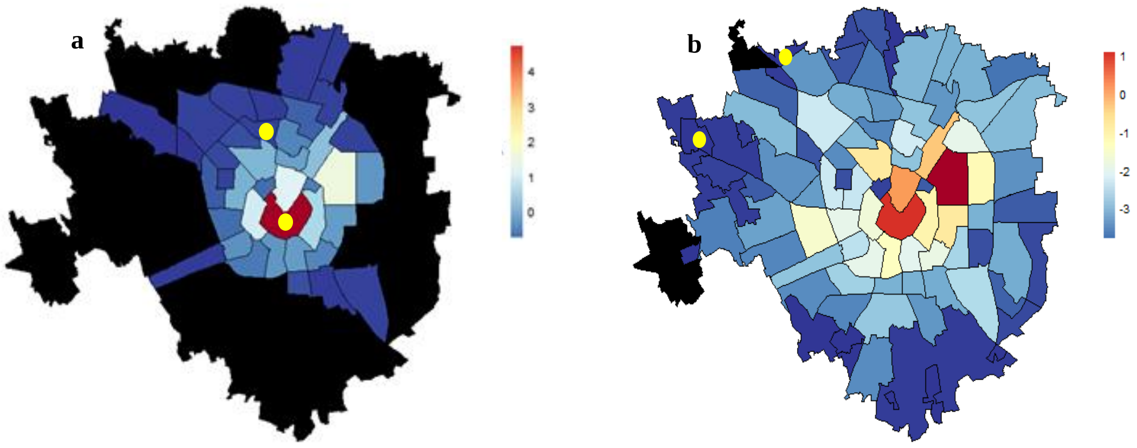

Fig. 2 The figures show the strength distribution of the two modes in Milan. A score proportional to the number of trips has been assign to each NIL of the city. Blue is related to the lowest strength score and red to the highest, meaning that the activity of the mode in the red zones is more intense. The yellow dots represents the network diameters, which are the further vertices in terms of edges needed to be crossed. (a) Bike Sharing (b) Car sharing

d. *Key Performance Indicator: Congestion Factor*

There are two peaks in the overall bike sharing traffic during the day. The first one is from 8 to 9 a.m. and the second from 18 to 19 p.m. This means that rush hours coincide with the time where the majority of the people uses to reach the place where he works or studies and with the time he comes back home.
This link with people daily routine is less strong for car sharing usage. In fact, the traffic has just one peak from 7 to 9 pm. This suggests that users do not use that mode to reach a work or a study location. This is evident in the

