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ANALYSIS OF SHARING MOBILITY NETWORKS: A STUDY OF MILAN

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Abstract (Italian)

La mobilità rappresenta un problema complesso che coinvolge diversi attori sia del settore pubblico che privato. Questa è radicalmente cambiata dopo la così detta rivoluzione della Sharing Mobility. Gli studi, accademici e non, sull'argomento stanno proliferando. Tra gli altri, i benefici, le motivazioni, le barriere e il tasso di sostituzione sono stati esplorati per i singoli programmi di mobilità condivisa. Nonostante questo, una mancanza di ricerche supportate dalla teoria dei network emerge in questo campo. Questo studio esamina i servizi di bike e car sharing offerti nella città di Milano, con lo scopo di analizzare la struttura dei network delle modalità di trasporto "shared". Per fare questo, sono stati raccolti dati traccianti i movimenti degli utenti da BikeMi, il programma di bike sharing milanese e dalla piattaforma digitale Urbi che possiede informazioni in tempo reale sullo stato dei servizi di car sharing di compagnie come Enjoy, Car2go e Share'nGo. Il seguente lavoro da informazioni sul ruolo di ogni distretto o NIL (nucleo di identità locale) della città di Milano nei network delle singole sharing modes. Un set di KPIs, ciascuno dei quali associato agli adeguati stakeholders, è stato definito per stimare l'impatto che car sharing e bike sharing hanno in termini di convenienza, sostenibilità e salute. I risultati ottenuti rappresentano interessanti informazioni che possono essere usate a supporto dei processi decisionali nel campo della mobilità.

Abstract

Mobility is a complex problem with many actors -both public and private- involved. It has been radically changed by the introduction of the so-called *Sharing Mobility revolution*. Academic and practitioner studies on the topic are proliferating. Among others, benefits, motivations, barriers and substitution rate have been explored for the main sharing mobility programs. Nevertheless, a lack of researches relying on the theory of networks emerges in the field. This paper examines bike and car sharing services in the city of Milan, with the aim of analysing the structure of the networks of sharing mobility modes in the city. To do that, data tracking users' movements has been collected from *BikeMi*, Milan's bike sharing program and the user-centred digital platform *Urbi* that handles real-time information of car sharing companies such as *Enjoy, Car2go* and *Share'nGo.* The study provides information about the role of each Milan's *district* or *NIL -nucleo di identità locale-* in the network of each sharing mobility mode. A set of mobility KPIs, each one associated to the adequate stakeholders, has been defined to assess the impact of each mode in terms of *convenience, sustainability* and *health.* The outcomes achieved represent interesting insights that can be used as a support tool to decision making processes in the mobility field.

1. Executive summary

1.1 Problem definition and objectives

Access based consumption, better known as the less precise term *sharing*, is taking its momentum. This concept has been applied 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 were successfully launched in the last years (e.g. Airbnb). We are living now, in what has been defined as the *sharing economy revolution* (Pilzare, 2012) and mobility, has been strongly impacted by that.

Just in 2014, car sharing increased worldly by 39%. In Italy its growth, from 2013 to 2015, has overcome 70%, and the number of members is now around 22 thousand with Milan representing almost 80% the market (Albè, 2016). Similar results have been observed for bike sharing programs that are present in 60 Italian cities with 11 thousand of bikes, -the double with respect to 2011- (Car e bike sharing: Grande crescita (confermata dall'ISTAT).2016). 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 and behaviours. However, data driven approaches, which are common in traditional mobility studies are still few in the sharing mobility field. In particular, the opportunities to apply *network theory* to sharing mobility modes have not been explored yet. Besides that, researches on sharing mobility field are quite focused on a single mode losing the view of mobility as an integrated system. Finally, even though Italy is the country with the highest number of active bike sharing systems, few studies on the topic have been performed compared with local studies in cities like Paris and London (Saibene & Manzi, 2015). Milan, as the first Italian city in terms of bike and car sharing, is the perfect place to develop an analysis that could help to fill this lack and provide an integrated view of these two modes of transportation.

The following document is a study on bike sharing and car sharing set in the city of Milan. The objectives are: A) To analyse the structure of the networks of sharing mobility modes in the city of Milan, B) to identify dynamics and impacts of the two sharing mobility modes in terms of *convenience, sustainability* and *health*. The research relies on network analysis to achieve those objectives.

In the context reported above, our purpose is to provide a comprehensive study of the overall sharing mobility system of Milan - pointing out similarities and differences of the two most common sharing modes, since their accelerated expansion, carries -naturally- particularities and impacts for all the stakeholders involved. This way is possible to understand the mobility needs that each mode is covering and its opportunities from a strategic and operational point of view.

So far, the attention of the researches has been involved mainly understanding the nature of the phenomenon but ad hoc mobility studies of geo-localized displacements have been mostly carried out just for traditional transportation modes (public and private). Nonetheless, the available data tracking of the sharing mobility mode trips and its current volumes presents an opportunity to deployed a further analysis that not only goes along portraying the new mobility patterns but also exhibits other potentialities: from user benefits to public administration decisions support system for policies, passing by the identification of market opportunities for providers and support services.

To accomplish its objectives, the research relies on the theory of *networks.* Six weeks of data tracking users' movements within the city have been collected from the major service providers - *BikeMi* for bike sharing, *Enjoy, Car2go* and *Share'nGo* for car sharing - and are deployed to build up two networks, one per mode aggregating them in vertices, attached to geo-spatial information of the city, particularly to Milano's *districts* or *NILs* -*nuclei di identità locale*. Thus the objectives of the study have been translated into a set of indicators measuring network performances and each measure has been associated to the stakeholders that could be interesting in the insights provided by it.

For the methodological path of the analysis, was considered as first step the design of performance indicators - given goals, dimensions and criteria related with urban mobility - aiming at fulfilling research objectives. Then, the further development is divided in three main phases: (1) data acquisition, exploration and preparation; (2) network construction and analysis supported by *Rstudio* software package and finally (3) the design of the performance measurements.

1.2 Main results

The results state that both bike and car sharing networks are really dense (density is respectfully 85% and 74%) but they have different concentrations. While car sharing trips are geographically spread, bike sharing activity is concentrated in few NILs, *Duomo* alone for instance account for 18% of the total. Opposite results have been founded concerning time concentration. Bikes trips are more constant during the day with two peaks – at 8a.m. and

18p.m.- while cars are more used in the evening. Those last differences suggest a possible discrepancy in journey purposes between the modes. While Milano's BSP (bike sharing program) seems to be used to perform mainly journeys related to people's job or occupation, it does not seem the same for car sharing. This hypothesis is supported by the fact that just 10% of the total amount of bike trip is performed during the weekend – when people usually do not work - against the 30% in the case of car.

Moreover, the study highlights that considering separately in-coming and out-coming journeys of each NILs, traffic peaks do not happen at the same time across the network. We highlight two opposite NIL behaviours that are likely to be function of the nature of each district: *residential* or *working/school*.

Concerning the mobility efficiency, and therefore convenience of the mode average velocity of movements with *shared* bikes and cars has been calculated for each NIL, considering also the velocity reduction during peak hours for each of the two modes. That measures presents car sharing as the fastest mode, but also the most variable since its velocity reduces due to congestion by 20% against a tiny 1,13% in the case of bikes.

Another result, relevant for the service providers and the public administration is the information about the relative importance of each NIL for the single sharing service. We believe this outcome can truly help policy makers understanding if the level of infrastructure and the action taken in a specific area are in line with the way people move in that area. Or in the other way, individuating critical zones for a specific mode and trying to understand the causes behind those criticalities to solve them.

Finally, has been calculated - under certain assumptions discussed in chapter 7 - that during the 6-weeks-period analysed, 129.907 kg CO_2e has been saved thanks to bike sharing and 18.305 kg CO_2e thanks to electric car sharing. This result confirms the fact that sharing mobility modes are essential for the development of sustainable plans within cities.

1.3 Structure of the work

In particular, this document is structure as follows. *Contextual analysis* introduces the general field of the research, discussing: a) why and for which players mobility is relevant, b) what is the so-called *sharing economy* and how it has been re-shaping mobility, c) which are the factors that have been allowing the growth of *sharing mobility* in nowadays society. This chapter clarifies terms such as *sharing* and *access based consumption* that sometimes are used in a not precise way. Besides it presents a framework designed by (Bardhi & Eckhardt, 2012) useful to classify bike and car sharing modes of consumption.

Chapter 3. State of art provides a literature review on the sharing mobility modes object of the study: car sharing and bike sharing. It purposes is to present the aims and the main results of the researches conducted on that topic. Section 2.2 is focused on those studies that applied Big Data analysis to the mobility. This discussion was particularly useful for us to find out which are the available data, their characteristics and the opportunities they represent. Concluding the chapter, section 2.3 discusses the most used key performance indicators (KPIs) in the field. This latter part was needed as support and inspiration for the design of indicators used in this research. The revision of the academic literature reveals the gaps that this work aims to cover. Those gaps are fully recapitulated in *chapter 4. Research Justification*.

Chapter 5 represents the theoretical framework on which we based the study and that is needed to fully understand it. Its central part focuses on theory of network and discusses about type of networks, their elements and the most important measures worthy to extract from them. The last part of the chapter provides insights coming from performance measurement system development. After presenting which measures are relevant for networks from a scientific point of view, this part provides complementary theoretical instruments to design KPIs relevant also from a managerial point of view.

The methodology used to perform the analysis and all the phases of project can be found in detail in chapter 6 where they are fully discussed. Chapter 7 is dedicated to the results while conclusions, limitations of the work and possible future researches can be found in chapter 8 that is the last one.

2. Contextual Analysis

Mobility is a central issue in several spheres of urban development. Not by chance, liability and economic success of communities have been, to a major extent, determined by the efficiency of the transportation infrastructures (Bhat & Koppelman, 1999). Essentially, transportation allows people to take part in human activities, and understanding its transformations, trends and patterns remains from an urban perspective a crucial challenge.

Since the real-time information and contact with the users is nowadays crucial in the major urban centres mobility has being also used as a testing ground for IT services and Analytics. The networking of different modes of transportation, the spread of smartphones and the availability of data plus the ability to process them are key drivers of change in urban mobility (Berger, 2014). They set the base to a new user-centred mobility where the users have access to real-time information about the status of the system and can moves within it using the mode of transportation that fits better his needs, often integrating different modes within the same journey.

One of the features of the current mobility is its *intermodal* attribute, which, in most of the cases, implicates the role of different providers, creating usually a disjointed mobility chain. This tend to enlarge the stakeholders involved in the mobility scenario, since, besides the user and the public administration - that traditionally has also a supplier role - additional actors are directly involved. In recent years a new type of providers, the one appertaining to the denominated shared mobility, has grown in popularity (Laporte, Meunier, & Calvo, 2015), affecting not only the flows and interaction of passengers within the city, but also generating alongside disruptive business models (Freese & Schönberg, 2014). The first part of this chapter aims to analyse who are the actors in nowadays mobility and what is their role.

Beside traditional modes, such as public and private transportation, new forms of travelling are today integrated in the mobility system and have been reshaping it in the last years. The gaining of popularity of car and bike sharing has been possible thanks to the revolution of the so-called "Sharing Economy". The second part of the chapter has the scope to understand what this term refers to and why it is now having its "momentum". Besides, a clarification of the differences between renting, sharing and access-based consumption will be provided, along with a classification tool for access-based consumption modes introduced by (Bardhi & Eckhardt, 2012).

The third and last section narrows the focus to the sole Sharing Mobility highlighting the factors that fostered its growth in recent period and that enabled modes such as car and bike sharing to become concrete alternatives.

2.1 Mobility's stakeholders

The recent changes in cities' dynamics associated with their accelerated growth are also feeding and branching the common mobility-related problems such us as congestion, air pollution, and accidents; especially in city centres where the level of human activities is higher (Farahani, Miandoabchi, Szeto, & Rashidi, 2013). In this scenario, stakeholders must conceive comprehensives decision–making processes that include strategic, tactical and operational decisions. Strategic decisions are long-term decisions related to the infrastructures of transportation networks; tactical decisions are those concerned with the effective utilization of infrastructures and resources of existing urban transportation networks; and operational decisions are short-term decisions, which are mostly related to traffic flow control, demand management and scheduling problems (Farahani et al., 2013).

Other -recently new- stakeholders caught up in the urban transit systems are the communication-technology providers and developers (telecom companies, internet suppliers, app designers) since the real-time information and contact with the users is a crucial part of the service, especially with the increasing amount of suppliers. Therefore, the networking of different modes of transportation, the spread of smartphones and the availability of data plus the ability to process them are key drivers of change (Berger, 2014). Indeed, it has been a raise in the number of platforms -not directly associated with providers- with the exclusive aim of communicate the current urban transport network state. The figure below, shows the layers of the different stakeholder's aggregations.

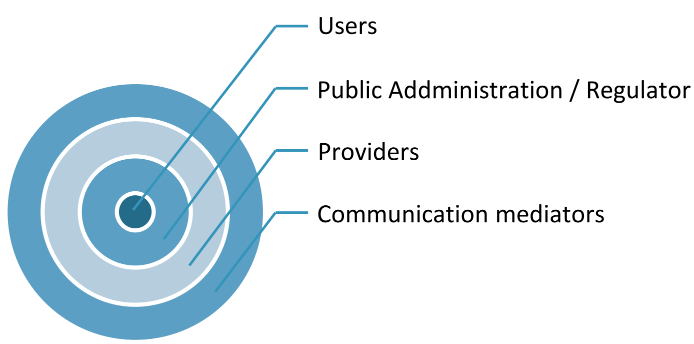


Figure 1. Mobility Stakeholder Layers

In the intermodal circumstances, a particular type of providers, the one appertaining to the so-called shared mobility systems, like bike and car sharing, have grown in popularity in recent years (Laporte et al., 2015).

2.2 Sharing Economy: types, trends and impacts

Sharing Economy is a term largely used to refer to certain consumption modes despite "Access-based economy" is a more correct term to be used to refer to some of them. *Access-based consumption modes* are defined as transactions that can be market mediated but where no transfer of ownership takes place (Bardhi & Eckhardt, 2012).

They root in the no profit and public sector. In libraries or museums for instance people have access to books or art without owning them (Chen, 2009). In private sector an ancestor of this mode of consumption is the rental form. If the common sense strongly prefers ownership to rental (Cheshire, et al., 2010), why nowadays new form of consumption that occurs without transfer of ownership are becoming more and more popular? It seems in fact that own an object is no longer the desire of the current population. Nowadays we live in a so-called liquid society where things change fast and suddenly. What is valued today maybe will not be valued tomorrow and almost anything can be considered riskless. The spreading of alternative modes to ownership has been helped also by the economic crisis. Acquiring cost of goods increased and since labour and families are more and more unstable that in the past people prefer more flexible solutions.

Access based consumption versus Sharing

It is true that in both sharing economy and access-based economy no transfer of ownership occurs, but there are some differences between the two terms. A shared object is an object jointly owned by the users or partners without differences of rights among the partner themselves. Each partner is responsible for the object and perceives a sense of ownership towards it. The family is a perfect example of sharing. Sharing a car within a family for instance brings responsibility for family members that take care of the vehicle, keep it clean and signal eventual damages. Moreover, they perceive the object as their own and do not value it just for the use value it has. In access-based consumption instead, disparities among the parties can occur. It is clear if we consider for instance car sharing or *AirBnB* case where the property rights of the vehicles or of the houses are detained only by one of the partners involved in the transaction, in these cases the service provider and a private. Another difference between sharing and access-based mode of consumption is the fact that the second one is not necessary drawn by pro-social or an altruistic motivation (Belk, 2010). Taking into accounts all those differences, *sharing* has been classified -according to the six dimensions explained in the next part- as a particular form of the more general access-based consumption.

Six dimensions of Access-based consumption

(Bardhi & Eckhardt, 2012) clearly identify access-based consumption as a self-standing way of consumption, clarifying the differences with other modes such as rental and ownership, and gave six dimensions to classify its different forms. According to (Chen, 2009) the consumption mode of a good shape consumer's value of the good itself. In ownership for instance the object-self relationship is stronger and there is a form of identification with the object by the owner. This is more difficult to happen in an access based contest since the duration of the object-self relation is usually temporary limited. Even in car sharing, where the access is longitudinal (several short-duration usages) and people could even re-use the same vehicle each time, has been proven that there is neither attachment nor identification with the good itself (Bardhi & Eckhardt, 2012)

So far access-based consumption could be considered as a form of short-term rental but it differs from rental because the transactions usually happen through a digital technology (e.g. Car sharing versus car rental service), it is more self-service, more collaborative and not necessary mediated by the market.

The dimensions that identify the different forms of access-based consumptions are:

1. Temporality
2. Anonymity
3. Market Mediation
4. Consumer Involvement
5. Type of Accessed Object
6. Political Consumerism

Each dimension is characterized by a continuum of level that goes from one end to another. For instance, for the dimension 'Market Mediation' there are various levels that can go from a totally non-mediated mode (e.g. sharing a good within a family) to a totally mediated one (e.g. car sharing) passing from intermediate forms. The latter is the case of consumption modes such as *BlaBla Car*'s where even if the drivers are paid their aim is not to make profit but to meet costs and they are moved by other social and sustainable motivations.

The first dimension, Temporality classifies modes in term of length of the relationship and length of usage. Regarding the first, we could have a short-term relationship in the case of booking a room in a hotel or a longitudinal as in the case of being part of a community like AirBnB's one. In the second case the relationship is characterized by long dormant periods and shorter period of activity. The longer is the length of usage the more the user perceives the sense of ownership. To remain within the same field of the last example, renting a house for years leads to a greater attachment than rent one for just a week.

The second dimension is Anonymity in terms of anonymity towards the other users and spatial anonymity or object proximity. The higher is the degree of anonymity towards the users the less social and farther from sharing the mode of consumption is. If the object is close to the user (e.g. a car sharing vehicle usually parked near home) is more probable to observe a perceived sense of ownership. When we have no interaction with the other users, as in the case of bike sharing for instance, the transactions occur in a so-called society of strangers (Simmel & Wolff, 1950).

The third dimension (already discussed in the example at the beginning of this part) is the level of Market Mediation that divides profit from no-profit activities.

The other dimensions are Consumer Involvement (self-service versus full service), Type of Accessed Object (material versus digital, experiential versus functional) and Political Consumerism (the transaction is politically motivated or it occurs just to fill a market gap).

According to these dimensions (Bardhi & Eckhardt, 2012) classify car sharing as an access-based consumption mode that is longitudinal, limited in the duration, anonymous, close to home, market mediated, self-service, foster by utilitarian and not altruistic motivations and which accessed object is functional and material.

For what concerning bike sharing we can state that some dimensions remain the same of car sharing's: temporality, anonymity towards other users, market mediation, consumer involvement and accessed object. Differences can occur in spatial proximity since bikeshare is often used as complement or as a connection between other modes (Saibene & Manzi, 2015) - e.g. different modes within the same trip such as train, bike and underground - meaning that the vehicles are not necessary close to the user's house. Another difference could be in the Political Consumerism dimension since the motivations beside the use of bike sharing could not be merely driven by convenience – as at the end has been proved for the case of car sharing, at least in US (Bardhi & Eckhardt, 2012)- but also by sustainability or health-related reasons.

According to the six dimensions, described before, "Sharing" could be a particular form of access based mode of consumption characterized by the fact of not being market mediated, having a low anonymity and pro-social motivations. Clarified the difference, **in the following sections we will use the term *sharing* even if, as stated before, in some cases it is not the most appropriate. This choice has been taken for simplicity and comprehension reasons: *car sharing* and *bike sharing* are the common ways to call these specific transportation modes** as *shared economy* is the most spread name for the phenomenon in general.

The shared mobility, a specific segment of the shared economy, is particular interesting for two reasons. The first is that the mobility sector is one of the fastest-growing segments of the shared economy and it has also the highest growth potential. The second is that in no other sectors of shared economy is possible to find so many big players entering the market.

2.3 Sharing Mobility

As stated, shared mobility sector is one of the fastest growing of shared economy. The car sharing sector for instance is expanding at annual rate of 30% (Freese & Schönberg, 2014). One of the reasons is the change in the *consumption culture* we are seeing nowadays. Relevant status symbols in the past, such as owning a house or a car, are no longer valued. In the industrialized world about 50% of car owners could imagine to share their car in the future (Freese & Schönberg, 2014).

A second factor that fosters the growth of shared mobility is *digitalization*. People today feel very comfortable with technology because it is embedded in their lives. Is not strange today to buy a book or a dress or even to book a restaurant with a smartphone. For this reason, "innovative" mobility services that use mobile application to run the business do not have to face a technological barrier of the user. We put the world "innovative" inside quotation mark because actually shared mobility is not brand new. Bike sharing programs for example exist for almost 50 years (S. A. Shaheen, Guzman, & Zhang, 2010). So, why the topic became so prominent and popular in the last decades? The answer is that these new mobility modes are having their momentum thanks to changes in the society that are fostering their growth. One of those radical changes is the digitalization.

The third factor driving the growth of shared mobility segment is the *lack of resources*. The rising of energy prices due to the scarcity of raw materials and the lack of money to spend in new infrastructure due to the economic crisis led cities to look for alternative solutions to guarantee an efficient mobility. Furthermore, the lack of space in the city make impossible to expand traffic infrastructures (Freese & Schönberg, 2014)

The last factor is the *demographic trend*. Cities are forced to face traffic congestion, noise and pollution issues caused by the overpopulation. Also, ecological and environmental reasons are finally gaining importance in a world where climate changes are now evident.

Finally, cities are also seeing a shift to a more individual and customized travel demand given by the increasing number of single-person households and the longer life expectations. The most important markets of shared mobility are: *car sharing, bike sharing, ride sharing* and *shared parking* (Freese & Schönberg, 2014). In this study we are focusing in the two most common ones: Car Sharing and Bike Sharing. Bike sharing programs provide short-term rental of bicycles from several docking stations in a city. A user can pick-up a bike from a docking station and hand it over to another one in another point of the city. Usually the user is required to provide credit card details to pay registration and usage fees and an e-mail address. For the majority of the programs the first 30 minutes of usage are free. After that time, they are charged by fee with a sharply rising scale (Fishman, Washington, & Haworth, 2013).

In car sharing, consumers access cars owned by a company, which makes it distinct from carpooling or peer-to-peer car sharing programs, such as BlaBlaCar. Its market is growing and, in the US, revenues from car sharing are expected to reach $3.3 billion in 2016, from $253 million in 2009 (Florida, 2011). New players are entering the market as in the case of Italy where the last October BNW launched its car sharing service – *DriveNow* – in Milan (Valtellina, 2016). As for bike sharing users are charged by a fixed annual fee plus a variable fee dependent on the usage. There are two type of car sharing programs: *fixed station* and *free-floating* car sharing. The first form allows handing over the vehicle only in dedicated stopping point or even exclusively in the very pick up point as in the case of *GuidaMi*, ATM's car sharing service. The second model, that in Italy was introduced by *Car2go* in Milan in 2012, allows instead dropping vehicles wherever the user wants, just as a private car.

In the following section we will go deeply in reviewing the literature about these two mobility modes to individuate the gap where our research has been placed.

3. State of Art

The world of transportation has witnessed a mini-revolution in June 2007 with the launching of the Vélib' bicycle sharing system in Paris (Laporte et al., 2015), even do this type of systems have been tested in Europe since the 1960s – the first one was 'the White bicycle plan' an initiative developed in Amsterdam in 1965 (Lin & Yang, 2011)-, they really took off with the advent of communication and information technologies which allow for automatic billing and monitoring.

Today there are currently over 7000 bicycle sharing systems in the world, involving over 800,000 bicycles in 855 cities (Fishman, 2016a). Simultaneously, a number of car sharing systems have also been put in place. Today, car sharing has grown to include approximately 18 nations and 4 continents (S. A. Shaheen & Cohen, 2008). The numbers in this particular sector are not trivial, recently the world's largest car sharing network, Zipcar, announced that by September of 2016 it would have reached 1 million members (Zipcar., 2016). Not by chance, the projected market growth has an annual rate of 30% according to the strategy consultant firm Roland Berger (Berger, 2014) and by 2020 the revenue forecast is between 3.7 and 5.6 billion of euros.

This accelerate expansion, carries -naturally- particularities and impacts for each mode, that have caught the attention of the stakeholders involved in the urban mobility and also of researches in several fields. The first part of this chapter focuses on reviewing the main literature about sharing modes our study is focused to: bike sharing and car sharing.

The second section addresses, given the volume of mobility data we need to handle in the study, how some researches attempted to apply Big Data analysis techniques to mobility aiming the extraction of useful information. On one hand technologies like *GPS* and *smart travel cards* able data collection and, on the other hand, the availability of modern software that can handle with huge amounts of data facilitate the spreading of this type of analysis also in the mobility field.

Subsequently, the information extracted by Big Data analysis can be employed to evaluate mobility performances that can be synthetized into key performance indicators (KPIs). A review of the most used KPIs in mobility is the scope of the third and last section.

3.1 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 -like in the car sharing and bike sharing case- and provide users with different forms of services.