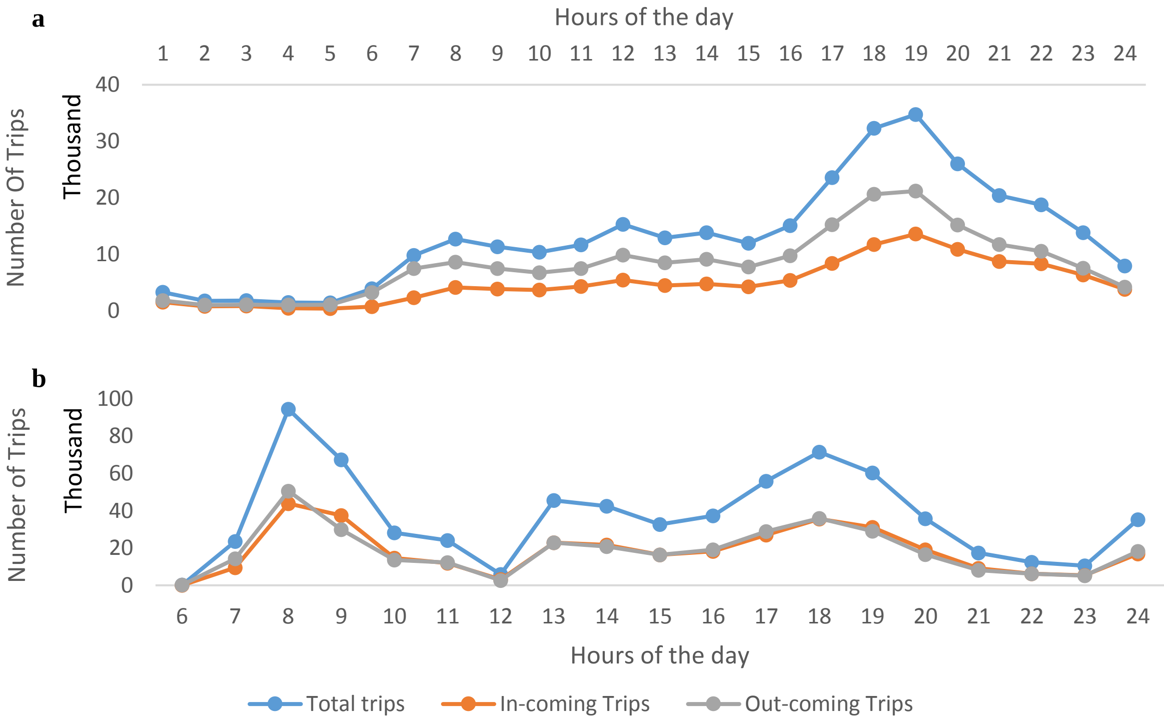

Fig. 3 Traffic Peaks a) Car sharing: b) Bike sharing

morning when from 8 to 9 a.m. just the 4% of the total trips made with shared cars are perform against the 13% of bike sharing's one. 49% of car sharing activity is heavily concentrated from 5 pm to 10 pm.

Another feature that the previous plots illustrate, is the rebalancing activity required for the continuity of the system. In particular, for the car sharing system is notorious the gap from the out-coming and the in-coming trips for almost all the time slots -expanded especially during the rush hour-. The analysis of this delta of trips in detail for each location allows to individuate the most critical areas where rebalancing should take place and provide some suggestions about the most efficient way to do it (e.g. the closest area with the capacity of filling up the gap of a critical zone). Nevertheless, this can only be tested with the effective information of the rebalance trips.

In general bike sharing's traffic is more variable that car sharing's one (see appendix A); on average the traffic of the bike sharing during its peak time increases by a factor of 2,32 against the 1,62 of the car sharing one. Again, this difference is probably related to the impact of external conditions such as weather on bike activity. Is important to highlight that CF is an absolute indicator that gives the maximum factor by which the traffic in a NIL increases, regardless the amount of traffic. Duomo, for instance, despite being very active in terms of in- and out-coming trips, in both tables appears close to the bottom meaning that the traffic there is one quite constant during the day. Once individuated the critical zones, for the service provider, is fundamental to understand also the main directions of the travels during peaks to program rebalancing of the system. This information can be drawn by INCF, t_in , OUTCF and t_out. For instance, if we analyse bike sharing in Biccoca we can see that from 9 to 10 a.m. the traffic is 3,29 times bigger than the average while from 6 pm to 7 pm the out flow increase by a factor of 3,05. This means that around 10 am Bicocca's docking station will be full of bikes while around 7 pm the station will have a lack of bikes, incurring in the risk of stock-out. A rebalancing trip before the evening peak would reduce that risk.
Moreover, opposite traffic patterns allow us to identify different natures of the NILs. In particular, studying the daily peak times regarding inflows and outflows of the trips, led us to classify areas into residential and working or scholastic. If a district has a peak of incoming trips in the morning and one of 'out coming' trips in the evening that is likely to be a working or a scholastic district. On the contrary, a district with an opposite behaviour will be probably a residential district. The information about the time when the peaks of incoming and out coming trips have been registered within the different NILs can be found in the Appendix A.
Since the literature states that bike share in Milan is often used as commuting or end mode (Saibene & Manzi, 2015) we are not sure that the destinations of a displacements performed by bike is the final destination of the whole trip. For example, a worker that lives outside Milan could use the bike to reach the railway station where he will take the train to home. For that reason, we substituted the residential district label with the more general residential/bridge district. We labelled undefined those NILs with a behaviour not classifiable with one of the first two categories. The result is shown in the appendix B. Further studies could develop this idea and try to test the hypothesis behind that.