3.1.1 Bike Sharing

The expansion of the bike-sharing programs is evident. The number of cities operating a BSP (Bike sharing program) has increased from 13 in 2004 to 855 as of 2014 (Fishman, 2016a). This development had catches the attention of several researches who have wondering mainly: the profile of the users, the barriers and incentives to join the system and the possible impacts in terms of mode substitution, health and environmental benefits.

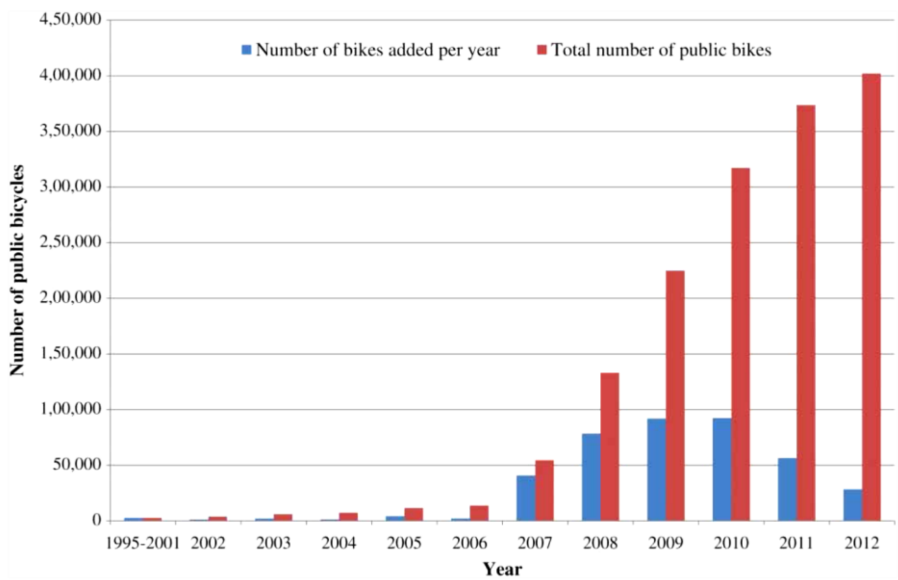


Figure 1. Global growth in bike share programs.
Source: (Fishman, Washington, & Haworth, Bike Share: A Synthesis of the Literature, 2013)

User preferences and impacts

Concerning user preferences, the main perceived benefit of bike sharing programmes (BSPs) is *convenience*, particularly Capital Bikeshare in Washington, D.C. performed a survey were 69% of respondents noted "get around more easily, faster, shorter" as 'very important' in their motivation for bikeshare use (LDA Consulting, 2013). A stimulus aligned with responses also in London and in the programs in Australia. Subsequent motivations are near-by work docking stations, heath benefits, fun, and environmental benefits as shows the figure below.

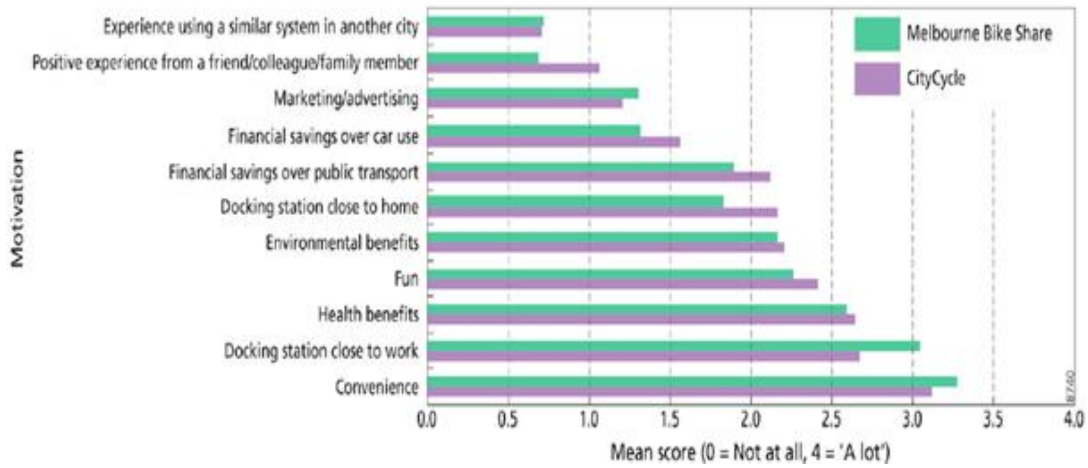


Figure 2. What motivated you to become a CityCycle/Melbourne Bike Share member? Source: (Fishman, 2016a)

The main motivations of the users also involved actively the attention of other stakeholders, such as the provider (service level, docking station location, promotion) and the public administration (health and environmental benefits). Indeed, efforts have been made trying to identify the extent and implications of the mentioned effects.

Concerning health benefits, the focus is mainly correlated with level of physical activity achieved with the program from both, an individual and a societal level. An active mobility has been identified as one central feature of a 'healthy city' (Woodcock, Tainio, Cheshire, O'Brien, & Goodman, 2014) and it has been manifest that to promote and maintain health, all healthy adults 18–65 years of age need moderate-intensity aerobic physical activity (De Hartog, Boogaard, Nijland, & Hoek, 2010). The benchmark of the desired level of this activity, according to the World Health Organization (WHO), is of at least 150 minutes in the moderate-intensity stage throughout the week.

On the other hand, in many European cities, support for cycling in daily mobility is considered an efficient mean to reduce air pollution, traffic jams, and carbon emissions (Jäppinen, Toivonen, & Salonen, 2013). BSP (bike sharing program) of Milan actually provides to its users a feedback of the CO2e (carbon dioxide equivalent) savings of each trip. The CO2e is a universal unit of measurement that allows the global warming potential of different greenhouses gases to be compared. The same scenario can be evaluated with car sharing mobility companies that deals with electric cars, like *Share'nGo*.

Other studies focus on the question: is bike sharing a substitution mode of transportation to private car? This refers to an implicit assumption: thanks to bike sharing a significant proportion of users would give up with private vehicle transportation. This has been proven to be an optimistic assumption.

The literature reports a little impact of bike sharing on private car use. As shown by several studies - in Washington DC (LDA Consulting, 2013), Melbourne and Brisbane (Fishman, Washington, & Haworth, 2014a), London (Transport for London, 2010) and Minnesota (Nice Ride Minnesota, 2010) – most of them summarized in Figure 3 (Fishman, 2016b) -public bikes are substitutes mainly to other sustainable modes such as walking or public transportations.

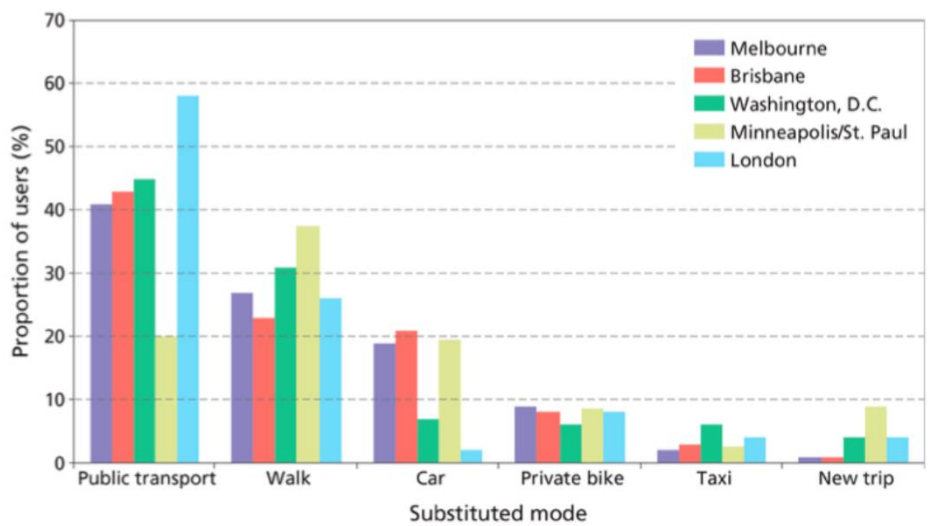


Figure 3. Mode substitution.
Source: Melbourne and Brisbane (Fishman, et al., 2014a), Washington, D.C. (LDA Consulting, 2012), Minnesota (Nice Ride Minnesota, 2010), London (Transport for London, 2010).

Despite the negative result obtained in London (only 2% of car mode substitution rate), a survey conducted there in 2010 shows a positive influence of bike sharing program in encouraging cycling with 60% of respondents that begun to cycle in the previous six months, probably due to the bike sharing program that have been introduced few months before the period of the survey (Transport for London, 2010). Low car mode substitution rate resulted from a similar study conducted in North America (S. A. Shaheen et al., 2010). As stated by Fishman, et al. 2016, further studies on this topic are required.

A summary of the factor affected by bike sharing, can be found in the Figure 4, introduced by Efthymiou, Antoniou, & Waddell (2013), where it shows that bikes have the potential to benefit traffic congestion and parking-shortage problem while providing health benefits, but in terms of infrastructure it requires bike lanes (in charge of Public Administration) and docking stations.

		Bike-sharing
Factors affected		
Transport	Traffic	✔
	Parking demand	✔
Social-environmental	Emissions	✔
	Time	✔
	Cost	✔
	Urban design	✔
Personal	Physical health	✔
	Psychological health	O
Before and after installation concerns and amenities		
Installation	Infrastructure	✖
	Parking	O
	Insurance	✔
Information Technology	GPS tracking	✔
	Internet booking	✔
	Telephone booking	✔
Movement	Gasoline	✔
	Electricity	O
	Human power	✔
Other	Flexibility	✔
	Access	✔

✔ Positive O Unclear or insignificant ✖ Negative.

Figure 4. Bike sharing impacts

Barriers and incentives

Even if barriers to bikeshare is a critical topic for public administration and private providers that want to boost the usage of this mode, few studies focus their attention on that. The main barriers founded are lack of convenience and competitive advantage with other modes, safety concerns and anything that makes the experience not immediate (e.g. fuzzy subscription processes) (Fishman, 2016b).

A study conducted in Brisbane on *CityCycle* regarding the main barrier to join a bikeshare program

A similar study on user of *CityCycle* (Brisbane's BSP) reported one third of them not willing to re-subscribe the program. The main reasons were the mandatory helmet laws and the subscription process. Moreover, 54% of short-term subscribers pointed the subscription process as the main area to improve (Roy Morgan Research, 2013). Even if *CityCycle* case is particular since is one of the only modern programmes that do not allow subscription on the spot it is clear that users look for an easy and fast experience when subscribing.

The helmet concern is not always present since it depends on country rules. In Seattle the BSP estimated a 30% of reduction in bikeshare usage due to the mandatory helmet law. Some providers tried to solve the problem making helmets available in each docking station dealing with costs and issues related to this measure. Anyway studies have shown that for those who do not ride a bike there are higher barriers to the program than mandatory helmet (Fishman et al., 2013).

User profile and usage rate

A study conducted in Milan in 2015 reveals that the average BikeMi – Milano's bike sharing service – is a 41 years old male professional who cycles to work for the last mile of his daily commuting journey (Saibene & Manzi, 2015). The same study reveals that the majority of users are managers or consultant/entrepreneurs (26,53% for male and 19,87% for female respondents) and that more that 25% of them lives outside Milan's urban area. (Saibene & Manzi, 2015) state also that the daily usage rate of each bike in 2013 was almost two and provide a map of the city that highlights the most important area in terms of check-ins (Figure 5).

Rebalance

Another branch of researches about bike sharing programs is the one related to the rebalancing issue. Rebalance refers to the activity – perform by service operators - of moving bicycles across the network to maintain a reasonable distribution across docking station (Fishman, 2014). Peaks and "tidal flows" in fact lead to have some stations full of vehicles while other (almost) empty. A trade off occurs between the significant cost of rebalancing and the lack of reliability that affects user's satisfaction.

To help solving this trade-off many researchers individuated and studied the factors influencing the level of activities of the docking station such as weather and topography. (Faghih-Imani, Eluru, El-Geneidy, Rabbat, & Haq, 2014; Frade & Ribeiro, 2014; Jurdak, 2013; Rudloff & Lackner, 2013). Other investigates solution such as altering the price (Parkes, Marsden, Shaheen, & Cohen, 2013) or incentives to achieve fleet redistribution (Fricker & Gast, 2014). (Pfrommer, Warrington, Schildbach, & Morari, 2014) for instance suggested a hybrid scheme that relies on both user and operator redistribution given that while incentives may be sufficient during weekends, operator's activity is required during the week.

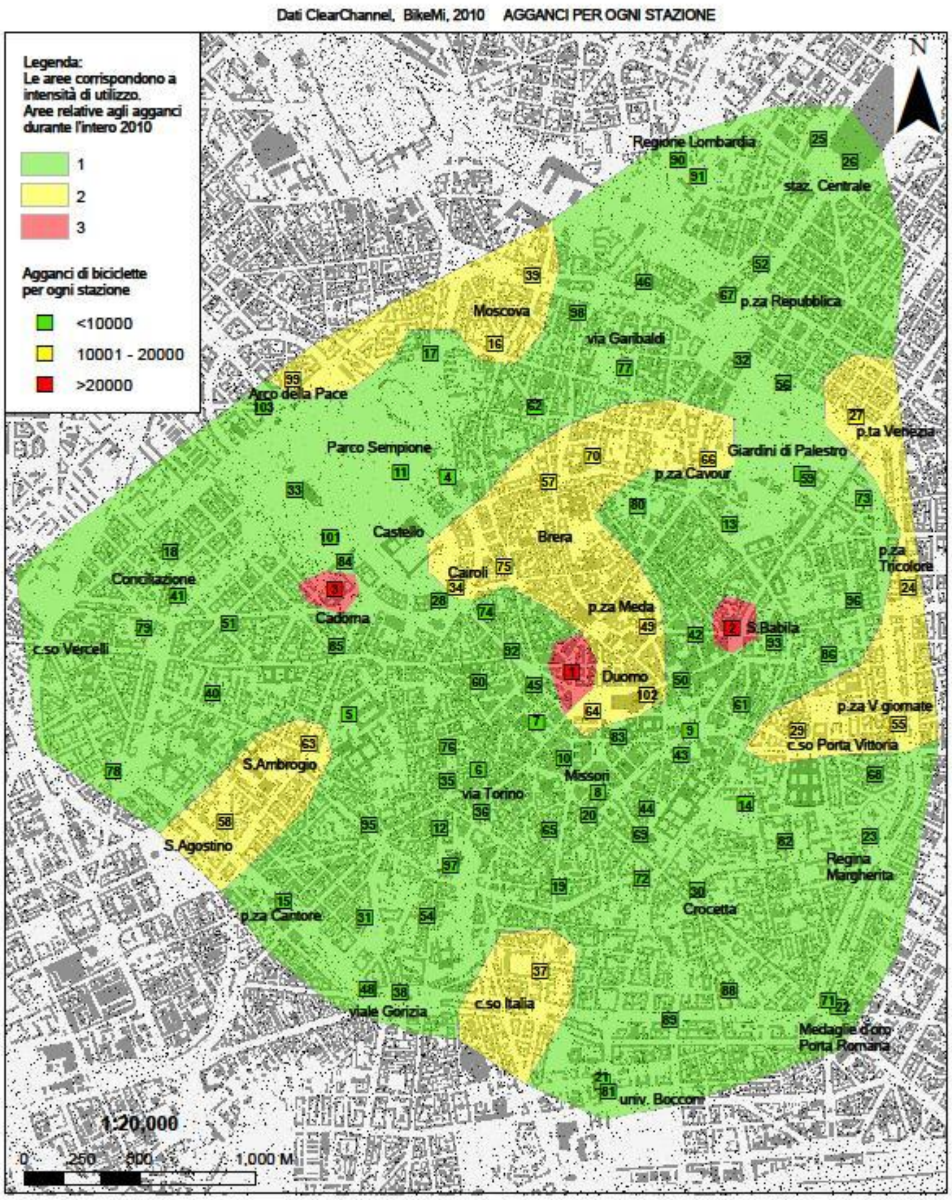


Figure 5. Milan's important area in terms of BikeMi's bikes check-ins (Saibene & Manzi, 2015)

3.1.2 Car Sharing

Even if car sharing is having its momentum and several players entered in the market in the last few years it is not a brand new concept. It was introduced in Zurich in 1948 (S. A. Shaheen & Cohen, 2008) but only recent cultural and economic changes (treated in the previous parts) made it popular since 90s and permitted its "boom" in the last decade.

The idea is simple: users can enjoy the privacy of potentially any type of car without the commitment of a purchase, maintenance and insurance costs but basically paying for the use. Those benefit could be already sufficient to attract young people such as students or whoever for whom car ownership is difficult to afford. 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).

User characteristics and behaviour

Results from the first type of researches confirmed what could be drawn from the general value proposition of CSPs (car sharing programmes) namely that the usage is recommended to users that drive no more than 10,000-16,000 km per year (S. A. Shaheen & Cohen, 2008), to students and low-income households (S. Shaheen, Schwartz, & Wipyewski, 2004). The "join the model" scheme introduced by Efthymiou et al. (2013) showed that people belonging to a low-mid income class (15-25K Euros) are more likely to join CSPs. Similarly, study conducted in Austin revealed that adults of higher income have no will to join the scheme (Zhou & Kockelman, 2011). Moreover, members are usually well educated and they care about environmental issues. Due to insurance restriction for young drivers the highest concentration is between 25 and 35 years old and half of the members have income more than 60,000$ (Burkhardt & Millard-Ball, 2006). Furthermore, 72% of the users do not have other cars in their households and the average households size is 2.02 persons (Burkhardt & Millard-Ball, 2006).

To the first category belong also studies related to benefits and adoption barriers. Understand which are the factors that affect the willingness to join car sharing (and bike sharing) programmes are very relevant for policy maker whose aim is to foster a better and better mobility and for service providers to understand their customers. According to a research conducted on both bike and car share main benefits are the reduced cost, environmental benefits of sharing, ease of parking, social benefits and freedom of responsibility for the vehicle (May, et al., 2008). Partially in contrast to that statement are the results from an analysis conducted on users of Zipcar, a US car sharing company (Bardhi & Eckhardt, 2012). According to it, consumers are not motivated by altruistic concern or pro-social reasons but only from *convenience*, thus they act in a utilitarian way. Applying the *six dimension* of access based consumption to car sharing with the help of semi-structured interviews Bardhi et al. identified car sharing as a "unique non-ownership mode" that is close to commodity exchange and contrasts the altruistic model of sharing. This lead to a lack of identification with the vehicles, a use value dominance, a negative reciprocity among users and a "big brother" governance mechanism based on penalties for actions that damage other users. Moreover, users are not willing to be part of the brand community (Bardhi & Eckhardt, 2012). All this concerns are probably related to the high level of market mediation in CSPs (car sharing programmes) that position them far away from a sharing context.

Efthymiou et al. (2013) state that most important factor affecting car sharing (and bike sharing) adoption are related to the stations' positions meaning their distance to potential users' house or job. Again according to them other important factors are the possibility to hand over a vehicle in a station different from the one it was picked up and the ability to return it without informing service provider. CSPs offering that advantage are named free-floating services (e.g. Enjoy in Milan). Besides, potential users seem to be indifferent to the use of electric vehicles.

Impacts of car sharing

Several studies had highlighted the importance of car sharing to achieved sustainable urban mobility, especially when still for many people private cars are the first transport choice due to its convenience and mobility (Qu, Yu, & Yu, 2017a). An efficient car usage is crucial, particularly in Europe, where 80% of cars circulating in the city travel no more than sixty minutes a day carrying an average of 1.2 people (Zavaglia, 2016). This is aligned with other worldwide studies that estimated that a car owner has his car parked 92% of vehicle's lifetime, 1% caught in traffic jam, 1.6% looking for parking and the other 5% driving. (MacArthur, Zumwinkel, & Stuchtey, 2015)

Automobile usage is a major source of air and noise pollution and improper use of private car is responsible for many of the serious environmental problems (Qu et al., 2017a). Categorized as one of the best practice, car sharing is expected to become an efficient sustainable transport service, able to limit the use of private cars and to facilitate multi-modality for public transport (Zavaglia, 2016) helping individuals to maintain a high level of mobility meanwhile.

The beneficial effects that car sharing can produce on the environment are the loosening of the grip of vehicle traffic in urban centres and the promotion of a more rational individual behaviour of an energy intensive transport. So far, on the literature, the sustainability transport index covers typically traditional transport modes measuring for example the usage of fossil fuel energy for transport (Gilbert, Irwin, Hollingworth, & Blais, 2003), considering that a sustainable transportation system is the one that minimizes consumption of non-renewable resources. Others have considered assessing sustainability through the amount of Greenhouse gas emissions (GHd), to make it comparable, customizing this classic measure per capita and by mode (Gillis, Semanjski, & Lauwers, 2015). These techniques are not particularly hard to translate to a sharing mobility environment, nevertheless the actual computation have not been the main focus on the car sharing area. On this field (Qu et al., 2017a) developed an approach that evaluates these and other indicators for car sharing environment but without a data driven method, that is, considering it mostly under uncertainty, having as an output only potential options.

Figure 6, introduced by Efthymiou, Antoniou, & Waddell (2013), summarizes and compare social, environmental, personal and transport effects car and electric car sharing systems. Besides the fact that both modes benefit traffic congestion and parking-shortage problem, differences occur for example in infrastructures requirements. Electric vehicles require recharging points while car sharing does not require any particular infrastructure even if parking reservation is a main issue (Shaheen et al., 2010b, 2010c). Obviously carshare does not offer direct health benefits.

		Car-sharing	Electric Car-Sharing
Factors affected			
Transport	Traffic	✔	✔
	Parking demand	O	O
Social-environmental	Emissions	O	✔
	Time	✔	✔
	Cost	O	O
	Urban design	✔	✔
Personal	Physical health	✖	✖
	Psychological health	O	O
Before and after installation concerns and amenities			
Installation	Infrastructure	O	✖
	Parking	✖	✖
	Insurance	✖	✖
Information Technology	GPS tracking	✔	✔
	Internet booking	✔	✔
	Telephone booking	✔	✔
Movement	Gasoline	✖	✔
	Electricity	✖	✔
	Human power	✖	✖
Other	Flexibility	O	✖
	Access	O	O

✔ Positive O Unclear or insignificant ✖ Negative.

Figure 6. Car sharing impacts

Service optimization and rebalance

Vehicle repositioning or rebalance has been one of the most studied subjects on the sharing mobility systems, falling usually into the scope of the operational research community. The flexibility of the free-floating Car Sharing Systems –where users do not need to return to the station of origin- tends to lead to a vehicle relocation problem, which should be addressed carefully to avoid concentration of vehicles in certain areas of the city (Febbraro, Sacco, & Saeednia, 2012).

The spatial distribution of vehicles within this system is either self-organized, which means it is only dependent on the customer's demand or in a few cases the positioning is manually controlled by system operators. On practice, none of the known free-floating Car Sharing Systems has a clear defined relocation strategy or is online optimized based on the current demand (Weikl & Bogenberger, 2013).

The dynamic relocation problems, in which cars must be relocated throughout the day by employees working on different shifts, are formulated minimizing the generalized cost that regularly includes relocation cost and, staff cost, and penalty costs for rejected demands (Kek, Cheu, Meng, & Fung, 2009). While, the programs which assumed that the users will sometimes be requested to relocate their car at the end of their trip have the aim of minimize the rejection ratio of reservations (defined as the percentages of the reallocation request refuses by the users) in any period of the day, stressing the importance of offering adequate discounts to users in order to incite them to relocate their car (Febbraro et al., 2012).

Relocation is a key point for managers, since leaving the system on its own without intervention has serious disadvantages – even do, apparently it saves costs and working time-. In a self-organized system, the few frequent users might adapt the system to their behaviour, so that it is difficult to gain new customers. Furthermore, the vehicles might get stuck in areas of low demand causing a loss of money. Finally, if no intervention is carried out to improve the system, no knowledge of the system optimum both for the users and the system owner is available (Weikl & Bogenberger, 2013).

3.2 Mobility and Big Data

As mentioned before, in relative terms, there are few studies with a data-driven approach focusing exclusively on the access based consumption arena. In fact, also from an overall perspective, a quite large number of empirical studies on general mobility rely on travel surveys, because they provide detailed descriptions of demographics, place of residence, and travel attributes at an individual or household level to support modelling (Calabrese, Diao, Di Lorenzo, Ferreira, & Ratti, 2013). Nevertheless, travel surveys hold important limitations, they usually can only cover a small sample, have a restricted space-temporal scale and are perform with low frequency.

Nowadays, these limitations, can be overtaken by the amount of real-time data collected, and sometimes, available of the urban ecosystem.

Particularly for a mobility perspective, a rich amount of information containing individual's coordinates is automatically recorded 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, Schneider, Ukkusuri, & González, 2013). There is now an increasing momentum in the analysis of networks and flows in cities using data that are collected routinely from digital sensors that pertain to the movements of travellers.

The challenge remains in the exploration, preparation and characterization of the data. Some types such as the GPS data have an accurate granularity and detailed spatial-temporal travel information. 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.

Falling also in this category, one innovative and recently spread 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, the mobile phone trace data provide researchers new opportunities to examine individual mobility from an alternative perspective with a lower collection cost, larger sample size, higher update frequency, and broader spatial and temporal coverage, in other words, this datasets allow for studying individual mobility of millions of people across the metropolitan area over a longer time period (Calabrese et al., 2013).

So far, some studies that utilizes CDR data or mobile phone traces for studying mobility have had as an aim: predicting traffic zone -commercial or residential- division of a city (Dong et al., 2015); computing the regular mobility analysis in terms of congestion -volume/capacity- of a road, and travel times for road segments (Toole et al., 2015), or understanding the intraurban variation of mobility and the non-vehicular component of overall mobility (Calabrese et al., 2013).

In general, data driven studies could enable researchers to better understand the laws governing people's movements and improve the efficiency and responsiveness of urban policies. But as stated before, this level has not been developed or explored extensively with new transportation modes, as the access based consumption ones. Nevertheless, is a remarkable opportunity, especially since the new players, such as the IT platforms emerging on the scenario, gathering mode's availability and status manage to collect, upload and share the required information.

3.3 Mobility KPIs

Performances indices are relevant to planners and decision makers that intend to reduce the complexity and volume of performance-related data that must be regularly monitored or factored into a specific decision (Kaparias et al., 2012). In the transportation field, one of the issues highlighted by the literature is the fact that a deep multidimensional evaluation of the mobility of a city is strongly attached to its contextual situation -depending on the actual policies and infrastructure (Kaparias et al., 2012). Therefore, due to the complexity and singularity involved in mobility topics, most of the transport scientific papers delimitate their focus into individual scheme measures supporting typically tactical or operational decisions, which are related with infrastructure and resources utilization in the first case, and traffic flow control and demand management in the second (Farahani et al., 2013).

One way to approach the situation is to cover and interconnect single indicators from different dimensions. (Alonso, Monzón, & Cascajo, 2015) proposed the concept of "composite indicators" on the basis of a benchmarking approach recognising the 9 most significant factors in the sustainability evaluation of transport system for European cities. (Qu et al., 2017a) proposed 24 indicators for transport systems from four dimensions: economic, environmental, social and system performances. Following a similar line, (Gillis et al., 2015) applied SMART (Specific, Measurable, Achievable, Relevant, and Timely) methodology identifying a list of 22 indicators for sustainable mobility evaluation from four dimensions: global environment, economic success, quality of life, and performance of the mobility system.

Despite the dimension coverage, or the way the indicators are derived, the mobility indicators selection, according to (Haghshenas & Vaziri, 2012) must follow certain criteria:

- Target relevance: each indicator must show one aspect of transportation.
- Data availability and measurability: indicators must be measurable with the accessible data;
- Validity: indicators must actually measure the issue it is supposed to measure;
- Sensitivity: able to reveal cities sustainable transport changes;
- Transparency: should be easy to understand and possible to reproduce for intended users;
- Independent: indicators should be independent of each other's;
- Standardized: indicators should be standardized by city size for comparison.

Aligned with the criteria, (Gillis et al., 2015) and (Litman, 2007a) coincided with 5 properties, that can be adapted for the car sharing mobility modes. An indicator should be:

1. Specific: indicator stands for a relevant aspect of car sharing option exactly and can be assessed independently;
2. Comprehensive: should cover all relevant aspects of a potential car sharing option and reflect its economic, environmental, social and system operational performances comprehensively. With a focus on personal transport of car sharing systems;
3. Understandable: clear for decision makers and for the general public to ensure that they represent the actual degree of achievement as to the particular objective. The more information included, the less understandable they are;
4. Measurable: with enough accurateness. Data collection should be easy to conduct and standardized to ensure comparison between different options; and,
5. Neutral: Indicators themselves do not favour or disfavour a particular type of mode sharing service.

From an institutional point of view, it has been also evident the challenge of determine a common framework for mobility, which manage to integrated, not only several dimensions, but an operational, tactical and a strategic level. The Transportation Planning Handbook (Meyer, 1992) shows the performance reporting hierarchy used by VicRoads (the state's transportation agency) in Victoria, Australia, which deploys its 5 levels in following a thoughtful chain of command.

In the base line the context information is evaluated, that is, the conditions of the available infrastructure in terms of location, route, section and area. Acknowledging that infrastructure shapes mobility, and that no major change in transport will be possible without the support of an adequate physical network (European Comission, 2011). The following section inspects the previous evaluation programs and its conditions, emphasizing the role of continuous improvement of the process, this also supported by the subsequent piece, which examines the level of integration between the planning process and the programming one. Finally, the last two pieces are feed by the operational performance measures and the impact of those measures with the major goals.

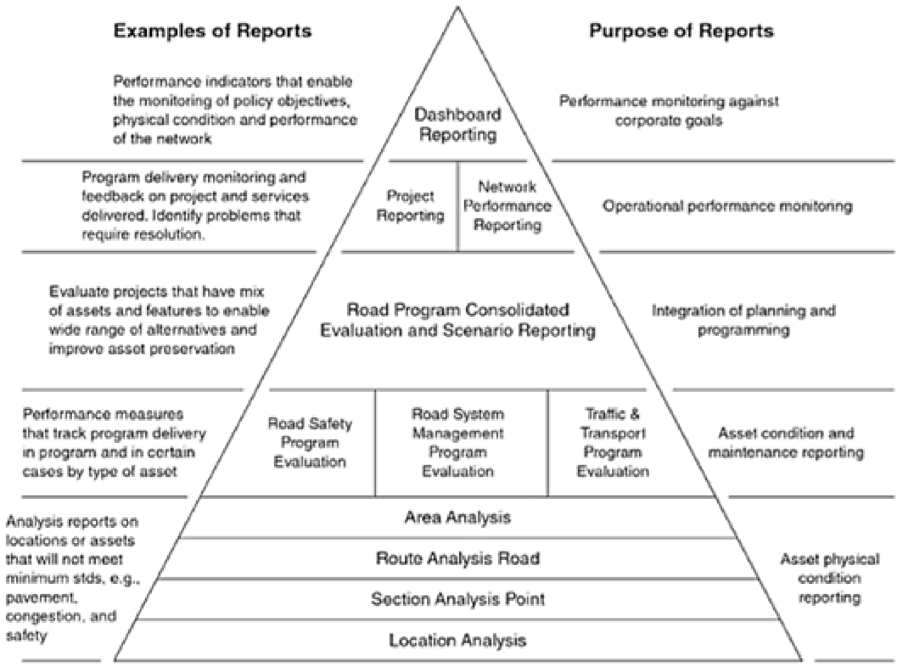


Figure 7. Performance Reporting Hierarchy. Source: FHWA, 2005

On its side, the European Commission, has established as one of its objectives to set up Urban Mobility Plans, and organize a European Urban Mobility Scoreboard based on common targets that can be derivate from goals of urban traffic management (EC–European Commission, 2011). In particular, four strategic themes or goals have been tackled (Kaparias, 2012): Traffic efficiency, traffic safety, traffic pollution reduction, and social integration and land use. These four goals are clearly affiliated with the dimension selected for this research.

Traffic efficiency:

The quantification of the performance in terms of traffic efficiency is a common denominator in most of the urban traffic management policies. It expresses the easiness or difficulty of carrying out trips.

The primary consistent performance measure of mobility is the *average travel time*, defined simply as the time required to traverse a segment, addressing in this way the intensity of the congestion component (National Cooperative Highway Research Program, American Association of State Highway, Transportation Officials, & Cambridge Systematics, 2008).

Complementing its traffic efficiency indicator, (Kaparias et al., 2012) consider a pondered weight sum of the travel time given the particular route or zone of the city for each type of transportation.

Traffic safety:

Safety remains a central issue in transport planning. Improving road safety refers to a reduction in the expected number of accidents, a reduction in injury severity or a reduction in the rate of accidents or injuries per kilometre of travel (National Cooperative Highway Research Program et al., 2008). This particular item differs considerably for some mode of transportations: bikers and pedestrian are considered in general vulnerable users. In the Netherlands for the 2008 there were about 5.5 times more traffic deaths per kilometre travelled by bicycle than by car for all ages, and cycling was riskier than travel by car for all age groups except young adults (De Hartog et al., 2010; Haghshenas & Vaziri, 2012). Therefore, safety, is a item of singular attention specially for the recent expantion of PBS in several cities allover the world.

(Kaparias et al., 2012) introduces its indicator contemplating weight factors for specific accidents, severity categories, traffic modes and also a weight for the importance of the link where the accident occurs.

Other studies, that focus mostly in bike sharing programs attempt to measure if the health benefits associated with biking eventually overcomes the risk of traffic accidents that involves this mode. The results of the study (De Hartog et al., 2010; Haghshenas & Vaziri, 2012; Woodcock et al., 2014) suggest that on balance, the programme in London delivers more benefit than harm, but this effect is not equally distribute for all age groups or gender.

Traffic pollution Reduction:

Mobility plays an important role in global sustainability. The transportation sector accounts for 22% of primary energy use and 27% of CO_2 emissions all over the world (du Can, Stephane de Ia Rue & Price, 2008). An amount not composed mainly by freight transport, since individual mobility uses about two thirds of the total transportation energy (Calabrese et al., 2013). Therefore, policy makers and providers from a strategic point of view must be prompting a modal shift of the demand, and simultaneously, from a tactical an operational approach need to be encouraging greater service level and efficiency in the transport system.

The scenario is challenging since, despite the efforts, the reality is that the transport system is not sustainable. Looking 35 years ahead, developing along the same path, the oil dependence of transport might still be little below 90%, with renewable energy sources only marginally exceeding the 10% target set for 2020. CO2 emissions from transport would remain one third higher than their 1990 level by 2050. Congestion costs will increase by about 50% by 2050 (EC–European Commission, 2011).

No doubts, that measuring traffic pollution is a key step for any mobility plan, this can be demarcated by: air pollution and noise pollution

- Air pollution: correlated with the most important type of emission. The influence of a vehicle to the Greenhouse effect is measured usually in carbon dioxide equivalents;
- Noise pollution: This type of indicator effects mostly life quality of a city, since permanent disturbance in cities can have a significant impact in human health and motorised road transport is a major source of noise pollution in urban areas.

Given the above, the characteristics of the service providers play a key role in the urban transport ecosystem, they must be suitable to cover the demand, and most importantly, they should be able to engage users for doing it in a sustainable way.

Social Integration and land use

Finally, is important to track the space consumption of the transport systems and the density of passenger they support. The goal from the European commission consist in a higher share of travel by collective transport, combined with minimum service obligations, that will allow increasing the density and frequency of the service, generating in this way a virtuous circle for public transport modes. (EC–European Commission, 2011). It has been stablished that demand management with land-use planning can impact positively traffic congestion.

4. Research Justification

The majority of the approaches studying sharing mobility modes has been carried out to circumscribe user preferences, user frequency and barriers or incentives, using regular surveys to members. Similarly, it has been deployed demographic information of the user's profile: sex, age, level of income, ethnicity, etc. The more data-driven studies have tackled the relation between certain factors such as weather and near-by locations of the vehicles with the level activity of the services. Is important to highlight that a data-driven approach allocating the trips in the urban areas, which is common in most of the traditional mobility researches, has not totally explored access based consumption modes yet. Probably because the topic still carries a socio-economic and cultural transformation that is still far to entirely be defined, and therefore most of the inquiries are allocated in understanding first its nature.

For instance, in the analysed literature, there is an evident lack of studies approaching sharing mobility with a network perspective. This approach facilitates to link the analysis of mobility data to the urban spatial structure of a city offering a way to study and represent data tracking people's movement in an area. Given the fact that mobility data required to develop this type of studies are already available – even if, sometimes, they are not public – it would be a loss of opportunity not to use them.

Mobility service providers, in fact, generally track users or vehicles movement to optimize the service even if they have just a slice of the total information. What is missing is a third impartial actor that gathers information by all the single providers and integrates them to find out insights about the mobility system of a city as a whole. Those findings would be useful to all the stakeholders – e.g. providers and public administration could better tailor mobility project to cover effectively mobility needs. Digital platform providing comprehensive interfaces to users, such as Urbi, could play this role since they already have access to the information thanks to partnership with service providers. This would help to promote a cooperative user-centred environment.

No studies about the sharing mobility as a whole system have been delivered yet in Milan. Besides, although Italy is the country with the highest number of active bike sharing systems, few local studies has been published on this topic if compared to cities like London and Paris where "ad hoc" research centres has been established with the development of BSP (Saibene & Manzi, 2015).

For the reasons reported above, our purpose is to provide a comprehensive study of the overall sharing mobility system of Milan - pointing out similarities and differences of the two most common sharing modes- using the theory of networks. This way is possible to understand the mobility needs that each one of the sharing modes is covering. Moreover, the analysis of their networks will remark in which area of the city each mode has a higher impact in terms of usage and efficiency. This is a starting point, e, that could eventually be extended by other researches in order to cover other cities and integrate also the analysis of traditional transportation modes.

5. Theoretical Framework

This chapter contemplates the theoretical frame required to understand the following discussion of this paper. It is divided into two parts.

To face the challenge of studying mobility patterns in a city several tools has been deployed, one of the most relevant due to its approach that facilitates the modelling and analysis of complex systems, are networks. That is the reason why the first part provides the definition of a network structure and its properties, eventually highlighting how them are perceived and adapted in the mobility environment. Besides it considers also analytical tools to better study the structure of a network, such as clustering methods.

The second part moves to a more managerial side that defines the good practices needed to design a performances measurement system in a transportation environment. Explicitly here, we evaluated the criteria performance measures need to satisfy and its development process. The whole section maintains the focus on the urban mobility field.

These two main topics (networks and performances) represent the technical support of our research. Network theory, on one hand, was requested to understand what is worthy to be measured in a network and what information can be drawn from it. Performances measurement theory, on the other hand, was fundamental to translate the research objectives into a synthetic set of indicators that fit them and that take into account the actors those indicators could be useful to.

5.1 Networks

A network is, in its simplest form, a collection of points, called *vertices*, joined together in pairs by lines or *edges*. A network can be directed or undirected, in the first case each edge has a direction, pointing from one vertex to another, as illustrated in Figure 8. The natural representation of a network is a *graph* and it is useful to capture the notion of elements in a system and their interconnectedness. Networks resembling transportation movements-from origin points to destinations- are called *Flow networks* (Kolaczyk & Csárdi, 2014)

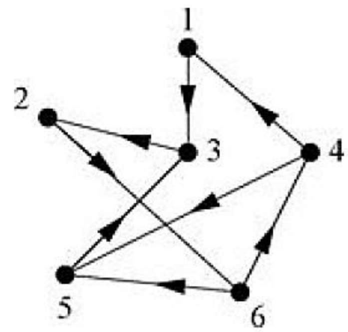


Figure 8. Representation (graph) of a directed network with 6 vertices.

In most of the flow or transportation networks studied the vertices representing geographic locations and the edges routes between them. For instance, in studies about road networks the vertices usually represent road intersections and the edges roads. Another usual representation is when vertices represent locations and two vertices are connected by an edge if a single trip runs between them (Newman, 2010). The road flexibility of the free floating access-based consumption modes, where the road is not fixed and can vary every time according to the user and the conditions, drove this study in the second type of representation that is: vertices as geo-graphical locations and edges that emerge if a trip happens in between two vertices during the period of analysis.

One of the conditions for a network to be a *simple network* is that the vertices should have only on/off connections (with only one edge in between). In this case, the information about the intensity of relationships between pairs of nodes is maintained by adding a weight to each edge. A network with weights-, is called *weighted network*.

Besides the intuitive bond among people flows and network's representation, another reason to explore mobility patters with this simple and yet robust tool, is that in the last years, it has been accompanied with a facility for high-throughput data collection, storage, and management (Kolaczyk & Csárdi, 2014), supported mainly thanks to statistical software packages that provides analysis of network data.

The *weighted networks* mentioned before are networks that have the intensity of connections – measured by a weight - as an attribute of each edge. Nevertheless, weights are not the only characteristics that can be consider between a pair of nodes. In general, any value of variables indexed by adjacent vertex pairs is an edge attribute.

Edge attributes values can be of both discrete and continuous. Examples of discrete edge attributes include whether one gene regulates another in an inhibitory or excitatory fashion, or whether two countries have a friendly or antagonistic political relationship (Kolaczyk & Csárdi, 2014). Continuous edge attributes, on the other hand, often represent some measure of the strength of relationship between vertex pairs. For example, we might define an attribute on edges between adjacent stations in a subway network to represent the average time necessary during a given hour of the day for trains to run from one to station to the next. (Kolaczyk & Csárdi, 2014).

For flow networks, time and distance is an important attribute to consider between the nodes. Also, regarding the availability of information and the target, road capacity or speed constrains tend to be useful attributes. In a similar way, is possible to add attributes also to the vertices of a network. In transportation networks for instance, infrastructure facilities -e.g. railway, subway, bus lines- of locations can be considering as relevant information to be attached to the corresponding node.

What to measure in a network?

Even do, visualization is an important part of a network analysis, is only really useful for networks up to a few hundreds or thousands of vertices, and for networks that are relatively sparse, meaning that the number of edges is quite small (Newman, 2010). Nevertheless, the structure of a network can be also explored through the calculation of a variety of useful quantities and measures that capture particular features. In general, despite the topology of the network, a general question that arrives from a network study is: Which are the most important or central vertices and edges in a network?

In the considered field, this question will arrive as: Which are the most important locations and the most frequent trips in Milano's transportation network? To answer properly, it is imperative to define what is intended as "important" from a mobility point of view and to understand centrality measures of a network.

5.1.1 Properties and measures

As stated, graphs are used to study and visualize networks thus they are graphical representation of networks. Anyway, in the following sections network and graph are used as synonymous.

The number of vertexes of a graph gives its the *degree* while the number of edges gives its *size*. In the following study we will denote the vertices by n and the number of edges by m, following the notation in the literature.

The maximum number of edges, and therefore all the possible connections between each pair of vertices that represent the maximum size of a simple graph is:

$$\binom{n}{2} = \frac{1}{2} n\,(n-1).$$

In the case of a directed graph with self-loops, when every node can be connected to every other node and also to itself, the maximum number of edges arises to n^2.

The density ρ of a graph is the fraction of edges that are actually present. For a simple graph it can be calculated as follow:

$$\rho = \frac{m}{\binom{n}{2}} = \frac{2m}{n(n-1)}$$

The density lies between the interval $0 < \rho < 1$. In a network with density close to 1 each vertex has direct connection to almost all the others. The density in a flow or transport network, for example refers to the percentage of locations or geographical points directly connected between them.

The information about vertices connections can be synthetized in a matrix, called *adjacency matrix* (Newman, 2010). The adjacency matrix A of a simple graph is the matrix with elements A_{ij} such that

$$A_{ij} = \begin{cases} 1 \textit{ if there is an edge between vertices } i \textit{ and } j \\ 0 \textit{ otherwise} \end{cases}$$

An example of an adjacency matrix is provided below.

$$A = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix}$$

In general, two vertices could be connected by more than one edge. In this case we have a *multi edge* or *multi edges*. Moreover, an edge could connect a vertex to itself and when it happens we name it *self-edge* or *loop*.

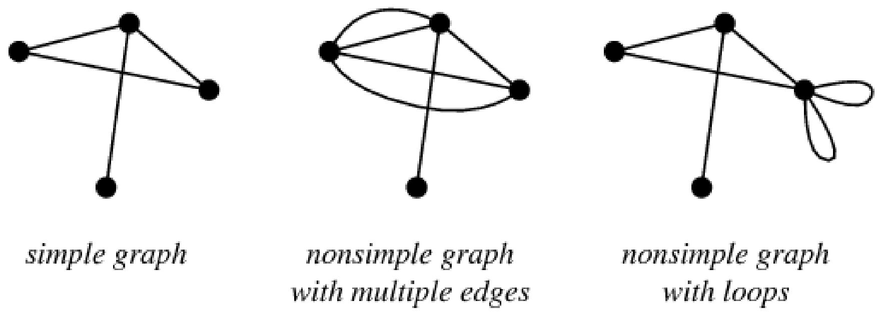


Figure 9. Simple and non-simple graphs

As observed in the Figure 9, a network without multi edges and self-edges is called *simple network* or simple graph otherwise it is called *multigraph*. It is possible to simplify a non-simple graph eliminating multiple and self-edges. The information contained in multi edges can be kept by adding weights or attributes to the simplified graph.

There are mainly 3 properties associated with networks: *centrality*, *betweenness*, and *cohesion*. This section, takes a close look to each one of them.

Centrality in a Network

A vertex can be relevant within a graph for several reasons, that is why there are several measure of *vertex centrality*. The most widely used is the *vertex degree*. The degree of a vertex is the sum of edges connected to it. In directed networks there is a distinction between in-degree and out-degree, considering separately the edges that stem from and the ones that arrive to that vertex.

A useful generalization of vertex degree for weighted networks is *vertex strength*. The strength of a given vertex is the sum of the weights of all edges incident to that vertex (Kolaczyk & Csárdi, 2014).

In a simple mobility network, where vertices are geographic point (e.g. neighbourhoods) and the edges emerge when a trip occurs between two nodes occurs, the in-degree of a vertex A indicates the number of locations from where started at least a trip that reached the vertex A. Instead the out-degree states the quantity of places reached by at least a trip started from A. The strength of a vertex refers to all the trips arriving and departing to and from the specific spot.

Analogous discussion can be made about *edge centrality* where instead of strength the centrality of an edge in a simple network is measured by its weight.

Betweenness in a Network

In some networks it is appropriate also to accord that a vertex has high centrality if it points to others with high centrality, therefore, another measure of centrality is represented by betweenness. It is aimed at summarizing the extent to which a vertex is located 'between' other pairs of vertices. This measure is based upon the perspective that 'importance' relates to where a vertex is located with respect to the paths in the network graph (Kolaczyk & Csárdi, 2014). To define betweenness we should before have in mind what is a *geodesic path*. In a network the *geodesic distance* between two vertices is the minimum number of edges that must be traversed to travel from one vertex to the other through the network. The shortest path between two vertices is the one that travels the geodesic distance and it is called *geodesic path.* Now we can introduce the mathematical definition of betweennees (Newman, 2010) that is:

$$c_B(v) = \sum_{s \neq t \neq v \epsilon V} \frac{\sigma(s,t|v)}{\sigma(s,t)},$$

where σ (s, t |v) is the total number of geodesic paths between s and t that pass through v, and σ(s,t) is the total number of geodesic paths between s and t (regardless of whether or not they pass through v). If in a graph there is only one geodesic path between each pair of vertices, c_B(v) just counts the number of geodesic paths going through v.

For weighted networks, the transaction between two nodes might be quicker along paths with more intermediate nodes that are strongly connected than paths with fewer weakly-connected intermediate nodes. This is due to the fact that the strongly connected intermediate nodes have, for example, more frequent contact than the weakly connected ones. For this reason (Brandes, 2001) proposed an algorithm for calculating betweenness that considers this issue.

The following figure, illustrates the In-degree and Out-degree label for directed networks and the betweenness property (which has the highest value for the node X).

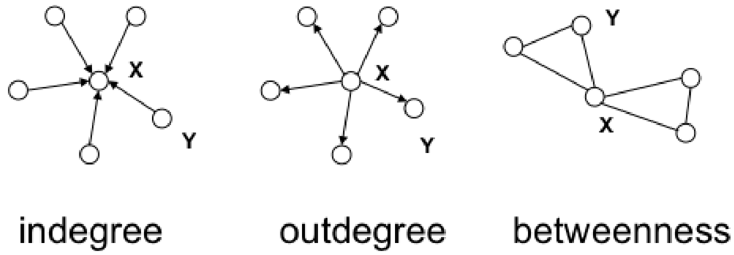


Figure 10. In-, Out-degree and betweenness in a Network

In certain environment, vertices with a high betweenness are considered *hubs.* Particularly, in urban structures, hubs refer to the significant areas that connect spaces between which urban stocks -represented in people movement- are transferred. These hubs, act within the urban structure as spatial bridges among different neighbourhoods.

Centres, on the other hand refer to the most relevant areas that accumulate urban stocks (easily associated with the strength measure), which can differ from hubs but occasionally are the same. (Zhong et al., 2014)

Cohesion of a Network

Besides the centrality, network analysis tends to focus in questions involving network cohesion, which attempt to analyse the extent to which subsets of vertices are cohesive, or 'stuck together' (Kolaczyk & Csárdi, 2014). Answering questions such as do friends of a given actor in a social network tend to be friends of one another as well? Or, how many locations do I need to pass on average to go from a point to another in a city?

There are many ways that network cohesion can be defined, depending on the context of the question being asked. Nevertheless, a basic question of interest is whether a given graph separates into distinct subgraphs. If it does not, we might seek to quantify how close to being able to do so it is (Kolaczyk & Csárdi, 2014). Intimately related to such issues are questions associated with the flow of 'information' in the graph, or the accessibility of a zone in a city.

If the removal of a particular set of vertices (edges) in a graph disconnects the graph, that set is called a *vertex-cut (edge-cut)*. A single vertex that disconnects the network is denominated an *articulation point*. Identification of such vertices can provide a sense of where a network is vulnerable (Kolaczyk & Csárdi, 2014). In a transportation network, it would highlight the points that would threat to stop the mobility of a fraction of the city if they become unavailable.