5. Discussion and Conclusion

This study developed a methodology that analyses how the sharing mobility modes are linked to the urban landscape. Modelling transportation modes as a network allows the implementation of different measures to study several dimension of mobility. This paper proposed a KPI measuring traffic efficiency – the congestion factor – but an entire dashboard of KPIs can be designed in order to cover other dimensions such as traffic safety, pollution reduction and social inclusion (Kaparias et al., 2012). The selection model for these measures depends on the focus and on the stakeholders the application concerns and can be developed in following studies.
The proposed approach clarify the role and concentration of the sharing mobility modes at each district along with the coverage and the cohesion of the modes within the territory. In the traffic efficiency dimension, time and location of the peaks within the network lead to foresee the nature (residential or commercial) of the districts. Those insights assess the providers improving their rebalance systems, the management of the asymmetrical demand can assures a better transport flow, and advice the urban administration about the infrastructure requirements of the city.
In the case evaluated, the city of Milan, the BSP is focus mainly in the in the city centre, the Duomo's location (out of other 88) accounts for the 18% of the trips alone, while the combined CSP has a larger coverage and a tendency to spread its activity beyond the core. In Milan, during the rush hours the congestion for bikes, on average in all the locations, increases by a factor of 2,23, reaching for some areas even 3 times its usual activity (the case of Magenta - S. Vittore). The CSPs instead handle lower peaks and a larger coverage of the territory (almost the entire city) but its activity follows a different pattern. Its peak goes from 7 to 9 pm, with a minimal morning activity suggests that this mode does not follow the typical commuters behaviours and therefore is not use to reach a work or a study location.

For further research, it could be interesting to study the activity of the sharing mobility modes along with traditional transportation modes in the different areas. A larger time span may show seasonality insights about mobility and a potential traffic zone division coming from these data (identification of residential and work areas) which in mega-cities tends to be a challenge. Besides this, ad-hoc studies of mobility experiments could be performed: what is the impact of adding a station in a new area of the city? Can an extension of a bike lane or of the free cycle time span boost the peripheral zones activity? Further studies implementing the model here proposed may answered to questions like those ones.

Acknowledgements. We kindly thank Clear Channel and Urbi for having provided the data used to perform the analysis.

Appendix A: Congestion factor by NIL and mode & Traffic zone division given bike sharing activity

Table 2 Car and Bike sharing Congestion Factor by NIL.

T_IN:
T_OUT:
W= working/scholastic district; R= residential/bridge district; U=unclassified