For cohesion, is also useful to recall the concept of the *geodesic distance* between two vertices, which states the minimum number of edges that must be traversed to travel from one vertex to the other through the network. *The diameter* of a graph is the length of the longest geodesic path between any pair of vertices in the network for which a path actually exists (Newman, 2010)

The identification of the Shortest Paths in weighted networks, has been also studied through different algorithms. (Brandes, 2001) algorithm's, finds multiple paths if they have exactly the same distance. For example, if one path is found over the direct tie with a weight of 1 (distance = 1/1 = 1) and a second path is through an intermediary node with two ties with weights of 2 (distance = 1/2 + 1/2 = 1), the two paths have exactly the same distance. However, if there is a third path through two intermediaries with three ties with weights of 3 (distance = 1/3 + 1/3 + 1/3), it does not exactly equal 1 as computers read these values as 0.33 and the sum of these values is 0.99. Therefore, this path is considered shorter than the other two paths of distance 1.

5.1.2 Clustering of a network

To reveal structure and organization within a network, when they are not visible by eye from its graph, methods to detect *clusters – groups or communities* - are employed. The most common of them rely on edges pattern to divide vertices into groups in the way that there are many edges inside groups and few edges between groups. The Figure 11 shows an example of a split of a network into communities. The motivation behind the willingness to divide a network into clusters can be divided into two general classes that lead to two general macro type of algorithms: *graph partitioning* and *community detection.*

Graph partitioning refers to a problem of dividing vertices of a network into a given number of non-overlapping groups of given sizes such that the number of edges between groups is minimized (Newman, 2010). Community detection problem attempt to find communities within a network as well but the number and the sizes of the communities is not previously defined. The aim of first class of algorithms is usually to divide the original network into smaller and more manageable parts in order to perform, for instance, calculations on them. For this reason, a graph partitioning will always return network's best division regardless of whether any good division exist. Community detection methods instead aim at find natural divisions of a network to understand its structure. Thus, on the contrary, they divide a network only if good division exist.

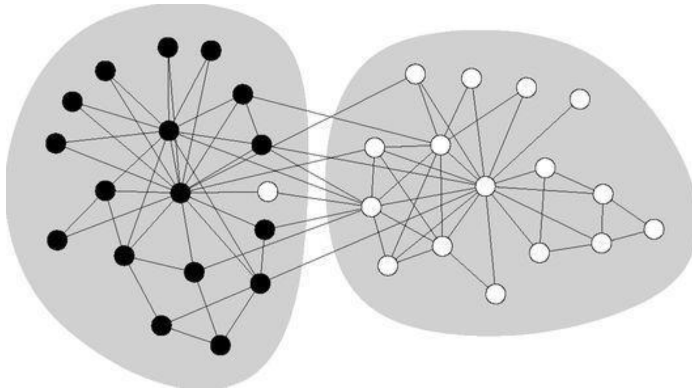


Figure 11. Result of a clustering algorithm compared to the actual communities of the network, given by the colours of the nodes

Since graph partitioning are out of the scope of this research the following part is focused on community detection and provides a synthesis of the most used algorithm to perform it.

Community detection algorithms

a) Modularity maximization

The most common method to solve community detection problem is to rely on *modularity.* This measure is employed to quantify how many edges lie within groups in the network relative to the number of edges expected on the basis of chance (Newman, 2010). Let imagine that vertices of a network are classified according to some characteristic. For instance, in the network of the relationship among musicians of an international orchestra we can classify the vertices – the musicians – according to their nationality naming similar those vertices that have the same nationality.

Modularity is defined as the measure of the extent to which similar vertices are connected in a network. To compute it is necessary to find the fraction of edges that actually connect vertices of the same type and subtract it from the fraction of edges expected to run if edges were positioned randomly. Below is possible to find the specific calculation.

Let denote by c_i the class or type of vertex i, which is an integer 1 ... n_c, with n_c being the total number of classes. The total number of edges that run between vertices of the same type is

$$\sum_{\text{edges } (i,j)} \delta(c_i, c_j) = \frac{1}{2} \sum_{ij} A_{ij}\, \delta(c_i, c_j),$$

where δ(·,·) is the Kronecker delta - which is 1 if the two arguments are equal and 0 otherwise - and the factor of $\frac{1}{2}$ accounts for the fact that every vertex pair i, j is counted twice in the second sum. A is the adjacency matrix.

The calculation of expected number of edges between vertices if edges are placed at random follows. Consider a particular edge attached to vertex *i,* which has degree k_i. There are by definition *2m* ends of edges in the entire network, where m is as usual the total number of edges, and the chances that the other end of our particular edge is one of the k_j ends attached to vertex j is thus $k_j/2m$ if connections are made purely at random. Under this latter assumption, counting all k_i edges attached to *i*, the total expected number of edges between vertices i and j is then $k_i\, k_j/2m$, and the expected number of edges between all pairs of vertices of the same type is

$$\frac{1}{2}\sum_{ij}\frac{k_i k_j}{2m}\,\delta(c_i, c_j),$$

where again the $\frac{1}{2}$ factor avoids double counting. Taking the difference of the two last expressions we have the difference between the actual and the expected number of edges between vertices of like types. Diving it by the total number of edges m we obtain the fraction of that difference that is given by the formula

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(c_i, c_j).$$

This quantity is the *modularity.* It is strictly less than 1, it takes positive values if there are more vertices than expected running between like vertices and negative in the opposite case.

Find communities in networks relying on modularity means look for divisions that have the highest modularity scores. Unfortunately, complete modularity maximization algorithms take long to run and this is why in most of the cases heuristic algorithms are preferred. *Simple modularity maximization* for example is a straightforward algorithm that divides network into two clusters starting from an initial division, such as a random division into groups of equal size. The algorithm calculates then for each vertex how the modularity would change if that vertices were moved to the other group and finally move the one whose movement most increase the modularity. The process is reiterated until each vertex has been moved exactly once. Then among all the states the network has passed through the algorithm select the one with highest modularity. That state in repeatedly subdividing a network in this way, an important question we need to address is at what point to halt the subdivision process. The answer is quite simple. Given that our goal is to maximize the modularity for the entire network, we should only go on subdividing groups so long as doing so results in an increase in the overall modularity will be the starting condition for another round of the same algorithm that keep repeating the whole process until the modularity no longer improves.

The algorithm could be extended to the case of more than two communities by dividing the network in two parts and then subdividing each of them in further sections. That procedure anyway carries the problem that is not guarantee that the best division of the network in three parts, for instance, can be found by previously dividing it into two and then subdividing one of the two (Newman, 2010).

b) Betweenness based algorithm

An alternative measure way to split networks into groups is to look for the edges that lie between groups using *betweenness centrality.* In particular, the algorithm proceeds in the following way. It detects the edge with highest score of betweenness and removes it. After that it recalculates edge betweenness and reiterate the first step. At some point the network will split into two communities, then three and so on. At the very end the algorithm will not provide specific divisions but different possible divisions that can be summarised into a *tree*

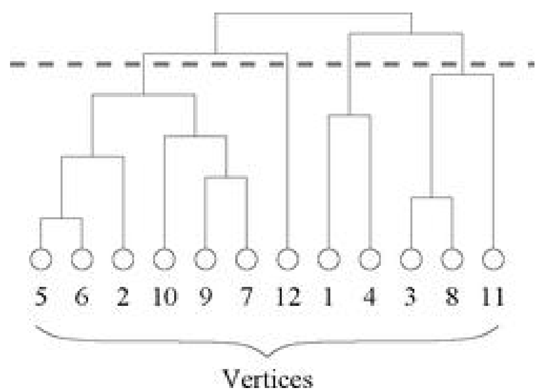


Figure 12. Dendogram with a cut

or a *dendogram* (Figure 12). It will be a task of the user to decide which *cut* of the tree better fits his purpose.

c) Hierarchical clustering

As the previous algorithm this one provides a set of nested communities visualized in a dendogram form. The difference is that *hierarchical clustering* refers to a class of *agglomerative* and not *divisive* algorithm. Most similar vertices are joined together to form groups bigger at each step till just one group with size equal to the original network is formed. To run those algorithms two decisions, have to be taken: how to measure vertex similarity and how to measure similarity between groups. Concerning vertex similarity, a common measure is the already discussed *modularity* (Kolaczyk & Csárdi, 2014). Alternative methods are cosine similarity, correlation coefficients between rows of the adjacency matrix or the Euclidean distance but their discussion is outside the purpose of this research.

Concerning the similarities between groups the method used are substantially three: *single-, complete- and average-linkage clustering.*

The first one uses as similarity measure between two groups the similarity of the two most similar elements of the groups resulting to be a lenient method; *complete-linkage clustering* considers instead the similarity of the two least similar element while *average-linkage clustering* employs the average value of similarity of the elements of the two groups. As mentioned, also for this algorithm the result is not a single division but a collection of possible divisions, synthetized in a dendogram, as shows Figure 13.

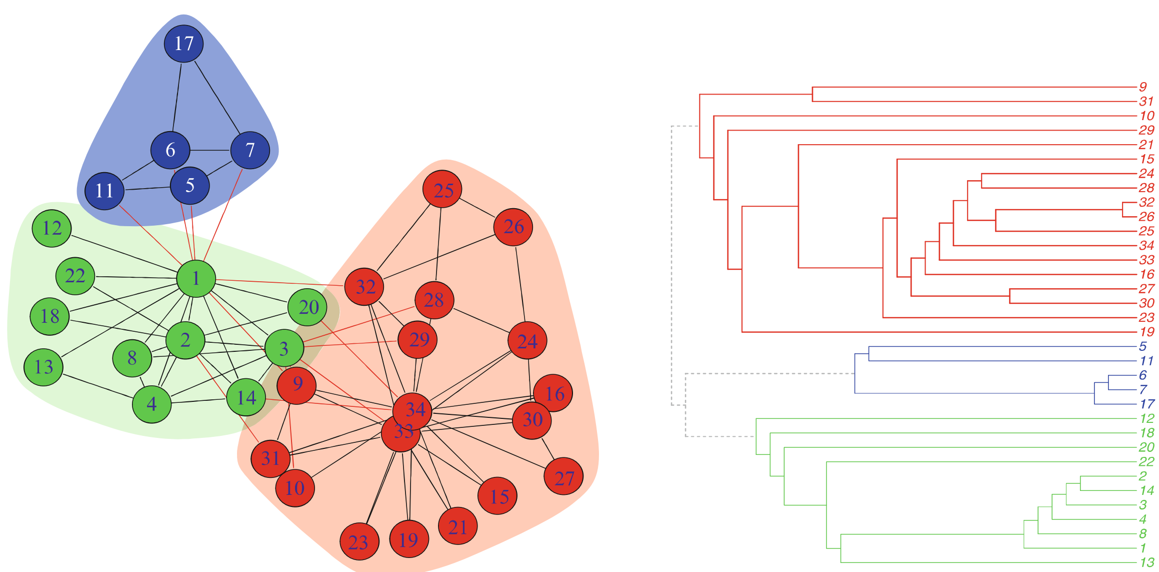


Figure 13. Cluster of a network (left) and its dendogram representation (right)

5.2 Key performance indicators (KPIs)

Effective measurement is an integral part of the management of a process since the way of things being measured has a direct influence on their perceived value (Kaplan & Norton, 1995). In particular performance indicators are instruments that help us to evaluate progress toward goals and objectives (Litman, 2007b). Indeed, Performance measurement impact significantly the development, implementation and management of existing plans and programmes, and largely contribute to the identification and assessment of alternatives. (Kaparias et al., 2012).

Fielding (1987) goes through the concept of key indicators to monitor performance, stating that 'these indicators may not capture every activity of an agency, but they do indicate progress in crucial areas''. Nonetheless performance measurements are applied in numerous context, the particular complexity of the transport field, where many dimensions need to be addressed -such as traffic efficiency, traffic safety, pollution reduction and social inclusion-, make performance based planning much more challenging than in other narrower focused sectors (Kaparias et al., 2012).

Besides considering the multidimensional feature, is also vital to contemplate that the performance and delivery of a transit service depends significantly upon perspective (Ryus et al., 2003). As an example, traditional cost efficiency indicators (e.g., operating expense per vehicle revenue kilometre and/or hour) and cost-effectiveness indicators (e.g., operating expense per passenger kilometre and/or passenger trip) can be considered as performance measures from the provider or the transit agency perspective, while they are not related to customers and community issues (Eboli & Mazzulla, 2011).

The current section summarizes the established requirements of performance indicators in the urban traffic management as well as a possible development methodology of this measures with the aim of delineating a common framework.

Requirements of performance measures

Transportation measures should be, as mentioned, linked to a broad goal category, but also, as the Figure 14 illustrates, they can be classified according to: the particular transport mode they are related to; the type of transport -freight or passenger transport- they apply to; and according to the system level of the planning jurisdiction for which they are most relevant. Lastly, also according to the perspective of the stakeholder they target (user or planner) (Kaparias et al., 2012).

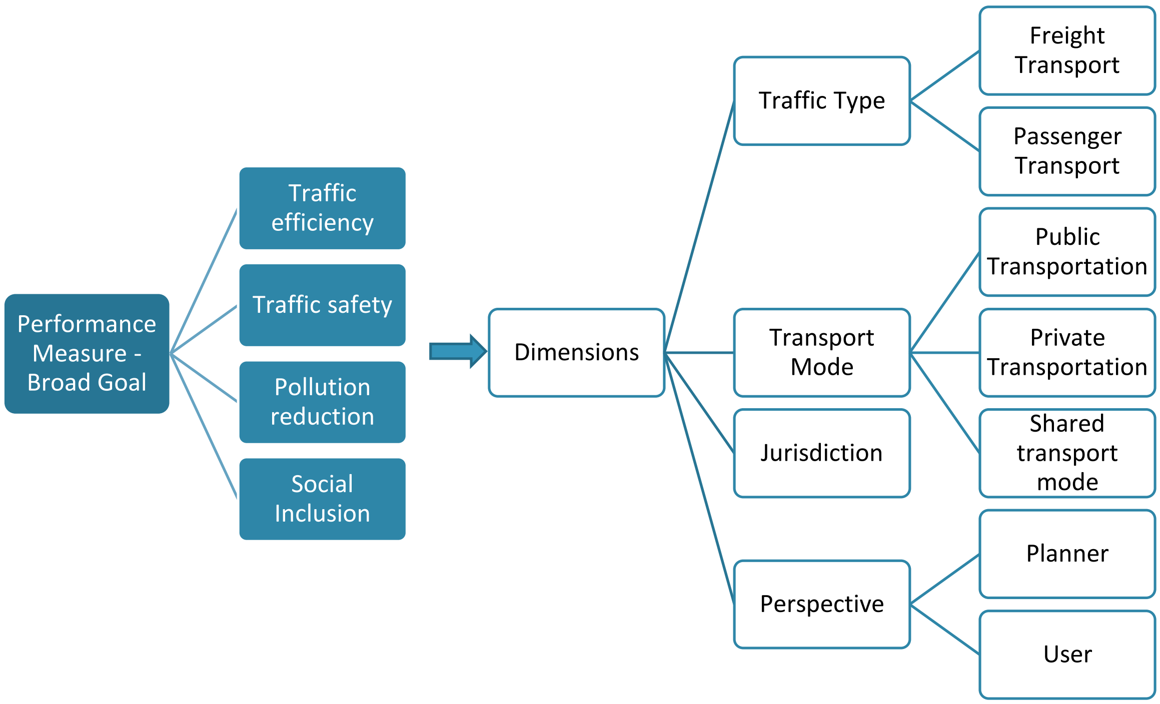


Figure 14. Classification of performance Indicators

Performance indices, on the other hand, combine various measures into single indicators, covering potentially multiple dimensions. For example, several instance of travel time as a performance measure of different links, routes and transport modes of a network can be used to form a composite performance index of mobility (Kaparias et al., 2012), in the same way as the Consumer Price Index in Microeconomics reflects through a single number the cost of a broad market basket of goods and services regularly purchased by the typical consumer (Kaparias et al., 2012).The classification considerations should be driven from and cater for the needs of the users of the measures and indices. (Zavitsas et al, 2010) developed a focus group on European cities, where a common compilation of requirements of performances measures was defined. The main requirement was that a performance measure, should assess the evaluation of benefits of a specific investment against its cost, other desired features were that performances should:

- Promote cities interest, reflecting both customer satisfaction and operator system concern;

- Make use of existing data – as the one collected already by the city-;
- Consider the individuality of cities;
- Easy to apply and simple to convey to public;
- Be projectable by means of incorporation with existing models.

Development of performance measures

The process associated with the development of performance measures involves, as illustrates the Figure 15, first the definition of goals and objectives, followed by the specification of the dimensions of performance measures and then the identification of its the selection criteria, finally it involves the description of the data required and analytical tools for monitoring performance. (Kaparias et al., 2012)

Figure 15 Development of performance measures

Furthermore, the development of performance measures assumes relevance as composite indices are constructed for the purpose of comparing and evaluating different projects under different timeframes and future scenarios.

Performance measures are required to satisfy as many as possible of the properties that by definition constitute their selection criteria which are:

1. *Measurability*: First and foremost, performance measures should be measurable with the tools and resources available;
2. *Predictability*: They should enable comparison of future strategies through existing forecasting tools;
3. *Clarity*: Be understandable to policy makers;
4. *Usefulness*: Provide a direct measure of the issue of concern, to either motivate further study or action or to diagnose deficiencies and their causes;
5. *Multimodality*: Encompass, as possible, all relevant transport modes;
6. *Temporality*: Fit the timeframe of analysis and actions;

7. *Geographical scale*: Applicable and useful to the national, regional or local levels, as required;
8. *Control*: Facilitate the control and correction of measured characteristics and have;
9. *Relevance*: For the planning and project design processes so as to provide support to decision makers.

Performance measures are selected also according to the data requirements, as it is often the case in practice that all the needs and costs arising from the collection of necessary data cannot be addressed. Operations-oriented measures rely to some extend on traditional data collection programmes and techniques, but more broadly defined outcome measures are likely to required additional types of quantities of data. For example, traffic efficiency measures frequently necessitate sample data on travel time or speed, while social inclusion measures require spatially allocated travel and socioeconomic information. In general, the data needs of performance measures can be covered by the following sources: surveys, traffic monitoring, or intelligent traffic systems (ITS) (Eboli & Mazzulla, 2011). The most used approach in practice consist on identifying the ideal measures that relate to a specific purpose, and then working backwards to surrogate measures developed using more readily available data.

Data requirements vary according to the spatial concern, the availability according to the authority levels and the timeframe of the evaluation. The reliability of the collected data is a further issue affecting data requirements, as in the case of surveys it is depend on the rigorous preparation and conduct, and in the case of traffic monitoring, relies on the correct installation and functioning of the equipment.

Most importantly, data requirements concern simplicity of collection and elaboration, as performance measures and indices should be easily understandable, since they also must be readable by the general public.

6. Methodology

The following part reports how we have conducted the analysis. First of all, we contemplated the design considerations of the key performance indicators developed to fulfil the research objectives and defines the scheme they will follow in terms of goals, dimensions and criteria. The further development of the project can be split in three main phases: The first phase is the data acquisition, exploration and preparation; the second one is the network construction and analysis; and finally, the fourth phase, is associated with the detailed information of the designed KPIs. The interpretation of the results will be the object of the next chapter.

To deployed a comprehensible path for the reader, the design considerations of the measures are attached to the last phase, since, even do they constituted a preliminary session, they provided the main configuration for the KPIs construction. Section 6.1 (phase 1) and 6.2 (phase 2) are before the detailed performances, since these sections provided other needed information to fully understand them.

Punctually, Section 6.1 is all centred on *data*. It evaluates the data used in the project, its sources and features and the cleaning and preparation required. Besides, it goes into the construction of sub-sets that were used to assess how Milano's sharing mobility network changes according to the day of the week (weekdays vs weekend) and to external factors such as the weather.

Complementing this chapter, some technical considerations that were essential to perform the network analysis on *RStudio* -the statistical software used- and a summarized scheme, that mentioned the general path of the code implemented to construct the mobility networks and its outputs have been included in the section 6.2.

Finally, the last section -the phase 3- marks the KPIs descriptions, given its definition, formula, aim, frequency of measurement and other important details. Attaching first, as mentioned, the design considerations. The following table, condense the scope and the outputs of each one of the methodological phases.

PHASE	OBJECTIVE	OUTPUTS
1. **DATA MANAGEMENT**	Evaluation, cleaning and preparation of the data used in	-Database of origin-destination trips for each access based consumption mode.

	the project. Besides, it carries the construction of sub-sets of data that were used to assess how Milano's sharing mobility network is shaped according to factors such as day of the week and the weather.	-Subsets of data to explore how other factors (day of the week, weather) influence the mobility network.
2. NETWORK CONSTRUCTION AND ANALYSIS	Illustrates the general path of the code implemented to construct the mobility networks and the main features required for the software used. Deploys as well the sequence of the network analysis, from its visualization to the dynamic measures.	- Network of the overall trips of Bike sharing - Network of the overall trips of Car sharing -Networks of stablished subsets. e.g. Bike sharing trips in the week days, and bike sharing trips in the weekends. -Network properties by mode and subset -Static Network analysis attached to geo-spatial information -Dynamic Network analysis, attached to geo-spatial information
3. KPIS DESIGN AND CONSTRUCTION	Describe in detail the key performance indicators of the urban mobility, targeting the measurement of traffic efficiency, pollution reduction and health impacts.	-Performances exhaustive description for each one of the tree selected goals to measure urban mobility.

Table 1. Methodology's phases

6.1 Data

The following paragraphs deal with data sources and data preparation. In the first the type of data, the different providers and the time span are defined while the tasks necessary to transform them in the format required by the analysis are presented in the second passage.

Features and Sources of Data

Access based consumption providers and mobility digital platforms

The data of the trips of the access base consumption modes was asked first directly to the providers in the city of Milano. Which are currently: Car2go, Enjoy, Sharen'go, BikeMi, Guidami and E-vai. The first tree ones have a free floating modus operandi, which means that the cars are picked-up and dropped off freely within the city; while the last tree deals with fixed stations conveniently located. From this request, and due to the companies' privacy policies we managed to have successfully the data related with the bike sharing program of Milano BikeMi and the car sharing Guidami.

Going further, we got in contact with a recent digital platform that integrates the availability of all the sharing mobility modes in Milan: Urbi. It is also present in other cities of Europe and besides visualization, allows you to choose, search and reserve upon the different modes. After the formal request, Urbi provided us with the data of the trips performed by Car2go, Enjoy and Share'nGo.

The tables below summarize the information provided by each of them:

Provider	Features	Period	Number of trips	Comments
BikeMi	For each trip: Date and hour of departure, date and hour of arrival, departure station-number and name-; arrival station-number and name-, duration of the trip and kilometres. Format: xlsx	From the 25th of January of 2016 to the 7th of March of the same year.	350093 trips were performed and recorded in that period.	263 stations active in the evaluated period.
GuidaMi	For each trip: Car category, departure parking, arrival parking, Date and hour of departure, date and hour of arrival, duration of the trip and	From the 7th of January to the 7th of June	14520 trips were performed and record in that period.	Besides having fixed stations, they have the restriction that the station of arrival must be the same station of departure, so every trip is a

	kilometres. Format: xlsx			circular trip.
Urbi	For each trip: Car Id, plate, provider (Car2go, Enjoy and Share'nGo); Date and hour of departure, date and hour of arrival; coordinates of departure, coordinates of arrival; level of fuel of departure and level of fuel of arrival. Format: csv.	From the 25 of January of 2016 to the 7th of March of the same year.	254833 trips were performed and record in that period. 108067 trips coming from Car2go, 104772 from Enjoy and 41994 from Share'nGo	Rebalance trips performed by each provider are not labelled. Trips with long durations (some providers allows mid-period rentals). Trips with no return, considered outliers in the data. The route cannot be tracked.

Table 2. Data features.

Municipality Data

The scope of the project could not avoid the collection of geographic information. Geographic data of transport infrastructures of the city were accessible through the Comune di Milano platform: "dati.comune.milano.it" which has datasets related with mobility, public transportation and the zone division of Milan by NILs in a *shapefile* (SHP) format which allows to store information and geometry of spatial features.

Besides Milan and its zone division (the NILs), it was also possible to extract from this source (dati.comune.milano.it) the location in a *shapefile* format of the BikeMi stations, but this was updated only until the 2014. Meaning that only 189 stations, out of the 263, registered in the dataset of the trips for the period evaluated were present. The remaining 74 stations were recovered from the BikeMi website (BikeMi., 2016), that displays all the current stations on the map of the city.

The combination of the access based consumption data of the providers, the digital platform, and the geographic information of the Comune di Milano, were the data inputs of the current project as the Figure 16 illustrates.