NIL	Car					Bike					
	INCF	OUTCF	CF Car	T_IN	T_OUT	INCF	OUTCF	CF Bike	T_IN	T_OUT	Nature
BICOCCA	1,79	1,44	2,48	19	18	3,29	3,05	2,61	9	18	W
BOVISA	2,29	2,88	2,08	19	18	2,55	3,98	2,32	18	8	W
BRERA	1,23	1,06	0,82	19	18	3,03	2,06	2,19	8	18	W
BUENOS AIRES VENEZIA	0,78	0,87	0,95	19	19	1,85	3,43	2,04	18	8	W
CENTRALE	1,00	0,97	1,48	19	7	2,23	3,44	2,47	18	8	W
CITTA' STUDI	1,64	1,55	1,49	19	19	1,81	2,62	1,98	18	8	W
DE ANGELI MONTE ROSA	1,08	1,04	0,96	19	18	1,65	2,00	1,82	8	8	R
DERGANO	1,02	0,83	1,83	18	7	3,00	2,56	2,55	8	7	R
DUOMO	2,05	2,09	0,86	22	21	3,97	2,38	2,11	8	18	R
EX OM MORIVIONE	0,94	0,74	1,33	18	21	2,52	3,12	2,14	9	18	R
FARINI	1,03	0,92	1,62	19	18	2,46	1,61	2,02	8	8	R
GALLARATESE	3,63	4,18	3,74	19	18	-	-	-	-	-	-†
GARIBALDI REPUBBLICA	1,25	1,13	1,27	19	19	2,55	3,13	2,85	8	8	R
GHISOLFA	2,18	2,84	1,54	22	21	2,11	4,08	2,4	18	8	R
GIAMBELLINO	1,88	2,17	1,59	19	19	2,83	3,88	2,2	18	8	R
GIARDINI PORTA VENEZIA	1,62	1,41	2,14	19	18	3,76	2,22	2,22	8	17	R
GRECO	1,52	1,24	2,29	19	18	2,20	4,08	2,17	19	8	R
GUASTALLA	1,01	0,90	0,82	18	18	2,78	1,37	2,08	8	8	R
ISOLA	2,63	3,03	1,09	19	18	2,27	2,88	2,58	8	8	R
LODI CORVETTO	1,09	1,17	2,03	20	18	3,01	4,69	2,24	18	8	R
LORETO	1,68	1,78	1,72	19	18	1,95	2,47	2,14	18	8	R
MACIACHINI MAGGIOLINA	1,98	2,08	2,03	19	19	2,34	2,79	2,56	8	8	R
MAGENTA S. VITTORE	1,45	1,81	0,76	18	18	3,08	5,12	2,94	18	8	R
NAVIGLI	1,80	1,65	1,19	19	19	2,02	3,71	2,16	18	8	R

† Not enough bike trips were performed in the Gallaratese NIL

NIGUARDA CA' GRANDA	0,88	0,93	2,62	23	21	2,38	1,95	2,14	18	8	R
PAGANO	1,21	1,38	0,81	19	18	1,97	2,85	2,18	18	8	R
PARCO SEMPIONE	1,73	1,94	2,00	19	19	1,32	2,36	1,73	9	8	R
PORTA ROMANA	1,48	1,74	0,90	19	18	1,97	3,43	2,13	19	8	R
PORTELLO	2,15	2,52	1,31	19	18	2,03	3,78	2,75	18	8	R
QT8	2,15	2,33	1,62	19	18	1,57	1,92	1,47	15	20	R
SARPI	0,98	0,82	1,05	18	18	2,19	3,34	1,80	19	8	R
SCALO ROMANA	2,00	2,52	1,60	19	18	2,57	3,30	2,92	8	8	U
TICINESE	1,25	1,42	1,17	18	18	1,94	3,03	1,74	19	8	U
TORTONA	1,55	2,59	0,78	21	18	1,98	3,73	2,67	19	8	U
TRE TORRI	1,38	1,78	1,76	19	18	2,04	2,46	1,90	18	8	U
VIGENTINA	0,99	1,12	1,01	22	21	2,24	1,96	2,10	8	8	U
VILLAPIZZONE	0,80	0,88	2,08	18	8	3,28	4,39	2,35	18	8	U
WASHINGTON	1,62	2,01	0,91	19	18	2,10	3,07	2,48	19	8	U
XXII MARZO	1,04	0,86	0,93	18	18	2,18	4,08	2,32	19	8	U
Overall	1,53	1,66	1,5	19	18	2,51	3,13	2,32	8	8	

6. References

Bardhi, F., & Eckhardt, G. M. (2012). Access-based consumption: The case of car sharing. Journal of Consumer Research, 39(4), 881-898.

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira, J., & Ratti, C. (2013). Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. Transportation Research Part C: Emerging Technologies, 26, 301-313.