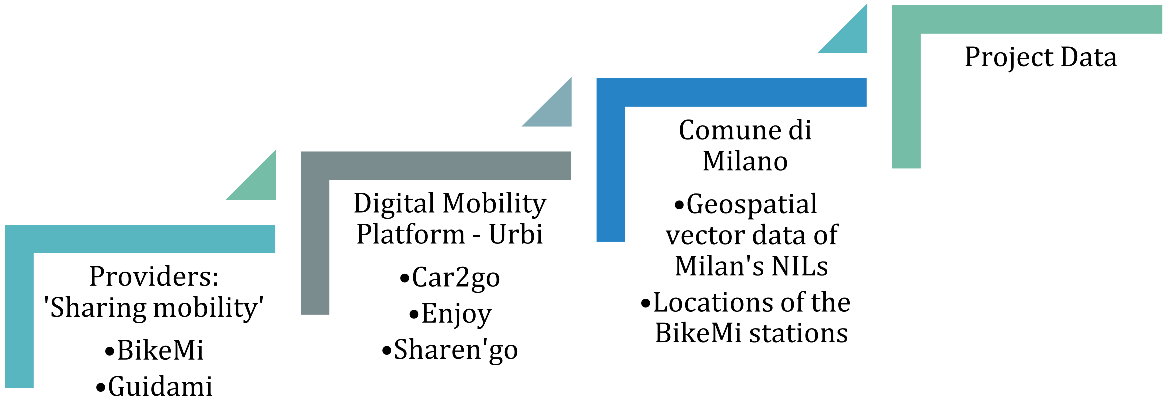


Figure 16. Data Sources

Data Exploration and Preparation

The following parts discuss all the operation needed to prepare the data to the analysis focusing on the process of *data cleaning* and *data aggregation*.

Data cleaning

Before analyse the data we cleaned them from outliers, blank values or information out of our scope. Data gathered was mainly comprehensive of three datasets*: BikeMi, Urbi* - containing *Enjoy, Car2go* and *Share'nGo* - and *GuidaMi*.

First screening we deal with regarded GuidaMi's data. GuidaMi is a service that only allows to drop cars in the same place they have been picked up. For this reason, in that dataset all the "rentals" were tracked with time, date and place but there was no information about the actual destinations of the single trips. Since GPS data have not been tracked we were not able to predict the path of the journeys just relying on the accessible information. Unfortunately, for that reason, we were forced to not consider this database in the following analysis.

The main data cleaning work was performed on Urbi's data, which we will refer to as *car sharing data*. Besides having 1.160 trips without drop time that were deleted, the dataset was comprehensive of *rentals*, journey with origin or destination *outside* Milano's metropolitan area and *rebalancing trips.* Car sharing service providers allow also long-period access to vehicles and for that reason we found in our database travels that lasted several hours and in sometime even days.

Since in those cases we deal with actual rentals and no more access-based consumption modes we needed to get rid of them. To do it we defined a 6-hours threshold stating that if a trip last duration overcomes it would be considered as a rental. The number of trip labelled that way and thus discarded was 83.405 (32,7% of the initial database size). The second category of data we had to discard in car sharing's datasets where those related to that started or finished outside Milan. Since the object of this paper is to study the mobility within the city those journeys were useless and moreover could biased the analysis. During that step 9.340 trips were discarded form the dataset. Last class of data that has been erased was the rebalancing one. The data provider stated that also the rebalancing trips have been tracked and included in car sharing dataset. For that reason, we designed a double-condition procedure to detect and delete them. Rebalance is performed with vehicles that transport several cars around the city the fuel level does not change during those type of trips, so this is the first condition we used. It happens that also short journey results in no fuel level variation because the difference in fuel was to tiny to be registered. For that reason, we add a second condition related to the time of the trip. Finally, we consider as rebalancing – and thus discarded – trips that did not result in a fuel level change and that lasted more than 30 minutes. We selected that time threshold assuming that a displacement longer than 30 minutes that does not change the fuel level is difficult to occur. Journeys deleted with that procedure were 67.759. To recap, from a sample of 254.833 journeys 32,7% were screened as rentals, 3,6% as out-of-Milan trips and 26,5% as rebalancing, resulting in car sharing's dataset final size of 108.761 trips.

BikeMi data did not need any cleaning so we keep the original sample for the following analysis.

Data aggregation

BikeMi data had a geographic granularity equal to the single docking stations in Milan. Since users are able to pick-up and hand over bike just from docking stations all the trips tracked in the data had as starting and arrival points one of those stations. On the contrary, since car-sharing data refer to free-floating systems, starts and arrivals could occur in whatever point of the city – and even outside it, as mention below. Moreover, bike sharing service was active just in the inner part of Milan, while car sharing had not geographical constraints. Those differences in the granularity and in the spreading of the services forced us to adopt a common level of aggregation that made the two datasets comparable. Our decision was to aggregate origin and destinations by NILs – *nuclei di identità locale* – introduced in Milan by the *Piano di Governo del Territorio*. NILs are 88 and they are defined as system of urban vitality: concentration of local commercial activities, gardens, aggregation points and services

(Dati.comune.milano.it). The 263 BikeMi stations happen to be concentrated into 39 of the 88 NILs meaning that on average, in the zone where the service is active, there are 2,99 docking stations per NIL Figure 17. Knowing geographical position of each docking station and the border of each NIL – thanks to data from *dati.comune.milano.it* - we use the *shapefile* function on *R* to link each station to the NIL it belongs. Concerning car trips we match origin/destination positions with the NILs they were set. Before doing that, coordinates transformation was needed since car sharing data were referred to *latitude/longitude* reference system while NILs to *Monte Mario Italy 1* system. We kept *Monte Mario Italy 1* as reference system for the analysis since also bike sharing data was referred to it.

From this point we will consider NIL as departure and destination for each journey in datasets and no more geographical points. Travels that in the original datasets occurred from two geographical points belongings to the same NIL resulted to be *intra-NIL trips*.

By aggregating we moved the analysis at a NIL level preventing from the possibility to study the inner mobility of single NILs. Changing level of aggregation resulted in a loss of precision but on the other hand linked all the findings to the official geographical division of Milan. This way the study can be enriched with demographic, social and behaviour information available for each NIL or could be a complement itself for future researches that will use the same district division. Finally, select NILs as level of analysis facilitated the graphical visualization of the data.

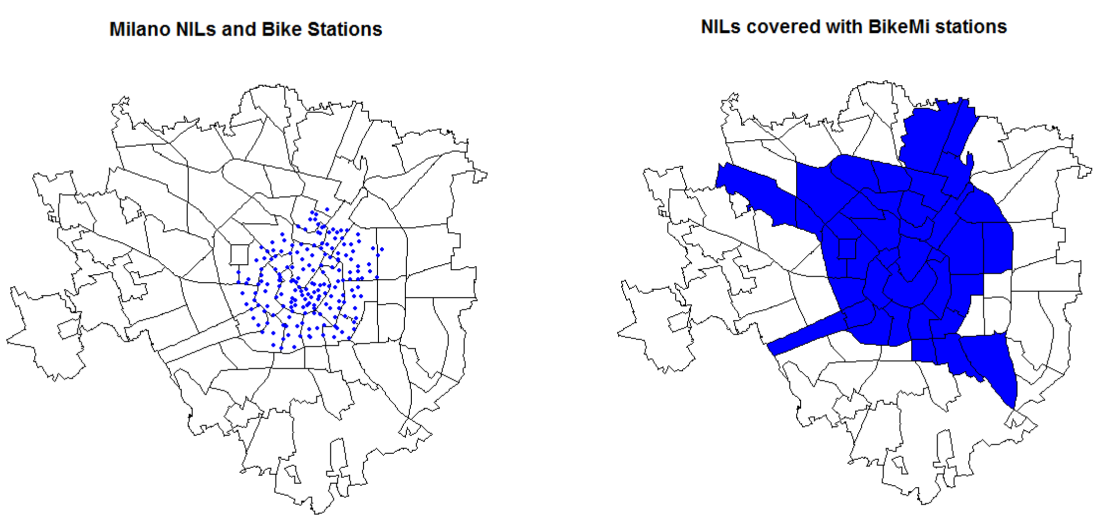


Figure 17. Left: Milano NILs and BikeMi Stations (blue dots) available on the website of Comune di Milano (last updated 2014). Right: NILs where BikeMi service is active have been coloured according to the information available on BikeMi.it (updated).

Data useful subsets

The dataset of each provider was analysed for the period of time as a whole, nevertheless, due to the existing link between urban mobility patterns and conditions or periods of time, a deliberate sub-setting of the available data for each type of mode was performed. In particular, datasets were between:

1. Weekdays and weekends
2. Rush hours and not peak ones (they may differ for each evaluated mode)

This has been done since intuitively the mobility flow, and therefore the trips patterns, tend to change whit the variation of the population activities (e.g working, studying during the week-days, and leisure activities during weekends). In addition, the nature of the Bike transport conditions makes this transport mode more sensitive to the weather circumstances. Positioning rain and temperature as factors that may play a role in the users' transport decisions. With this notion, several data arrangements for BikeMiwere created: Cold and not cold (considering temperatures below and above the average for the period evaluated); rainfall, foggy and not rainfall (this division, according to the historical register of a meteorological portal, which provides, between other others features the average temperatures, the humidity and the wind velocity for each day). The Figure 18 illustrates the anticipated partitioning of the data.

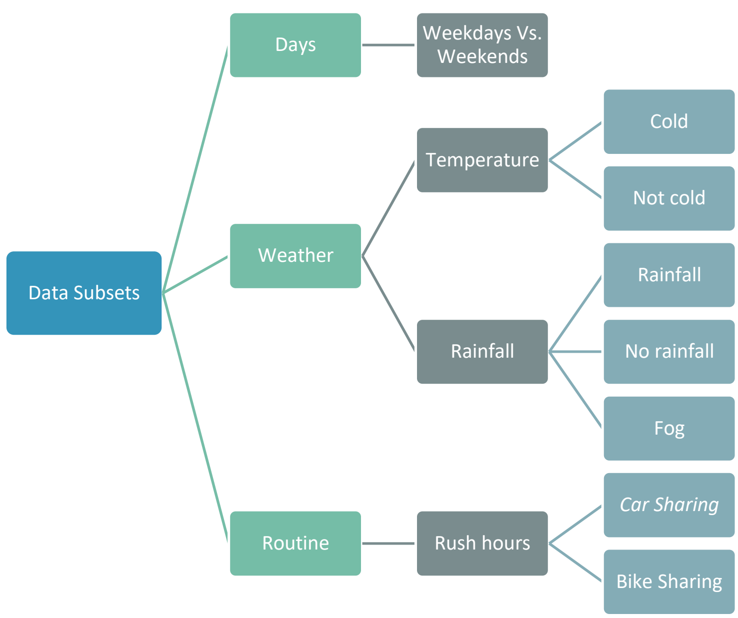


Figure 18. Data subsets

This partition was considered to further compare the behaviour of the urban flow in the network according to the external factors established.

6.2 Networks Construction and Analysis

The network construction was supported by the programming language and software environment for statistical computing and graphics 'R', which is widely used among statisticians and data miners, being a free open source.

The software has the advantage of extends its functionalities through a user-created packages, which allow specialized statistical techniques (Fox & Andersen, 2005). In particular, for creating a network with further urban-space attachments of it to the city of Milan, some of the most useful packages were[1]:

- 'igraph': A library for network analysis. The main goals of the igraph library is to provide a set of data types and functions for 1) pain-free implementation of graph algorithms, 2) fast handling of large graphs, with millions of vertices and edges, 3) allowing rapid prototyping via high level languages like R.
- 'data.table': It offers fast subset, fast grouping, fast update, fast ordered joins and list columns in a short and flexible syntax, for faster development.
- 'shapefiles': This package includes functions to read and write shapefiles, the data format of the geographical information of the Comune of Milano.
- 'maptools': Methods to translate and disguise coordinates placing in the real world.
- 'pheatmap': Implementation of heat-maps that offers more control over dimensions and appearance.
- 'RColorBrewer': provides sequential, diverging and qualitative colour schemes that are particularly suited and tested to display values on a map.

R programming and Networks Construction

The schematized path we followed to build up the network for each mode was a compilation of R codes that took care of: 1. Associated the trips to the geographical aggregation, 2 Tailored or adapted the data according to the conditions and 3. Build up and calculate network properties.

In the case of the Bike Trips, the summary goes as follow:

[1] R Documentation

Steps	Outputs
NIL & Bike Stations Input	
1. Read the shapefile of the data of the commune with its coordinates (NILs and BikeMi Stations) 2. Associates the coordinates of the BikeMi stations to a NIL (matching both datasets) 3. Update the BikeMi Trips dataset with the NILs. Aim, to identity the trips from NIL to NIL rather than from station to station. Also the trips occurring inside each NIL have been considered.	- *Dataset of BikeMi trip which also identifies the Nil of origin and the NIL of destination* - *Map of the NILs of Milano with Stations (only the ones available at the Comune)*
Bike-NIL complete Dataset	
1. Identify the stations that aren't in the Data of the Comune-> stations not associated with a NIL 2. Upgrade (manually, if info is not found) the NIL for each station. In this case, 74 Bike Stations' Nil locations were updated. 3. Integrate to the BikeMi Trips dataset the NIL of the initial and the final locations of the trips where the station NIL was not available. Save the Upgrade Dataset as an R data file to use building up the network	- *Dataset of BikeMi trips from NIL to NIL with the updated information (ready to build up the Network)*
Bike NIL Graph	
1. Build up the network, taking the 39 NILS as vertices and construct a directed edge between the departure NIL and the arrival NIL of each trip. 2. The trip connections (edges) are weighted up to the number of trips happening between two NILs. 3. Vertex Centrality, Cohesion, and Edge Analysis are performed. Properties such us: In- and Out-degree, strength of a vertex, betweenness, diameter (the longest geodesic path) are calculated.	- *Graph of the overall trips whit BikeMi from NIL to NIL* - Dataset of Properties, from both Vertices and NILs. - Map with Hierarchical clustering of the Bike sharing network

4. The dataset of the frequency of trips per each NIL is calculated with the graph-edge information. 5. A clustering method is applied to explore simultaneously differences and similarities between the vertices of the network	

Table 3. Bike Sharing Network Construction

For the case of the 108.761 car sharing trips, after the data cleaning and the coordinates transformation we did:

Steps	**Outputs**
NIL & Car Trips Input	
1. Read the shapefile of the data of the commune to get the map of Milano with the NILs 2. Associates the coordinates of the picking and drop point locations of each trip to a NIL (matching both datasets) 3. Update the Trips dataset with the NILS. With the aim to identity the trips from NIL to NIL rather than from station to station. Also the trips occurring inside each NIL.	- *Dataset of Car Sharing trips which identifies the NIL of origin and the NIL of destination*
Car NIL Graph	
1. Build up the network, taking the 88 NILS as vertices and construct a directed edge between the departure NIL and the arrival NIL of each trip. 2. The trip connections (edges) are weighted up to the number of trips happening between two NILs. 3. Vertex Centrality, Cohesion, and Edge Analysis is performed. Properties such us: In- and Out-degree, strength of a vertex, betweenness, diameter (the longest geodesic path) are calculated. 4. The dataset of the frequency of trips per each NIL is calculated with the graph-edge information.	- *Graph of the overall trips whit the car sharing systems from NIL to NIL* - Dataset of Properties, from both Vertices and NILs. - Map with Hierarchical clustering of the Car sharing network

5. A clustering method is applied to explore simultaneously differences and similarities between the vertices of the network: 4 clusters were obtained, all with a significant attachment to the geographical position of the NILs.	

Table 4. Car Sharing Network Construction

Static Analysis of the Network

The analysis of the network encompassed from the traditional network visualization in a form of graph, to the unsupervised learning method of hierarchical clustering. Passing by a careful analysis of the coverage, cohesion and centrality of the network. Associating these last tree steps with the geo-spatial information of the Milano's NILs. The sequence, of the analysis and some pertinent details are display in the Figure 19.

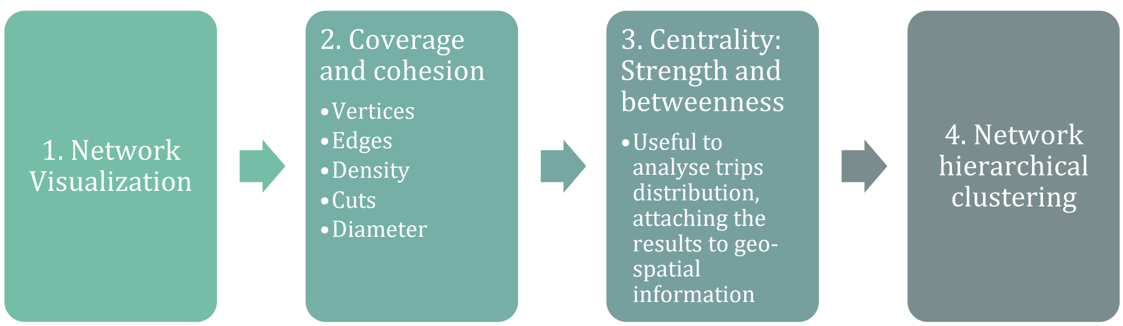


Figure 19. Sequence of the Static Analysis of the Mobility Networks

Given the graph potential dimension -since is restricted to the metropolitan area of the city-, vertices and edges are suitable to give information about the coverage of the sharing mobility network. This coverage can be analysed further with the cohesion features of the network, the density, the cut and the diameter. A network entirely connected, with an apparently large coverage could still have easily isolated or inaccessible zones if has only a few edges or if the intensity of the present connections is low.

How intense the connections are, starts telling also about how the trips in a city are distributed, and since trips are a derived activity -that is, they are born in order to fulfil the demand of some other activity, - this distribution somehow discloses as well the urban structure of a city, if the network is, as planned, translate into geo-spatial information.

Finally, for the 'static' analysis of the network a hierarchical clustering algorithm is performed. Is expected that, this unsupervised learning technique would be correlated, and therefore support, the previous analysis of cohesion, and trip distribution of the network, giving also further hints on the network structure.

Dynamic Analysis of the Network

The dynamic analysis had as an input the deliberated subsets of data considered in the first part, with the aim of taking into account the possible changes on the network given external conditions, such as the day of the week and the weather.

The subsets followed the regular network construction process in Rstudio. Developing then, for the corresponding mode, graphs associated with factors (e.g. Bike Sharing network of the weekends).

Subsequently, it was defined the percentage of time that the external factor was present during the period evaluated in theoretical terms (e.g. 70% of the timeframe evaluated for bikes was a week day). Then, to identify the relative importance of a zone of the city due to the particular factor, we compared the difference on the behaviour or activity level during that period with the theoretical one. The positive or negative delta, which highlights a higher or a lower level of activity, was attached to each one of the vertices (to each one of the NILs).

With this analysis, is possible to determine if a zone tends to be more active during the weekdays or during the weekend. Or given any other matter. The results are comparable and visualized thanks to heating scales on the nodes, that then are linked to the geo-spatial information of Milano.

6.3 KPIs design

Design considerations:

To take into account a comprehensive view of urban mobility in the design of the performances, we tried to tackle -given the data availability constraints- 3 out of the 4 pertinent wide goals categories previously defined for urban mobility, that are:

1. Traffic Efficiency
2. Traffic safety and
3. Pollution Reduction

Leaving out, the Social Inclusion goal because, despite its relevance, goes beyond the field of the study, requiring a deeper instruction in other areas.

In the literature, an increasing in the traffic safety has been defined as a reduction in the expected number of accidents, a reduction in injury severity or a reduction in the rate of accidents or injuries per kilometre of travel (National Cooperative Highway Research Program et al., 2008). However, some practical studies (De Hartog et al., 2010) -mostly focused in bike sharing programs- have measure if the health benefits of the mode eventually overcome the risk of traffic accidents. Therefore, in this study we are pointing the traffic safety in terms of health impacts.

Also, we do not intend to provide a spectrum of the entire mobility, just of the relative recent shared mobility modes, reducing the range of evaluation to only some features of specific dimensions. In particular, about *traffic type, passenger transport and transport modes*, we focused respectively on: *passenger transport*, *sharing mobility*, and *users and planner* -considering the providers-, as shows the Figure 20.

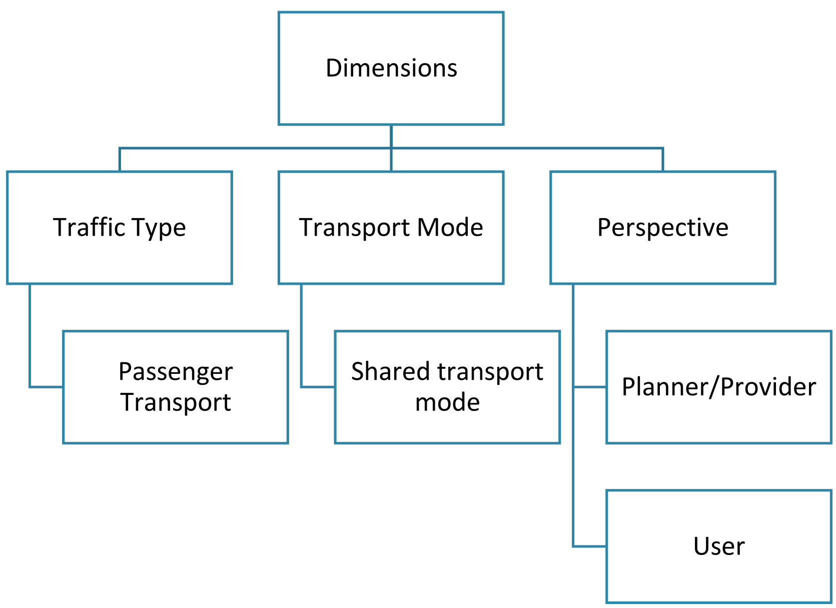


Figure 20. Dimension of mobility performance measures

Once delimitated the goals and the dimensions, to assure the accomplishment of the criteria of the performances, such as: measurability, predictability, clarity, usefulness, temporality, geographical scale and relevance (Kaparias et al., 2012). We decided to described, for each indicator particular features:

1. The details of the indicator: Referring to name, definition, the required calculation, the presentation, the frequency of measure and the literature justification.
2. Target: Aim of the measure and stakeholders.
3. Comments: From an internal perspective the strength and the weakness of the indicator, as well as the sources of data for its calculation.

Given the targets, the dimensions, and the required scheme for the criteria achievement, we select possible measures -coming from both the urban mobility literature and the network theory- depending on the accessibility of the data requirements we intended to gage. They are briefly introduced below and deeply analysed in the section 6.4.

Traffic Efficiency:

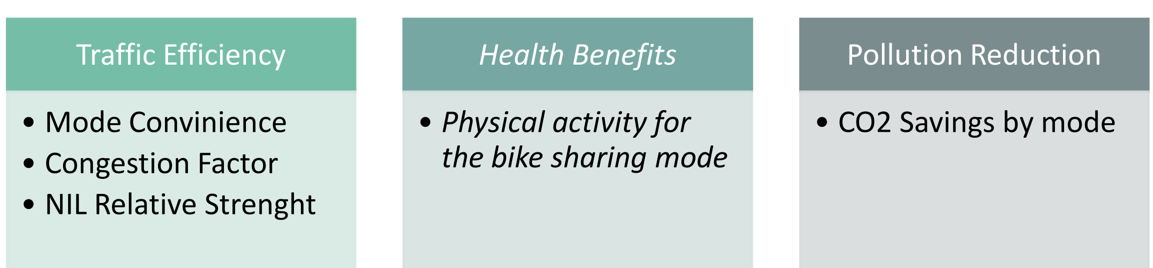
- Mode Convenience: Evaluate how convenient is, for the user, to move around Milano with each one of the access-based consumption modes of urban transport (bike sharing and car sharing).
- Congestion Factor: Detects when and where peaks in the demand have risen helping the service provider to understand the criticalities of the system and to identify the geographic zones where congestion is more likely to occur.
- NIL Relative Strength: identifies the relative importance of a geographic zone for a specific transportation mode, taking as a benchmark the importance of that zone in the whole sharing mobility system of the city.

Health Benefits

- Physical activity: the health benefit that derives from the physical activity involved by using the Bike sharing service of Milan.

Pollution Reduction

- CO2 savings: The whole C02 emissions in kilograms avoided due to the bike/car sharing mobilization of the city, according to an estimated conversion factor.



6.3.1 Detailed Indicators

Below details about each KPIs covering the mentioned objectives are reported. As stated, some of them are adaptations from the literature while some other were designed specifically for this paper.

NAME	**NIL MODE CONVENIENCE (MC)**
DETAILS	
DEFINITION	Measures the average velocity for each sharing mode: bike sharing and car sharing, evaluating on detail the velocity for each NIL, given the velocity of the in-coming and out-coming trips. Each edge (each connection) carries as an attribute the average velocity of all trips passing by, which is the input required to calculate further the velocity at each location.
CALCULATION (FORMULA)	$$MC_j = \sum\sum_{i,k \in NIL} \frac{Vel_{i,k\ in\ j}}{Number\ of\ Vertices_{in\ network\ mode\ j}}$$ $i = NIL\ (vertex)$ $k = NIL\ (vertex)$ $j = Transportation\ mode$ $Vel_{i.k\ in\ network\ j}$ $= Average\ velocity\ from\ i\ to\ k\ in\ mode\ j\ (attribute\ of\ the\ edge\ of\ the\ network)$ $$Vel_{i.k\ in\ j} = \frac{\sum_{k\ \in NIL\ in\ j}^{NIL\ in\ j} d_{i,k}}{\sum\sum_{i,k\ \in NIL}^{T} t_{i,k}}$$ $d_{i,k}\ = Distance\ in\ km\ of\ the\ trips\ from\ i\ to\ k.\ (Edge\ attribute)$[2] $t_{i,k} = Duration\ in\ minutes\ of\ the\ trips\ from\ i\ to\ k.\ (Edge\ attribute)$ $T = Evaluated\ period.$

[2]For the KPIs measures, the attribute of the trips distance was considered with the original location data and not the distance between the NIL's centres. That is, the actual distance between the pairs formed by the 263 stations in the case of the bikes, and the punctual coordinates of each trip in the case of cars. Providing in this way a more accurate scenario.