Cui, J., Liu, F., Hu, J., Janssens, D., Wets, G., & Cools, M. (2016). Identifying mismatch between urban travel demand and transport network services using GPS data: A case study in the fast growing chinese city of harbin. Neurocomputing, 181, 4-18.

Dong, H., Wu, M., Ding, X., Chu, L., Jia, L., Qin, Y., et al. (2015). Traffic zone division based on big data from mobile phone base stations. Transportation Research Part C: Emerging Technologies, 58, 278-291.

Efthymiou, D., Antoniou, C., & Waddell, P. (2013). Factors affecting the adoption of vehicle sharing systems by young drivers. Transport Policy, 29, 64-73.

Faghih-Imani, A., Eluru, N., El-Geneidy, A. M., Rabbat, M., & Haq, U. (2014). How land-use and urban form impact bicycle flows: Evidence from the bicycle-sharing system (BIXI) in montreal. Journal of Transport Geography, 41, 306-314.

Fishman, E. (2016). Bikeshare: A review of recent literature. Transport Reviews, 36:1, 92-113.

Fishman, E., Washington, S., & Haworth, N. (2014a). Bike share's impact on car use: Evidence from the united states, great britain, and australia. Transportation Research Part D: Transport and Environment, 31, 13-20.

Frade, I., & Ribeiro, A. (2014). Bicycle sharing systems demand. Procedia-Social and Behavioral Sciences, 111, 518-527.

Freese, C., & Schönberg, A. T. (2014). Shared Mobility–How new businesses are rewrit-ing the rules of the private transportation game. Roland Berger Strategy Consultants, München,

Hasan, S., Schneider, C. M., Ukkusuri, S. V., & González, M. C. (2013). Spatiotemporal patterns of urban human mobility. Journal of Statistical Physics, 151(1-2), 304-318.

Hawelka, B., Sitko, I., Beinat, E., Sobolevsky, S., Kazakopoulos, P., & Ratti, C. (2014). Geo-located twitter as proxy for global mobility patterns. Cartography and Geographic Information Science, 41(3), 260-271.

Horak, R. (2007). Telecommunications and data communications handbook Wiley Online Library.

Jurdak, R. (2013). The impact of cost and network topology on urban mobility: A study of public bicycle usage in 2 US cities. PloS One, 8(11), e79396.

Kang, J., Hwang, K., & Park, S. (2016). Finding factors that influence carsharing usage: Case study in seoul. Sustainability, 8(8), 709.

Kaparias, I., Eden, N., Tsakarestos, A., Gal-Tzur, A., Gerstenberger, M., Hoadley, S., et al. (2012). Development and application of an evaluation framework for urban traffic management and intelligent transport systems. Procedia-Social and Behavioral Sciences, 48, 3102-3112.

Nunes, A. A., Dias, T. G., Zegras, C., & e Cunha, J. F. (2016). Temporary user-centred networks for transport systems. Transportation Research Part C: Emerging Technologies, 62, 55-69.

Pilzare, P. Z. (2012). The sharing revolution. Retrieved November 23, 2016, from http://www.paulzanepilzer.com/sharing_revolution

Qu, M., Yu, S., & Yu, M. (2017). An improved approach to evaluate car sharing options. Ecological Indicators, 72, 686-702.

Rudloff, C., & Lackner, B. (2014). Modeling demand for bikesharing systems: Neighboring stations as source for demand and reason for structural breaks. Transportation Research Record: Journal of the Transportation Research Board, (2430), 1-11.

Saibene, G., & Manzi, G. (2014). The shared bicycle scheme in milan: A report on the development of a successful public transport system. Uscire Dalla Crisi: Città, Comunità e Specializzazione Intelligenti: Conferenza Scientifica Annuale AISRe,

Zhong, C., Arisona, S. M., Huang, X., Batty, M., & Schmitt, G. (2014). Detecting the dynamics of urban structure through spatial network analysis. International Journal of Geographical Information Science, 28(11), 2178-2199.