PRESENTATION (FORMAT, UNIT OF MEASURE)	It is an absolute value for each mode in Km/hour in the entire city. However, it can be (and should be) explored on detail in a NIL level, meaning that for the compilation, the velocity for each particular NIL is measured. So, even if the overall velocity of a mode is greater than other, can occur that in certain zones the situation does not follow the general statement. Meaning that, in some locations the users can go faster with the generally 'slower' mode.
FREQUENCY OF MEASURE	Measured once for the entire period of study. / It can be track for any specific time frame. (daily, weekly, etc.) A parallel is performed comparing the general velocity and the velocity in the rush hours.
REFERENCE (LITERATURE JUSTIFICATION)	"The main benefit identified by respondents was enhanced convenience provided by bikeshare (LDA Consulting, 2013). Specifically, some 69% of respondents noted get around more easily, faster, shorter as 'very important' in their motivation for bikeshare use." Bike sharing Recent Literature Review
TARGET	
AIM	Evaluate how convenient is, for the user, to move around Milano with each one of the access based consumption modes of urban transport (bike sharing and car sharing). Besides that, a comparison of this indicators with the analogous one calculated just considering peak hours can state the change in average velocity due to congestion. This way a comparison between different modes of transportation will take into account the time journey variability depending on traffic.
STAKEHOLDERS	User (convenience) Public Administration (infrastructure/congestion) Provider (Service level, Saturation)
COMMENTS	
STRENGTH	Feasible for each possible transportation mode. Immediate comprehension, synthetic measure.

WEAKNESSES	The nature of the car sharing services, that still remains strongly used as a rental form, may have an impact in the overall velocity of the car sharing service (increasing significant the time of the trips, without increasing the estimated distance travelled). To avoid this, a filter in the dataset of the car travels will be consider. Measuring the velocity of 'short' trips -that are less likely to have a split journey-.
DATA SOURCES	BikeMi for bike sharing and Urbi for car sharing data. Estimation of distances in the car sharing data given a par of coordinates.

NAME	**NIL RELATIVE STRENGTH (NRS)**
DETAILS	
DEFINITION	The ratio of the relative strength of a particular mode in a NIL of the city, over the relative strength of the aggregated mobility in that zone. This particular case, contemplates only as aggregated mobility the bike sharing and the free-floating car sharing modes. Giving a punctual inside on which of the two modes are more significant for the evaluated zone.
CALCULATION (FORMULA)	$$NRS_{i,J} = \frac{rs_{i,J}}{rs_{i\ mean}}$$ in a simple graph: $i = NIL\ (vertex) J = transportation\ mode\ (e.g. bike\ sharing)$ $rs_{i,J} = \frac{strength_{i,J}}{\sum_{k \in NIL} strength_{k,J}}$ m ∈ in the set of edges connecting the node i in the network related to the mode of transportation J $rs_{i\ mean} = mean\ relative\ strength\ of\ NIL\ i\ for\ the\ whole\ sharing\ mobility$
PRESENTATION (FORMAT, UNIT OF MEASURE)	Percentage
FREQUENCY OF	Once for the whole period. It can be track for any specific time frame, but

MEASURE	since is a general inside, a short/medium time measure -and not a real time one- like monthly is recommended.
REFERENCE (LITERATURE JUSTIFICATION)	(Newman, 2010)
TARGET	
AIM	The aim is to detect which are the NILs that play a relative bigger (or smaller on the contrary) role in each sharing mobility network. The *relativity* is the interesting part of the indicator. In fact, it is pretty clear, for instance, that *Duomo* is a central area in Milano's transportation networks but is not clear which is the modes - sharing modes in this case – that play a stronger role there. Once known that information, further analysis could be perform on the reasons that stand behind the result. Those could be diverse: geographic (e.g. long distances make difficult the selection of bike as a transportation mode), service related (e.g. the service is often saturated and force user to use other modes) or linked to the facilities (e.g. lack of cycle paths) and thus more than one plater tends to be involved. The motivations could be studied and used as benchmark or as leverage by the shareholders.
STAKEHOLDERS	Public Administration and mobility service because they have interest to have an effective network
COMMENTS	
STRENGTH	
WEAKNESSES	All the required data (of all the mobility modes) are not public thus an agreement with the owner is needed. Quite difficult calculation because the building of a network for each evaluated mode is required.
DATA SOURCES	For the indicator in this paper: BikeMi for bike sharing and Urbi for car sharing data.

NAME	**(1) BIKEMI MET** **(2) BIKEMI CAL**
DETAILS	
DEFINITION	(1) The physical activity involved by using the Bike sharing service of Milan in terms of MET (Metabolic Equivalent of Task) units for a specific interval of time. (2) Calories consumed using the Bike sharing service of Milan
CALCULATION (FORMULA)	$$\text{BikeMi MET} = {(\text{MET} \times \sum\sum_{i,k\in \text{NIL}}^{T} t_{i,k})}/{T}$$ in a simple graph $i = \text{NIL (vertex)}$ $k = \text{NIL (vertex)} \neq i$ $t_{i,k}$ = time in minutes of the trips from i to k. (Edge attribute)3 T = Evaluated period. MET = 4* Users may prefer the information under calories units for displacement: $$\text{BikeMi Cal} = \left(\text{MET} \times \sum\sum t_{i,k}{}_{i,k\in\text{NIL}}^{T}\right) * (Weight)$$ Weight= Weight on kilograms of the user *Established measure of bicycling as a moderate intensity activity-leisure, to work or for pleasure
PRESENTATION (FORMAT, UNIT OF MEASURE)	The single measure can be stablished for each possible trip: From station to station. But following the aggregation model it measures the physical activity involved by the mobilization from NIL to NIL by bike. Indicator (1) needs to be benchmarked with the recommended amount of MET/Interval of time according to a formal health institution like The

[3] Physical activity recommendations suggest that activity should occur in bouts of at least 10 minutes (WHO, 2010).

	World Health Organization (WHO).
FREQUENCY OF MEASURE	MET requirements are followed in the literature in a weekly format, but its aggregation can be daily or monthly Calories measure can be split fragmented or aggregated at any level.
REFERENCE (LITERATURE JUSTIFICATION)	"Active mobility has been identified as one central feature of a 'healthy city'" (Woodcock, et al., 2014) "To promote and maintain health, all healthy adults 18–65 years of age need moderate-intensity aerobic physical activity" (de Hartog, et al., 2010) "Overall physical activity and leisure time physical activity have been associated with risk reduction for a number of diseases and mortality" "The World Health Organization recommends that, "adults should do at least 150 minutes of moderate-intensity aerobic physical activity throughout the week or do at least 75 minutes of vigorous-intensity aerobic physical activity throughout the week, or an equivalent combination" (Götschi, 2016)
TARGET	
AIM	Measure the physical activity of NIL to NIL mobilization by bike, which has been correlated with potential improvements in public health, as a purported benefit of bikeshare.
STAKEHOLDERS	User (health awareness) Public Administration (Health service provider) Service Provider (Marketing agency, lifestyle promoter)
COMMENTS	
STRENGTH	Easy and fast calculation.
WEAKNESSES	The index should customized considering individual features such as age and sex of the user, for a precise benchmark. ID user, sex, age can complete the entire individual spectrum. The MET Index should be escalated into public health impact, such as health service cost reduction. To calculate the calories, also an individual spectrum (weight) is required.

DATA SOURCES	BikeMi for bike sharing

NAME	**CONGESTION FACTOR**
DETAILS	
DEFINITION	The *Congestion Factor* 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.
CALCULATION (FORMULA)	The two following indicators represent the maximum percentage deviation respectively of incoming and out coming trips for each NIL. The day has been divided into 24 time slots of one hour each (e.g. from 10:00 to 11:00 a.m.). To compute In-congestion factor of a NIL i, the average difference between incoming trips for each time slot and the mean of incoming trip per hour of the NIL i has been calculated. We refer to this latter value in the following way: $\Delta_{\mathrm{IN_i}}(\mathrm{t})$, where t indicates the time slot. For each NIL, the maximum value of $\Delta_{\mathrm{IN_i}}(\mathrm{t})$ among all time slots is selected and then divided by the average number of incoming trips of the NIL i. The result is then turned into a percentage by the multiplying it by 100. Similar discussion can be done for Out-congestion factor. *In-congestion Factor*: $$INCF_i = max_t[\Delta_{IN(i)}(t)]$$ i $\in$ NIL t = time slot $$\Delta_{IN(i)}(t) = \frac{IN_{(t,i)} - \mu_{IN,i}}{\mu_{IN,i}}$$ $\mathrm{IN_{(t,i)}} =$ average number of in − coming trips for NIL i during time slot t $\mu_{\mathrm{IN,i}} =$ average number of in − coming trips per hour for NIL i

	Out-congestion Factor: $$OUTCF_i = max_t[\Delta_{OUT(i)}(t)]$$ i $\in$ NIL t = time slot $$\Delta_{OUT(i)}(t) = \frac{OUT_{(t,i)} - \mu_{OUT,i}}{\mu_{OUT,i}}$$ $\text{OUT}_{(t,i)} =$ average number of out − coming trips for NIL i during time slot t $\mu_{\text{OUT,i}}$ = average number of out − coming trips per hour for NIL i
PRESENTATION (FORMAT, UNIT OF MEASURE)	Absolute value
FREQUENCY OF MEASURE	The indicator has been measured once for the whole period dividing working days from weekends and taking into account only the respective rush hours. However, it can be track for any specific time frame. (daily, weekly, etc.) Since is an operational measure, tracking it on real-time can give important insides for rebalance activities.
REFERENCE (LITERATURE JUSTIFICATION)	(Qu, Yu, & Yu, 2017b)
TARGET	
AIM	Detecting where peaks in the demand have risen helps service provider to understand the criticalities of the system and to identify the geographic zones where congestion is more likely to occur. Beside the maximum deviations is interesting to hold the information about the time slot when they 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 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 no more vehicle can be found in that specific

	NIL. Moreover, the time information gives us 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 a service provider to better organize its fleet within the city in order to not have the service saturated. Moreover, a company that has to design a local advertising campaign can understand in which NIL concentrate the broadcast of the message, according to the different moment of the day and to the different type of NILs.
STAKEHOLDERS	Mobility service provider and Public Administration that have to deal with mobility congestion. Advertising companies that can understand which are the most crowded areas at which time and forecast returns for advertising campaign. Clear channel, the provider of BikeMi service, for instance, is also an advertising company and reasonably uses information like that one to select location and price for the ads.
COMMENTS	
STRENGTH	Easy and fast calculation. Feasible for whatever transportation mode.
WEAKNESSES	The measurement should be repeated on a bigger sample that takes into account not only one working day but a longer period and also weekends. Required data are not public thus an agreement with the owner is needed.
DATA SOURCES	BikeMi for bike sharing and Urbi for car sharing data

NAME	**1) MODE $C0_2$ SAVINGS** **2) VEHICLES USAGE RATE**
DETAILS	
DEFINITION	1) It measures the whole $C0_2$ emissions avoided due to the bike/ car sharing mobilization of the city, according to the Defra's[4] conversion factor. 2) It is the average percentage of time each vehicle was actually used.
CALCULATION (FORMULA)	1) $C02\ Savings = Factor\ C02e_{Mode} \times \sum\sum_{i\ in\ t}^{T} (Km_t)$ $Factor\ C02_{Mode}$ $= Conversion\ factor\ established\ by\ Defra's\ carbon\ conversion\ factor$ $-\ according\ to\ the\ activity\ performed\ or$ $- the\ transport\ mode\ substitution.$ $Km_t = Number\ of\ kilometers\ traveled\ with\ the\ mode\ in\ the\ time\ T$ $T = Evaluated\ period.$ 2) $Usage\ rate = \frac{time\ of\ utilization}{total\ time}$ As a proxy of *time of utilization* total "rental" time of the vehicles has been used.
PRESENTATION (FORMAT, UNIT OF MEASURE)	1) Kilograms of carbon dioxide equivalent (CO_2e). CO_2e[5]. 2) Percentage
FREQUENCY OF MEASURE	Any time aggregation is possible, but is establish for the 6 weeks that is the overall period of evaluation.
REFERENCE	1) "In many European cities, support for public transport and cycling

[4] Department for Environment, Food and Rural Affairs (Defra), emits conversion factors that allow activity data (e.g. litres of fuel used, number of miles driven, tonnes of waste sent to landfill) to be converted into kilograms of carbon dioxide equivalent (CO2e).

[5] CO2e is a universal unit of measurement that allows the comparison of global warming potential of different Green House Gases (GHGs).

(LITERATURE JUSTIFICATION)	in daily mobility is considered an efficient means to reduce air pollution, traffic jams, and carbon emissions" "Bicycle sharing systems complementing the traditional public transport system could potentially increase the competitiveness and attractiveness of sustainable modes of urban transport and thus help cities to promote sustainable daily mobility "(Jäppinen, 2013) "These conversion factors allow activity data to be converted into kilograms of carbon dioxide equivalent (CO_2e). CO_2e is a universal unit of measurement that allows the global warming potential of different GHGs (Greenhouse gases) to be compared." (Consultancy, A. E. A, 2010) 2) On average people have cars parked 92% of its life time, 1% caught in traffic jam, they spend 1,6% looking for parking and the other 5% driving with only one driver in most cases. (MacArthur et al., 2015). Automobile usage is a major source of air and noise pollution and improper use of private car is responsible for many of the serious environmental problems (Qu et al., 2017a).
TARGET	
AIM	Those two indicators aim at measuring environmental impact of sharing modes. The first one measure a direct effect such as emissions savings while a more indirect one is cached by the second.
STAKEHOLDERS	User (consumer awareness) Public Administration (environmental savings) Provider (Marketing agency, lifestyle promoter.)
COMMENTS	
STRENGTH	Easy and fast calculation.
WEAKNESSES	Assumption that the bike trips are entirely substitute by a medium car trip with unknown fuel.
DATA SOURCES	BikeMi Data Defra's conversion factor

7. Results

This chapter evaluates first the results obtained by the static and the dynamic analysis of the sharing modes network, that is, the coverage, cohesion and trip distribution of car sharing and bike sharing in Milano; and the behaviour of the networks in specific scenarios (week days and weekends). After, examines the results of the key performances measures, covering traffic efficiency, health and sustainability impacts.

7.1 Static Analysis

The main characteristics of the built up networks for each transportation mode are:

Features	***Bike Sharing***	***Car Sharing***
NIL coverage- Vertices	39 out of 88	86 out of 88
Average degree	32	63
Maximum number of edges[6]	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

Table 5. Features of shared mobility networks

Cleary the coverage of the car sharing network overcomes in a significant way the coverage of the Bike Sharing one, but this last one has a more intense linkes in the present areas. The density of the Bike network is of 85% while the car network is only of 74%, and on average 8,9 trips by bike are made in a city for every single car sharing trip of the free floating providers analysed. The next scheme summarizes the network details in terms of connections and distances.

[6] 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.

The directed Graph is 4-vertex-connected, meaning that at least 4 edges need to be removed for cut-down the graph. If we consider an undirected graph, the number of edges becomes 8. **Edges that when removed, cut the graph:** The edges connecting GALLARATESE with any of the followings: [1] De Angeli --; [2] Duomo --; [3] -- Ghisolfa; [4] -- Magenta; [5] -- Portello; [6] -- Qt8; [7] -- Tortona; [8] -- Villapizzone. Partition one: Gallaratese Partition two: Rest of the nodes (39 vertices)	The Graph is not strongly connected, but the undirected one needs the removal of one edge to be cut down. **Edge that when removed, cuts the graph:** [1]. BUENOS AIRES VENEZIA -- PARCO DEI NAVIGLI[7] Partition one: Parco Dei Navigli Partition two: Rest of the nodes (85 vertices)
Average path length: 1,15 To go from one Nil to any other (of the 39) by bike, we need to pass on average through 1,15 other NILS	**Average path length: 1,22** To go from one Nil to any other (of the 86) by car, we need to pass on average through 1,22 other NILS
Farthest vertices: Duomo – Farini *Highlighted in the Figure 21	Farthest vertices: Figino – Sacco *Highlighted in the Figure 22

[7] The cut is reasonable, because Parco Dei Navigli is connected to the rest of the network only by one trip to Buenos Aires.

Trips distribution

Despite the bike sharing network density, the bike sharing trips distribution highlights the concentration of the 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 others 7 areas (Buenos Aires – Venezia, Brera, Magenta - S. Vittore, Guastalla, Centrale, Sarpi and Pagano), representing only the 20% of the entire locations covered by the bike sharing program, as the heat-map illustrates:

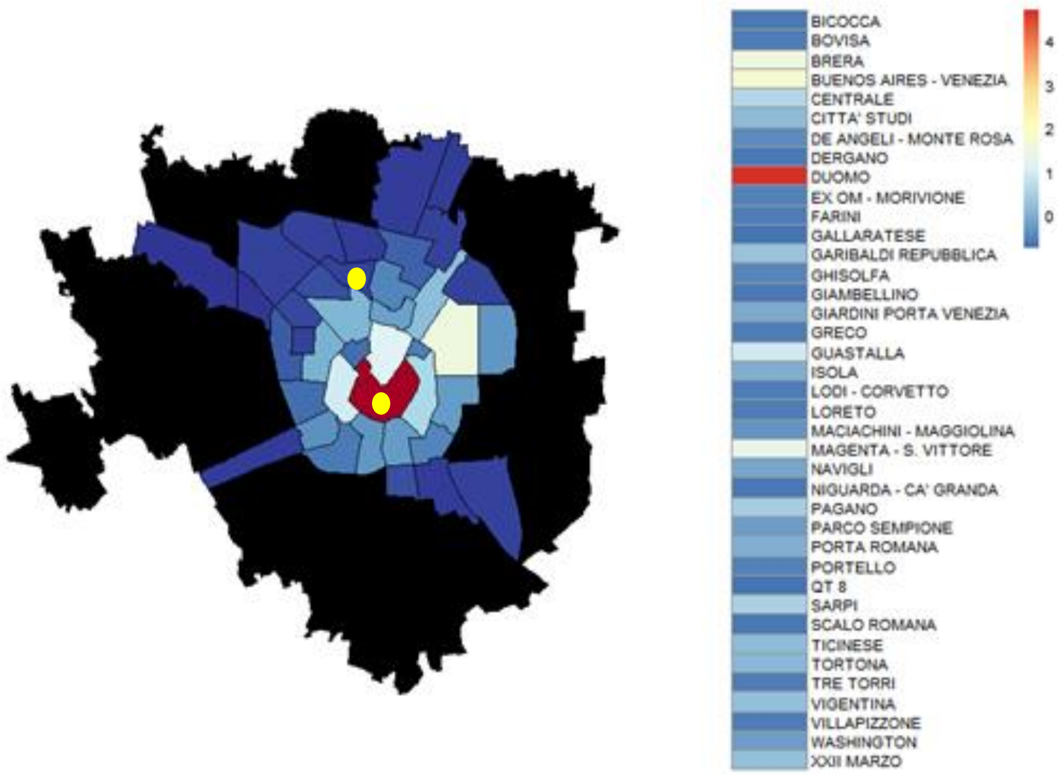


Figure 21. Bike Sharing trips strength by NIL with network diameter. 0 (blue)= low value of strength; 4 (red) = high value of strength

To reach the same relative amount of trip volumes in the car sharing mode, that is 59% of the overall, 28 NILS are required and in this case, the NIL with the highest concentration of trips (Buenos Aires) only reach 5% of the entire volume. Representing a smoother distribution of the trips across the city, which are still, in any case, focused mainly in the central zones (Buenos Aires, Duomo, Brera and Centrale).

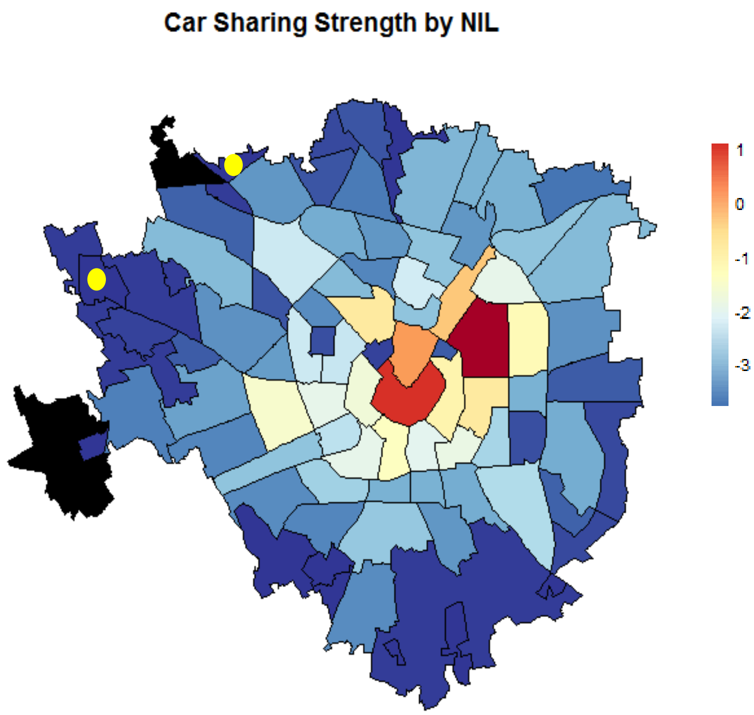


Figure 22. Car sharing Strength by NIL with network diameter.
Blue= low value of strength; Red = high value of strength.

The previous representation of the strength with a geographical association, highlight c*entres,* which are the more relevant areas that accumulate urban stocks (Zhong, Arisona, Huang, Batty, & Schmitt, 2014). These locations required the constant attention of the public administration and the city planners, and usually tend to be recognized in a city with a qualitative approach in urban studies. Geographical network analysis of movements, allows not only a more precise identification of these types of areas, but also can track easily their evolution.

The other interesting feature to evaluate with the network properties, are the zones of the city referred before as *hub*s, which characterize spatial bridges among different areas. These zones can be recognized as the nodes of a network with high betweenness, and in the particular case of the sharing mobility in Milano, tend to surround usually 'isolated' locations as the Figure 23 illustrates (e.g. the case of QT8 as a bridge for Gallaratese in the bike sharing network -that required the minimum cut in the graph to end up isolated-). As for the centres, furthers explorations can be conceived to track the patters and transformation of this areas, studying them in an integrate version of the overall trips in the city with other modes.

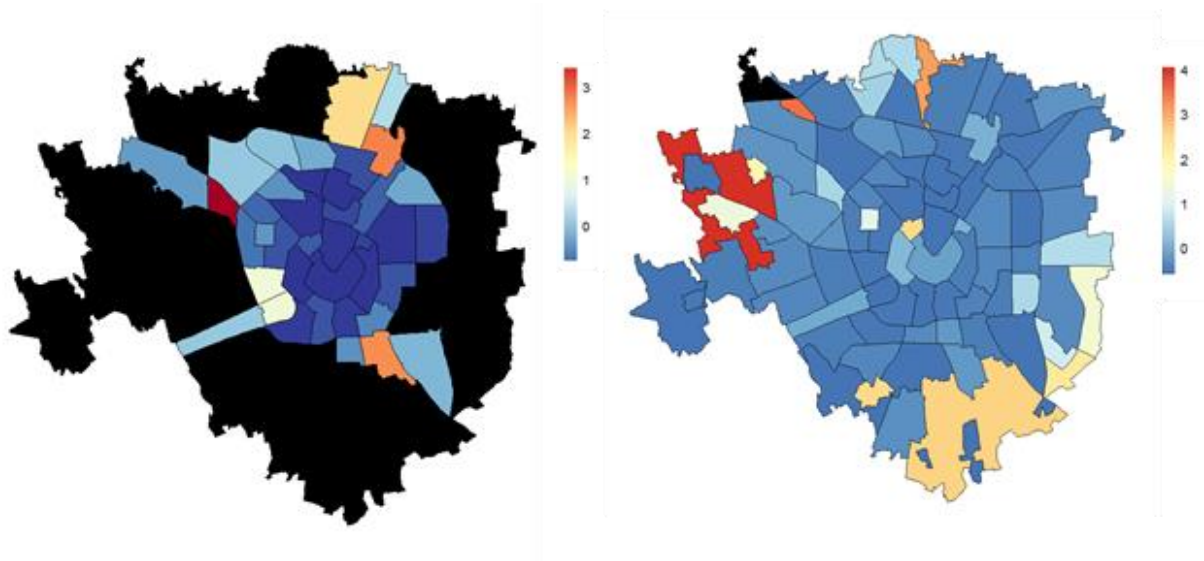


Figure 23. Left: Identified 'hubs' in the bike sharing network. Right: Identified 'Hubs' in the car sharing network. Red= high betweenness (hubs); Blue= high betweennees.

Edge Analysis

As mentioned in the trips distribution regarding the departure and the arrival points, the shared mobility networks tend to be highly concentrated in certain parts of the city. This behaviour is confirmed when observing the most common trips for each mode. Out of the factual 1.290 trajectories in the period evaluated for the Bike sharing, among 25 of them, the equivalent to 2% of the total, allocates 30% of the trips. With *Duomo* as the central location receiving and dispatching the majority of the journeys as the graph bellows illustrates:

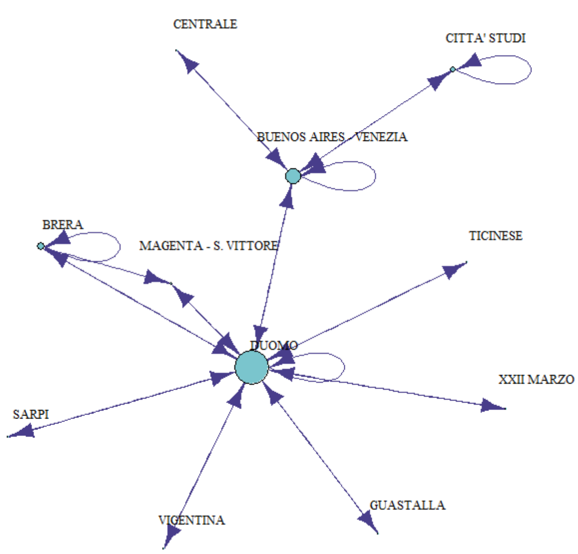


Figure 24. Bike Graph with main edges. The size of the vertices is correlated with the strength of the NIL

The most outstanding connection happens to be between Duomo and Magenta, but the strength of this last zone is negligible, due to its relatively poor connection with other zones of the city, what, for example, does not occur with Buenos Aires, which besides being connected with Duomo, plays an important role linking trips to other destinations (Centrale or Citta Studi)

Geographically, are notorious the physical constraints attached to the mode. Almost all the connections occurred within a neighbourhood, confirming as well the bike usage as 'last mile trip' mode.

In the case of car sharing trips to reach the same amount of trips (30%), 3,1% of the connections (170 trajectories out of the 5443) are required. Most of the focal nodes, such as Duomo, Brera, Buenos Aires are still dominant, but also -as expected- other players in less central areas of the city are considered. In the car scenario, 'the round trips' are common, that is, the trips star and finish within the same NIL. In total 17% of the displacements presented this condition and the 20 connections covering 10% of the entire trips are just round trips. The first relevant connection between NILs happens between Buenos Aires and Brera. The following maps illustrate the graph connection by mode, 30% of the trips in the case of the BikeMi service, and 10% for the car providers

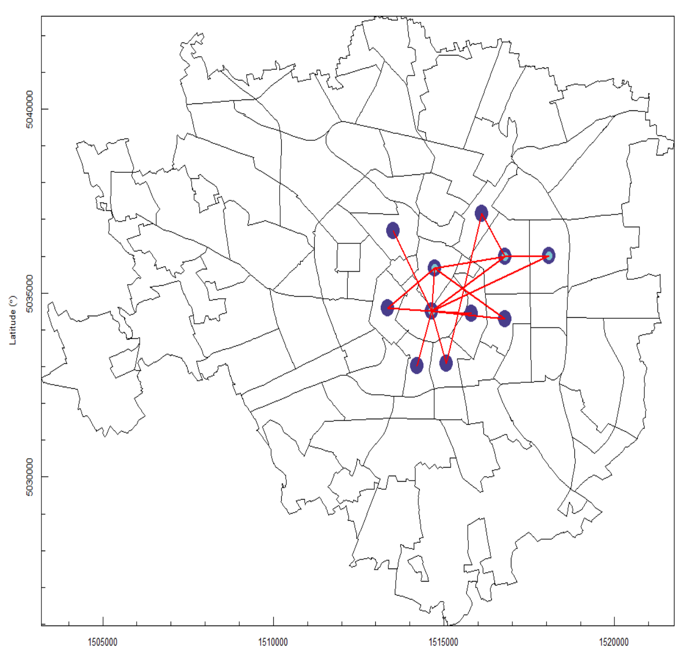


Figure 25. Connections of 30% of the bike trips

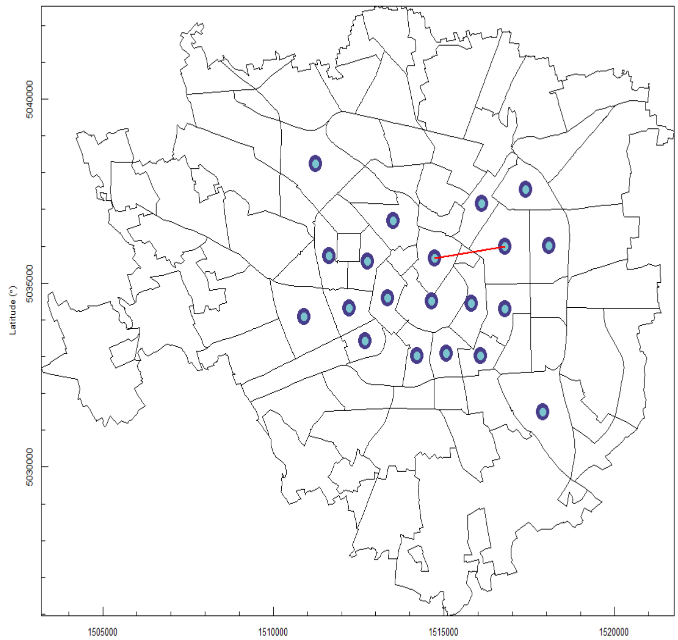
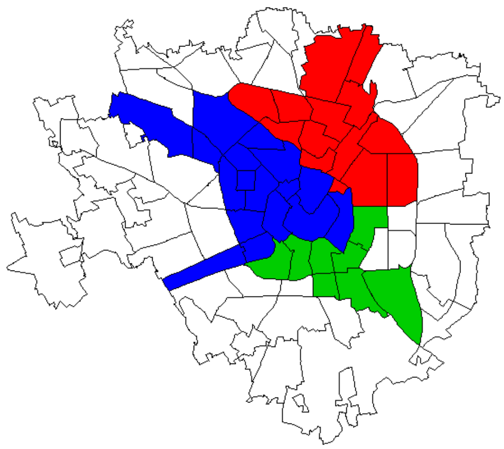


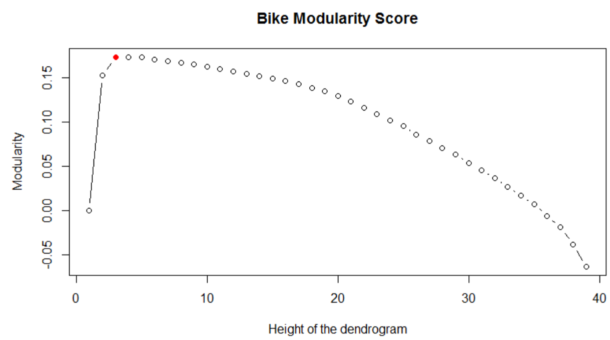
Figure 26. Connections of the 10% of car trips

Hierarchical clustering

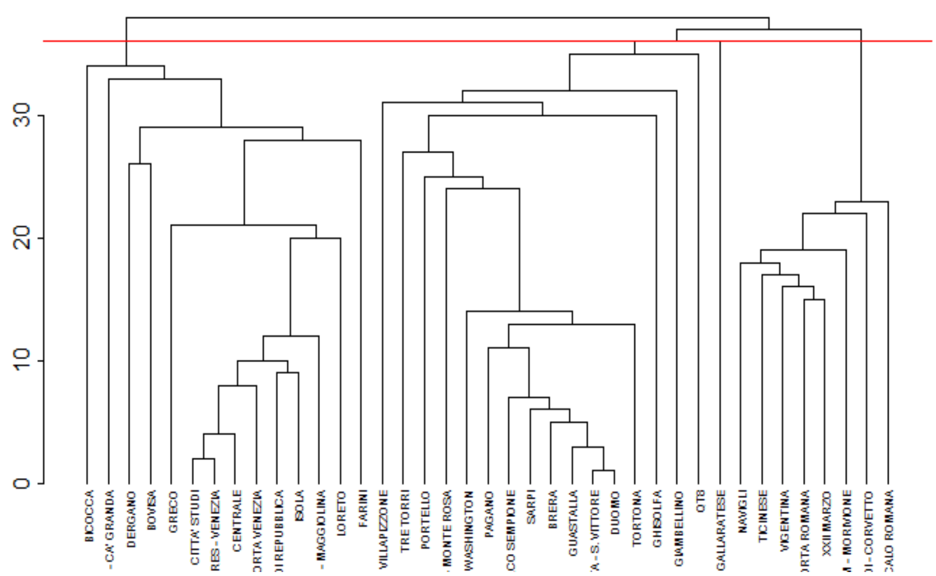
To explore sub-structure in the two networks the *fast greedy* algorithm proposed by (Clauset, Newman, & Moore, 2004) has been employed. The results have been summarized by the following figures. For BikeMi the algorithm recognized 3 clusters shown in Figure 27(a). They individuate three totally disjointed geographic area of the city: South, North-Est and North-West. This outcome is probably linked to 30-minutes-free period that encourages short trips making rare displacement between two distant NILs. Moreover, the result is in line with the fact that bikes are used often as last-mile trip and that other modes are preferred for long distances. In Figure 27 the dendogram coming from the algorithm application is presented beside the graph of modularity scores for the different heights of the dendrogram. In this latter one the red point represents the maximum modularity at which correspond the cut of the dendrogram and thus the number of cluster selected. Same procedure has been used for car sharing's network even if the result is more difficult to interprete and further studies are probably required. The number of communities founded by the algorithm is 7. Since car, as opposed to bikes, does not have distance issues, we expected to find cases in which distant NILs were part of the same cluster and that is what actually happens. The map illustrating the geography of the different communities – of NILs - detected and the graph with modularity score can be found in Figure 28.



(a)

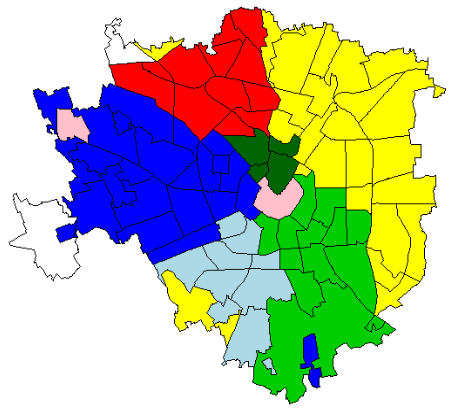


(b)

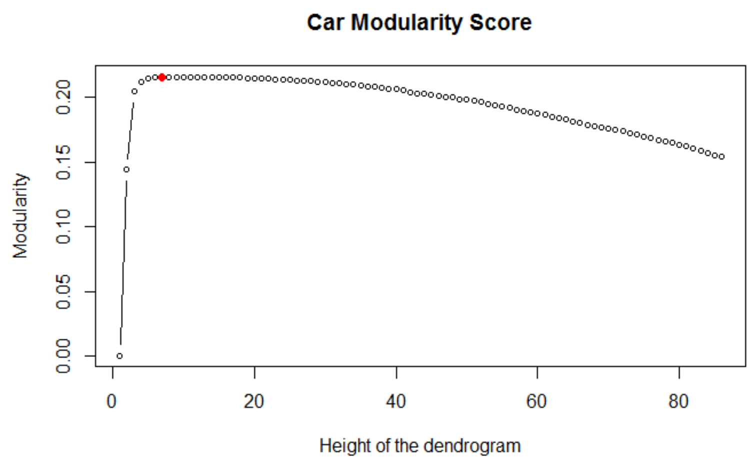


(c)

Figure 27. BikeMi clustering outcomes. Map of the cluster (a), modularity scores (b), dendrogram with cut at the height that corresponds to the maximum modularity (c).



(a)



(b)

Figure 28. Car sharing clustering outcomes. Map of the clusters (a), modularity scores (b

7.2 Dynamic Analysis

89,5% of the bike sharing trips in the dataset is performed during a weekday, even do this only represents the 70% of the total time exanimated. Assuring that this transportation mode is way more used during the 'working' days (so, somehow for routine trips) than for the weekends.

The particularity of attaching the trips divided into time periods to the geo-spatial information is the availability to identify which zones of the city are preferred according to the time.

The heat-scale in the Figure 29 shows that Gallaratese, Parco Sempione, and QT8 (all areas involved with green zones of the city) are much more active in the weekends, while Magenta, Biccoca, Bovisa and Garibaldi are dynamic locations for the week days, indeed, commercial and university sites are common denominators on this spots.

Is useful also to observe that an active NIL like Duomo, has rather an indifferent behaviour during weekdays and weekends. This highlights its attractiveness as both commercial and tourist/leisure location of the city.

For cars, there is not a considerable difference between week and weekend activity. 28% of the car trips are conducted on Saturdays and Sundays, matching with the time fraction of weekends in the period exanimated. Additionally, besides a couple of NILs that were covered in the 6 weeks studied for less than a couple of trips, the zone behaviour does not have any variability with the weekend arrival. In this scenario, one feasible hypothesis, -seeing the unchanging behaviour of the car network-, is that this mode is not used for routinely activities, and only matches when urban mobility users required additional flexibility on their displacements.

Figure 29. NIL week versus weekends bike trips activity. Red= stronger activity during weekends; Blue= stronger activity during the week.

The results in other sub-setting targets were not particularly relevant to be mentioned in detail. The weather conditions for example, remarks that green zones like Parco Sempione or QT8 are common destinations in warmer days. While the number of trips, when is raining, increases in relative terms in places with indoor activities like Brera of Vigentina.

The final sub-setting contemplation, the rush hours, are a central focus of mobility. Therefore, its implications are considered in a more active analysis inside the performance measurement evaluated in the next section of the chapter.

7.3 Result of KPIs

The following section presents the results of our KPIs analysis and their interpretation in the tree macro area considered: Convenience (Mode Convenience, NIL Relative Strength and Congestion), Sustainability (Sharing Mode C02 Savings) and Health (BikeMi MET).

Often, for better comparison between bike and car sharing system, just the 39 NILs - where both modes are active – out of 88 are taken in to account in the discussion.

7.3.1 Sharing Mode Convenience

The overall velocity for the Bike Sharing system in the city of Milan is of 11.38 Km/h, slightly higher than the one for the Car Sharing service that is of 11.24 km/h[8], for the trips that has until 60 minutes of duration**.** Nevertheless, the standard deviation of the velocity of the trips performed by car (8,8 km/h) is considerable higher, than the velocity for bikes (4,8 km/h), as the boxplots show.

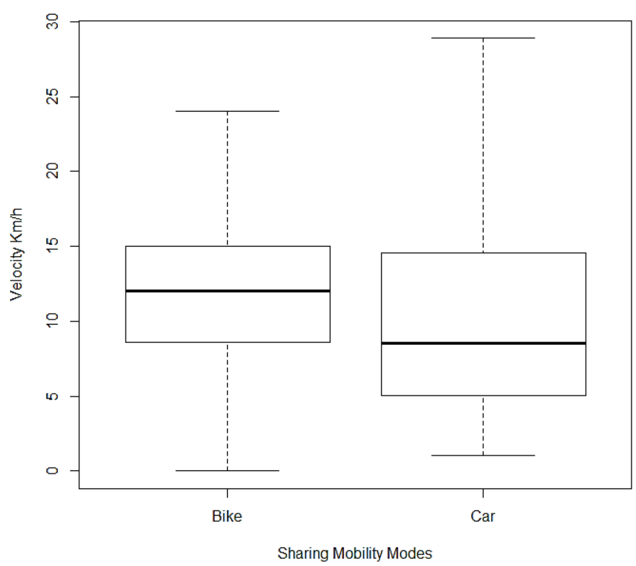


Figure 30. Velocity by Sharing Mobility Mode in Milano

The upper level of the trips duration (60 minutes) was decided by the fact that the actual path of each trip is unknown and the distance is always estimated given the initial and final

[8] The Bike velocity, was calculated with the entire dataset. For the car trips instead, the following trips were excluded: No return, 'rebalance trips', trips going out of Milan, trips starting and finishing in the same NIL (round trip likelihood) and trips longer than 60 minutes. Outliers (representing the 1% of the total database) were also discarded. The total number of trips considered that was 27.526.

location. The fact of not having the stops in the middle drove us to consider only the 'short' trips that, in a city environment, are more likely to avoid intermediate stops. In our case, the short trips are those that last up to 60 minutes (2 times the 'free' bike sharing ride).

Further studies on car sharing velocities variability, considering also externals factors, represent an interesting field of research for the city planners and the providers. Here, the comparison with the bike sharing mode, gives some hint according to the variability that eventually can be related with the geographical location of the trips.

The velocity scenario by mode tends to change when comparing the velocity of the incoming and out-coming trips inside the NILs shared by both modes: car sharing and bike sharing. In this case, the car is faster for the majority of the cases, while moving by bike is relatively more convenience in terms of velocity only for 2 NILs. The low general car-sharing velocity can be explained by the partial information used for the comparison (NILs that do not have a bike docking station have not been considered) and by the fact that the Inter-Nil velocity, has been computed as a result of the in-coming and out-coming trips per each NIL.

As displayed in Table 6, the fastest NILs by bike are: Parco Sempione and Tre Torri, and the slowest ones in relative terms are Bicocca, Gallaratese and Portello. Yet, the difference between the higher velocity in the bike mode (Citta' Studi, 13,6 km/h) versus the lowest one (Niguarda, 10,93 km/h) is only of 19,7%, while this difference is remarkably higher for car sharing trips (46,6%), coming from the trips that occur in Gallaratese (17,8 km/h) and Parco Sempione (9,5 Km/h).

NIL	Bike Km/hr	Car Km/hr	Delta
BICOCCA	11,594	15,795	27%
BOVISA	11,969	12,544	8%
BRERA	11,541	11,835	2%
BUENOS AIRES - VENEZIA	12,781	13,264	13%
CENTRALE	12,245	13,441	14%
CITTA' STUDI	13,627	14,895	22%
DE ANGELI - MONTE ROSA	13,117	12,709	9%
DERGANO	10,979	12,382	6%
DUOMO	11,474	12,292	6%
EX OM - MORIVIONE	12,531	12,403	7%
FARINI	11,500	11,651	0%
GALLARATESE	12,277	17,809	35%
GARIBALDI REPUBBLICA	11,797	11,692	1%
GHISOLFA	12,192	12,539	8%
GIAMBELLINO	12,939	14,159	18%
GIARDINI PORTA VENEZIA	11,366	11,897	3%
GRECO	11,150	13,311	13%
GUASTALLA	11,928	12,808	9%
ISOLA	11,678	12,606	8%
LODI - CORVETTO	13,217	15,017	23%
LORETO	12,651	13,846	16%
MACIACHINI - MAGGIOLINA	11,419	12,188	5%
MAGENTA - S, VITTORE	11,937	11,829	2%
NAVIGLI	11,568	12,574	8%
NIGUARDA - CA' GRANDA	10,932	14,787	22%
PAGANO	12,358	11,560	0%
PARCO SEMPIONE	11,118	9,512	-22%
PORTA ROMANA	12,164	12,788	9%
PORTELLO	12,468	11,791	2%
QT8	13,180	17,741	35%
SARPI	11,435	12,068	4%
SCALO ROMANA	12,431	14,873	22%
TICINESE	11,971	12,042	4%
TORTONA	12,249	12,721	9%
TRE TORRI	12,749	9,599	-21%
VIGENTINA	12,173	12,480	7%
VILLAPIZZONE	13,289	14,198	18%
WASHINGTON	12,664	12,186	5%
XXII MARZO	12,726	13,272	13%

Table 6. Mode Convenience in terms of Velocity by Mode and NIL

Despite the advantage in term of velocity of the car sharing programs respect to BikeMi in the overall city of Milano, it can be noticed that zones such as Brera, Porta Venezia and Pagano do not have great velocity differences between the two modes, favouring somehow the Bike utilization. While, Gallaratese, Loreto and Bicocca, for been also zones outside of the centre with a road infrastructure that allows greater velocities, tend to prioritize the use of cars, at least for the convenience in terms of speed. The map belows, shows which are where bikeshare happens to be more convenient (red zones) and the ones where car is the most convenient mode in terms of velocity (blue zones).

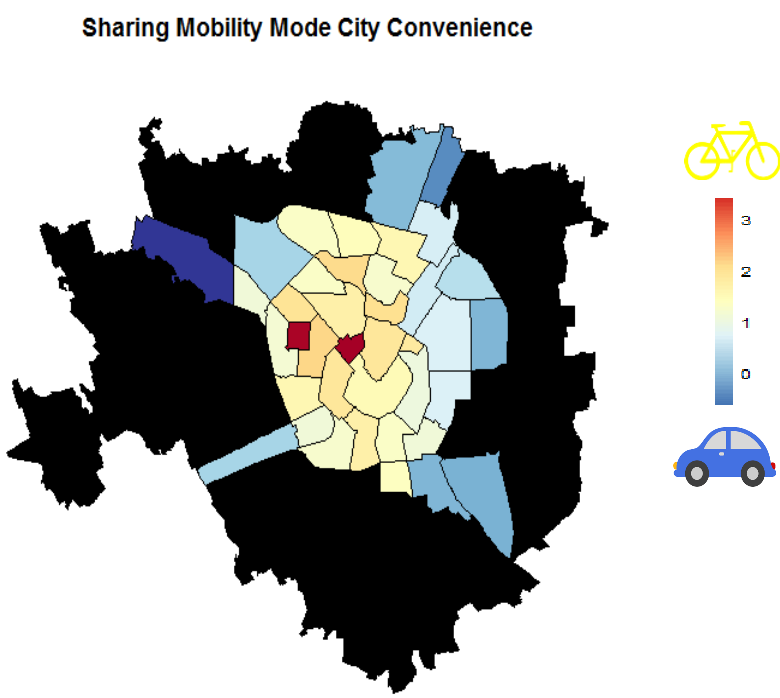


Figure 31 Sharing Mobility Mode Convenience in terms of Velocity

A case to remark is the one concerning **Citta Studi** where, in velocity terms, the bike is considered a less convenient mode than the car, but represents -in absolute terms- the location with the highest velocity for bike trips. Not considering this as a minor factor, an illustration with the absolute velocity information is displayed in the Figure 32[9]. As probably expected, the velocity for both modes increases significantly while leaving Milano's city rings, so while reaching the city peripheries (with the notable exception of the bike mode for the Bicocca location).

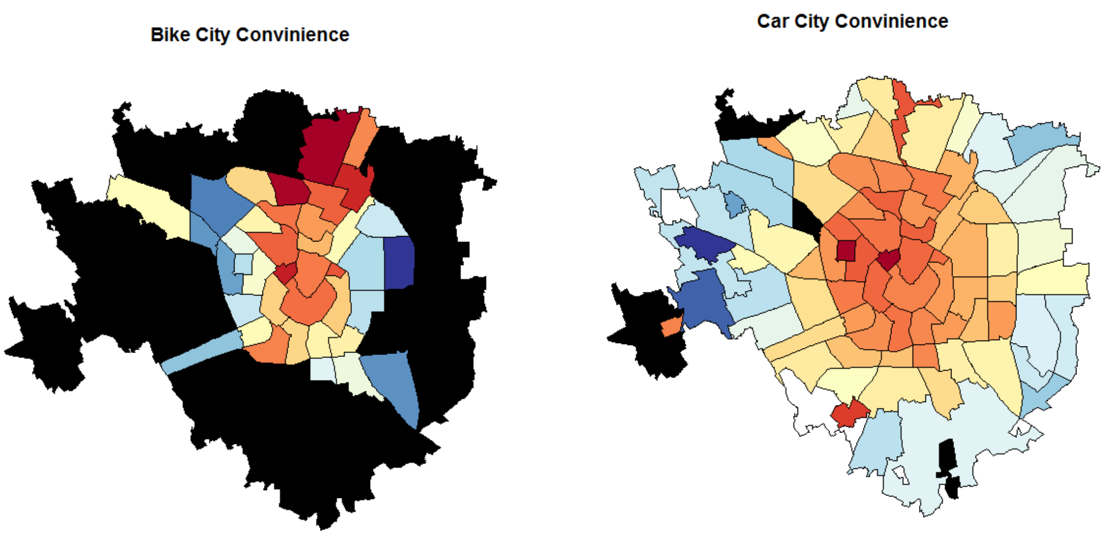


Figure 32 Absolute shared mobility mode convenience in terms of velocity for each NIL. Left: Bike sharing, Right: Car Sharing. Red = slow; Blue = fast

In the case of the bike sharing, the comparison with the allocated strength (trips distribution) illustrates that the areas with available infrastructures to reach high velocities are likely misused, or either that the locations that concentrated the larger number of trips tend to have poorly infrastructure conditions for bikes.

Indeed, this evaluation can be taken further to assess and reconfigure the current infrastructure for bike and car sharing services in the city. What does differ in Citta' Studi and Dergano to allowed a larger velocity in the first NIL for bikes? It is only a matter of the kind of

[9] Car Sharing mode, NILs omissions of the vertices connected only in one direction.

the place (evident in the case of the Parco Sempione for example, where moving faster may not be the main aim of the users) or is more related with the facilities available in the location.

Congestion velocity (delta rush hour) for mode

The rush hour, identified for the BikeMi program in the period evaluated goes from **8:00 to 9:00** in the morning and from **18:00 to 19:00 hours**. During these period, the average velocity of the trips by bike decreases only by **1,13%**.

While for the rush hour period of the car sharing providers, that goes from **18:00 to 21:00** (the peaks of the system starts at 19, but not the case for the general mobilization), the average velocity decreases by **19.95%** with respect to the overall velocity of the system.

Meaning that, as expected, in the rush hour the time of displacement (attached to the user velocity) of bike users has a minor increase compared to the one for the car users.

7.3.2 Congestion Factor

There are two picks 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. That 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 correlation with people daily routine is less strong if we talk about car sharing that has just one peak from 19 to 21 p.m. This suggests that users don't use that mode to reach a work or a study location. For some reasons, that could be detected and explored in further studies other mobility modes are preferred to car sharing to perform those journeys. This is evident in the 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. Moreover, while bike sharing is spread almost all over the daytime, 49% of car sharing's activity is concentrated from 5 p.m. to 10 p.m.

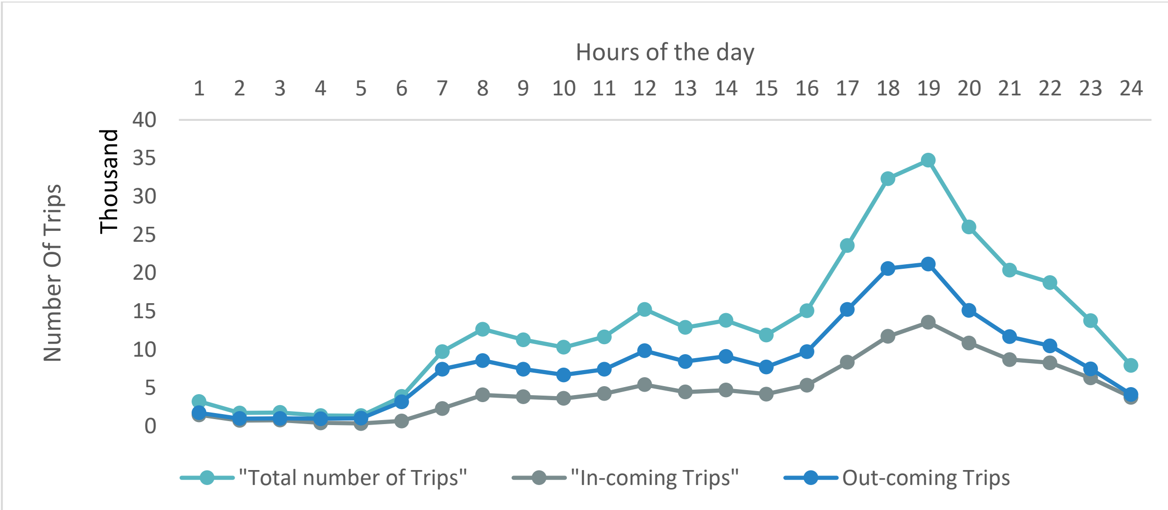


Figure 33. Car Sharing Traffic Peaks

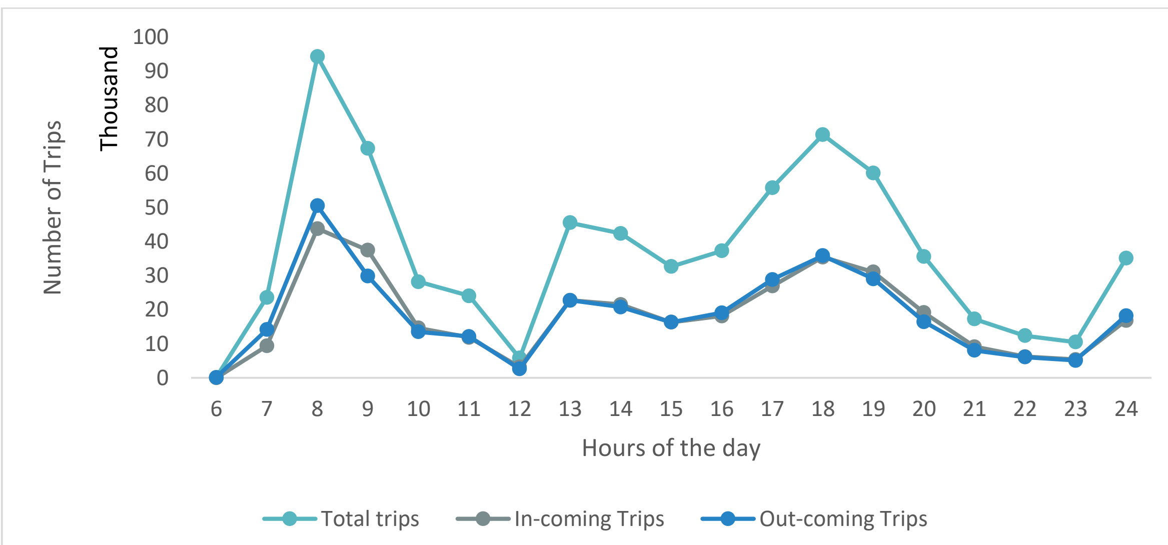


Figure 34. Bike Sharing Traffic Peaks

Another feature that the previous plots illustrates, is the rebalancing activity required to allow 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 specially during the rush hour-. Analysing this delta of trips in detail for each location can provided the most critical areas where rebalancing should take place and 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, that were estimated in our study.

Since Milano's users seem to access car sharing mode specially in the evening we can conjecture that it is perceived as a convenient mode for journeys that occur after the average working hours. This way of thinking car sharing would be in line with the general Milano's car sharing brands positioning. Models and colours of the cars, marketing campaigns and the app-based interaction with customers prove in fact that brands as Enjoy, Share'nGo and Car2go want to be perceived as funny, smart and fresh.

Since the analysed period was in winter, due to temperature the usage of bike after a certain hour is rare and results may differ during warmer months.

	Bike	**Car**
Peak hours (t)	8:00 - 9:00 a.m. 18:00 - 19:00 p.m.	19:00 - 21:00 p.m.
OVERALL CF	2,23	1,68

Table 7. Peak hours and overall congestion factor

We compute the IN Congestion factor (*INCF)* and Out Congestion factor (*OUTCF)* for each mode and each NIL with the respective peak time of the day- (*t_in)* and (*t_out)* - when they are calculated, as is shown in the Table 8 for bikes and Table 9 for cars. Besides those values a synthetic value – Congestion Factor (*CF)* - has been computed considering both incoming and outcoming trips. A t_in value of 9 means that the peak time in the NIL associated to that value occurred from 9 to 10 a.m. as a value of 22 corresponds to a peak between 10 and 11 p.m.

The results presented here consider only the 39 NILs where bike sharing's docking stations are present to compare the two modes. *Gallaratese* was excluded from the analysis for bike sharing because, since just 15 trips occurred during the tracked period, it results an outlier hiding the differences within the other NILs. In the upper part of the tables the most variable NILs for each mode appear.

In general bike sharing's traffic is more variable that car sharing's; on average the traffic of the first increase by a factor of 2,32 against the 1,62 of the second. Again this difference is probably related to the impact of external conditions such as weather on bike activity. Besides 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 from 9 to 10 a.m. the traffic is 3,29 times bigger than the average while from 6 to 7 p.m. the out flow increase by a factor of 3,05. This means that around 10 a.m. Bicocca's docking station will be full of bikes while around 7 p.m. the station will have a lack of bikes incurring in the risk of stock out of the service. A rebalancing trip before the evening peak would reduce that risk.

Moreover, opposite behaviour of NIL regarding the results obtained on bike sharing arose the hypothesis of identifying the different natures of Milano's zones with t_in and t_out. If a district has a peak of incoming trips during 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*. Since the literature states that bikeshare 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 Table 10.

Further studies could develop this idea and try to test the hypothesis behind that.

	BIKE				
NIL	**INCF**	**t_in**	**OUTCF**	**t_out**	**CF**
MAGENTA - S. VITTORE	3,08	18	5,12	8	2,94
SCALO ROMANA	2,57	8	3,30	8	2,92
GARIBALDI REPUBBLICA	2,55	8	3,13	8	2,85
PORTELLO	2,03	18	3,78	8	2,75
TORTONA	1,98	19	3,73	8	2,67
BICOCCA	3,29	9	3,05	18	2,61
ISOLA	2,27	8	2,88	8	2,58
MACIACHINI - MAGGIOLINA	2,34	8	2,79	8	2,56
DERGANO	3,00	8	2,56	7	2,55
WASHINGTON	2,10	19	3,07	8	2,48
CENTRALE	2,23	18	3,44	8	2,47
GHISOLFA	2,11	18	4,08	8	2,40
VILLAPIZZONE	3,28	18	4,39	8	2,35
XXII MARZO	2,18	19	4,08	8	2,32
BOVISA	2,55	18	3,98	8	2,32
LODI - CORVETTO	3,01	18	4,69	8	2,24
GIARDINI PORTA VENEZIA	3,76	8	2,22	17	2,22
GIAMBELLINO	2,83	18	3,88	8	2,20
BRERA	3,03	8	2,06	18	2,19
PAGANO	1,97	18	2,85	8	2,18
GRECO	2,20	19	4,08	8	2,17
NAVIGLI	2,02	18	3,71	8	2,16
LORETO	1,95	18	2,47	8	2,14
EX OM - MORIVIONE	2,52	9	3,12	18	2,14
NIGUARDA - CA' GRANDA	2,38	18	1,95	8	2,14
PORTA ROMANA	1,97	19	3,43	8	2,13
DUOMO	3,97	8	2,38	18	2,11
VIGENTINA	2,24	8	1,96	8	2,10
GUASTALLA	2,78	8	1,37	8	2,08
BUENOS AIRES - VENEZIA	1,85	18	3,43	8	2,04
FARINI	2,46	8	1,61	8	2,02
CITTA' STUDI	1,81	18	2,62	8	1,98
TRE TORRI	2,04	18	2,46	8	1,90
DE ANGELI - MONTE ROSA	1,65	8	2	8	1,82
SARPI	2,19	19	3,34	8	1,80
TICINESE	1,94	19	3,03	8	1,74
PARCO SEMPIONE	1,32	9	2,36	8	1,73
QT 8	1,57	15	1,92	20	1,47
OVERALL	**2,51**	**8**	**3,13**	**8**	**2,32**

Table 8. Bike Congestion Factor by NIL

	CAR				
NIL	**INCF**	**t_in**	**OUTCF**	**t_out**	**CF**
GALLARATESE	3,63	19	4,18	18	3,74
NIGUARDA - CA' GRANDA	0,88	23	0,93	21	2,62
BICOCCA	1,79	19	1,44	18	2,48
GRECO	1,52	19	1,24	18	2,29
GIARDINI PORTA VENEZIA	1,62	19	1,41	18	2,14
VILLAPIZZONE	0,80	18	0,88	8	2,08
BOVISA	2,29	19	2,88	18	2,08
LODI - CORVETTO	1,09	20	1,17	18	2,03
MACIACHINI - MAGGIOLINA	1,98	19	2,08	19	2,03
PARCO SEMPIONE	1,73	19	1,94	19	2,00
DERGANO	1,02	18	0,83	7	1,83
TRE TORRI	1,38	19	1,78	18	1,76
LORETO	1,68	19	1,78	18	1,72
QT 8	2,15	19	2,33	18	1,62
FARINI	1,03	19	0,92	18	1,62
SCALO ROMANA	2,00	19	2,52	18	1,60
GIAMBELLINO	1,88	19	2,17	19	1,59
GHISOLFA	2,18	22	2,84	21	1,54
CITTA' STUDI	1,64	19	1,55	19	1,49
CENTRALE	1,00	19	0,97	7	1,48
EX OM - MORIVIONE	0,94	18	0,74	21	1,33
PORTELLO	2,15	19	2,52	18	1,31
GARIBALDI REPUBBLICA	1,25	19	1,13	19	1,27
NAVIGLI	1,80	19	1,65	19	1,19
TICINESE	1,25	18	1,42	18	1,17
ISOLA	2,63	19	3,03	18	1,09
SARPI	0,98	18	0,82	18	1,05
VIGENTINA	0,99	22	1,12	21	1,01
DE ANGELI - MONTE ROSA	1,08	19	1,04	18	0,96
BUENOS AIRES - VENEZIA	0,78	19	0,87	19	0,95
XXII MARZO	1,04	18	0,86	18	0,93
WASHINGTON	1,62	19	2,01	18	0,91
PORTA ROMANA	1,48	19	1,74	18	0,90
DUOMO	2,05	22	2,09	21	0,86
GUASTALLA	1,01	18	0,90	18	0,82
BRERA	1,23	19	1,06	18	0,82
PAGANO	1,21	19	1,38	18	0,81
TORTONA	1,55	21	2,59	18	0,78
MAGENTA - S. VITTORE	1,45	18	1,81	18	0,76
OVERALL	**1,53**	**8**	**1,66**	**19**	**1,50**

Table 9. Car Congestion Factor by NIL

NIL	t_IN	t_OUT	Nature
BRERA	8	18	W
DUOMO	8	18	W
GIARDINI PORTA VENEZIA	8	17	W
BICOCCA	9	18	W
EX OM - MORIVIONE	9	18	W
GALLARATESE	9	18	W
DERGANO	8	7	R
PARCO SEMPIONE	9	8	R
QT 8	15	20	R
BUENOS AIRES - VENEZIA	18	8	R
CENTRALE	18	8	R
CITTA' STUDI	18	8	R
GHISOLFA	18	8	R
GIAMBELLINO	18	8	R
LODI - CORVETTO	18	8	R
LORETO	18	8	R
MAGENTA - S. VITTORE	18	8	R
NIGUARDA - CA' GRANDA	18	8	R
PAGANO	18	8	R
PORTELLO	18	8	R
TRE TORRI	18	8	R
VILLAPIZZONE	18	8	R
BOVISA	18	8	R
NAVIGLI	18	8	R
GRECO	19	8	R
PORTA ROMANA	19	8	R
SARPI	19	8	R
TICINESE	19	8	R
TORTONA	19	8	R
WASHINGTON	19	8	R
XXII MARZO	19	8	R
FARINI	8	8	U
SCALO ROMANA	8	8	U
VIGENTINA	8	8	U
DE ANGELI - MONTE ROSA	8	8	U
GARIBALDI REPUBBLICA	8	8	U
GUASTALLA	8	8	U
ISOLA	8	8	U
MACIACHINI - MAGGIOLINA	8	8	U

Table 10. NIL nature. W= working/scholastic district; R= residential/bridge district; U=unclassified

7.3.3 NIL Relative Strength (NRS)

The NIL relative strength relies in the network properties, particularly in the centrality of a vertex in terms of strength, to compare the importance of a district for a given sharing mobility in the overall sharing mobility network. In other words, it claims if for a mode – e.g. car sharing – a specific NIL is more central than it is for the overall sharing mobility.

The strength, measures directly the activity of a NIL on the network, consequently the amount of trips related to it. In our case, in absolute term there is not a significant difference between bikes and cars. In 20 out of the 39 NILs, car sharing systems have a larger relevance, leaving the rest of the share for the bike programs. Indeed, the average **relative strength of the bike system is 0,94** (a value larger than 1 implies superiority for this index).

Nevertheless, the detailed relative strength for each NIL reveals, in which locations a mode is totally dominant. As the Table 11 shows, BikeMi, rules in a significant way NILs such as Duomo, Giardini Porta Venezia, Brera and Parco Sempione, all central part of the city, while the car sharing systems (values < 1) is stronger in Gallaratese and Bicocca - peripheral areas- as the map bellow suggests.

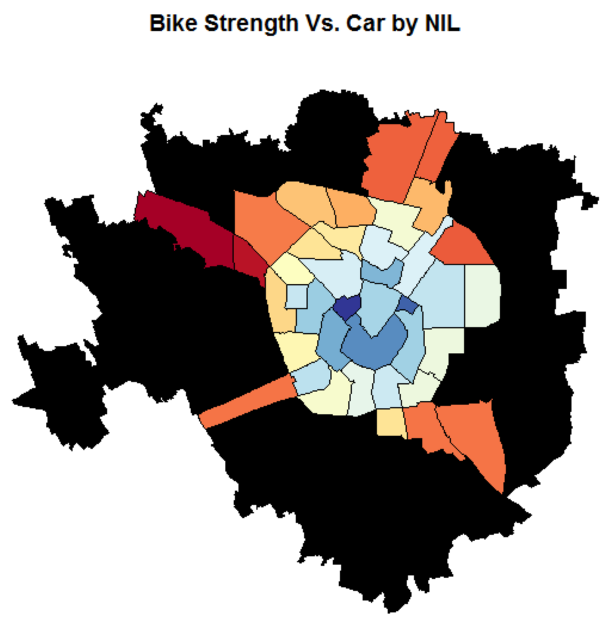


Figure 35. NIL Mode Relative Strength. The blue zones of the city have a larger relative intensity of Bike trips, while the red Zones have it for car trips.

This result, rather illustrate the complementary service of the sharing modes, since the geo-illustrated information does not display any abrupt change (a NIL significantly important for bikes, followed immediately by a NIL where the car sharing system dominates). Therefore, these results can influence the testing of certain policies to measure if the strength of a mode will expand itself to the nearby locations (e.g. 'free' rides longer than 30 minutes will start expanding the bike sharing network strength to the bordering zones).

NIL	Strength Bike Vs. Car
BICOCCA	0,34
BOVISA	0,65
BRERA	1,33
BUENOS AIRES - VENEZIA	1,23
CENTRALE	1,14
CITTA' STUDI	1,07
DE ANGELI - MONTE ROSA	0,73
DERGANO	0,57
DUOMO	1,60
EX OM - MORIVIONE	0,79
FARINI	0,83
GALLARATESE	0,00
GARIBALDI REPUBBLICA	1,45
GHISOLFA	0,78
GIAMBELLINO	0,40
GIARDINI PORTA VENEZIA	1,74
GRECO	0,59
GUASTALLA	1,34
ISOLA	1,13
LODI - CORVETTO	0,41
LORETO	0,33
MACIACHINI - MAGGIOLINA	0,99
MAGENTA - S. VITTORE	1,49
NAVIGLI	0,99
NIGUARDA - CA' GRANDA	0,35
PAGANO	1,36
PARCO SEMPIONE	1,86
PORTA ROMANA	1,04
PORTELLO	0,96
QT8	0,35
SARPI	1,16
SCALO ROMANA	0,41
TICINESE	1,09
TORTONA	1,26
TRE TORRI	1,23
VIGENTINA	1,20
VILLAPIZZONE	0,42
WASHINGTON	0,90
XXII MARZO	1,05

Table 11. NIL Relative Strength

7.3.4 Sustainability

Sharing Mode C02 Savings (Defra's carbon conversion factor)

In order to report the greenhouse gas emissions (GHG) associated with activities, is possible to convert 'activity data' such as distance travelled, litres of fuel used or tonnes of waste disposed into kilograms of carbon dioxide equivalent (CO2e). CO2e is a universal unit of measurement that allows the global warming potential of different GHGs to be compared (Hill, Walker, Choudrie, & James, 2012). This is achieved multiplying the 'activity data' (such as the amount of fuel used) by relevant emissions conversion factors.

These conversion factors, are yearly updated by a formal institution, and related to a wide spectrum of activities that goes from electricity distribution, to water supplier and treatment, passing by all the possible types of transportation, including the passenger vehicles, where is possible to related the conversation factor used in this study.

In our case, the common activity data was the distance in kilometres travelled by bikes, and estimated by cars, and then, the conversion factor that relies on the assumption that **the trip performed was likely to happen in any case by a medium-size Car with unknown fuel**. This would not make a difference with the car sharing trips of providers such as Enjoy and Car2go, but is comparable with the bikes and the energy usage of the electric cars of Sharengo.

The first input then is the **687.015 km** travelled during the period analysed by **BikeMI**, which out of 350.093 trips represent on average 1,9 km/trip. While we have, for the trips performed by **electric cars, 96.810 km**, out of 23.613 trips, leaving on average 4,09 km/ trips.

The conversion factor, which is a common parameter to use, defined in the GhG report of 2016 for passenger vehicles, particularly, a medium car with unknown fuel is **0,18909 Kg of CO2 by kilometre.**

In the case of bikes, not further equivalent of greenhouse gasses emissions is required (electric bikes of BikeMi are not considered in the scenario). Regarding Electric cars, the comparable emissions of their usage, which is clearly not related with fossil fuels is evaluated. In particular, it has been calculated that the wall-to-wheels energy use by electric car is 211 Wh/km (Wilson, 2013), and for this the conversion factor that translates this into Kg of C02 is **0,41205 for KWh**. Leaving as the saving of Electric cars, the remaining differences between this two energy usage.

a. Bike and electric car savings

Mode	Km	Conversion Factor [Kg C02e/km]	Energy Use [KWh/km]	Conversion Factor [Kg CO2e/kwH]	C02 Savings [Kg CO2e]
Bike	687015	0,18909	NA	NA	129907,67
Electric cars	96810	0,18909	0,211	0,41205	18305,72
Bike (50%)	343507,5	0,18909	NA	NA	64953,83

Table 12. Bike and Electric Car Kg of CO2 Savings

Taking into consideration that, is rather unlikely that all the trips performed by bike would happen in any case by a private car (which would not be strange in the car sharing scenario), a deflation of 50% of the CO2e savings for bikes was considered, passing from 129.907 Kg of Co2e saved on the period to not insignificant 64.954 Kg of Co2e. This is also in line by the fact that a good percentage of users commute to bike sharing from walking or public transportation.

b. Usage per car for car sharing

Being aware, that regardless the inexistent of a comparison of the previous nature with the other car sharing providers Enjoy and Car2go, there is also a positive impact associated with the greater utilization of the mobility resources, promoted, to some extent, by this type of Product Service Systems of Access based consumption.

It has been stablished in several occasions that among all the transport modes, private cars are still the first choice of many people due to its convenience and mobility. However, after a great amount of money spent on buying a car, people have it parked 92% of its life time, 1% caught in traffic jam, they spend 1,6% looking for parking and the other 5% driving with only one driver in most cases. (MacArthur et al., 2015). Automobile usage is a major source of air and noise pollution and improper use of private car is responsible for many of the serious environmental problems (Qu et al., 2017a).

Therefore, a particular feature to observe, is if this utilization rate of the vehicles is higher in the car sharing services. For the data comprising the six weeks, and a system of 2297 vehicles, **each car was used on average the 10,4% of the day**, implying a utilization of **2,5 hours per day**, against the 1,6 hours that private cars are used -according to the literature-. Not a minor improvement in sustainability if it manages to, eventually, replace the car ownership in the urban areas.

Besides that, this indicator also shows particular improving areas for the provider, 26% of the cars (598 to be exact) have a utilization rate less than 5%, as shows the figure bellow. With a medium of 22 minutes of usage per day, probably then making only one trip on a journey. Identify the origin and destinations of these trips, will gave possible hints into a better rebalance strategy.

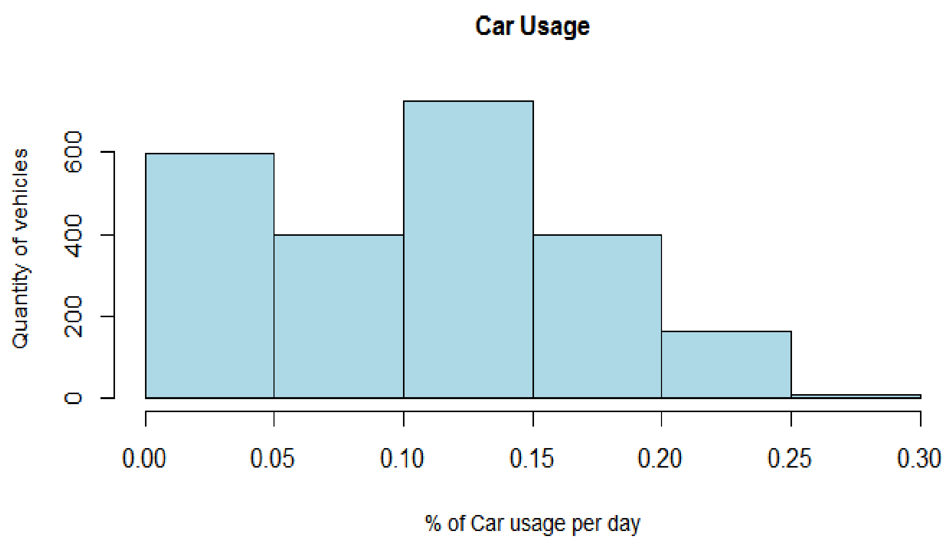


Figure 36. Daily Car Usage

7.3.5 Health

Health Indicators: BikeMi MET

One of the impacts considered for the bike sharing programs worldwide, is the benefits this could carried in the personal health. As mentioned in the previous sections, METs or "metabolic equivalents of tasks" is a measure of the intensity of physical activities. The reference value for leisure cycling or cycle to work, considered as a moderate activity, is 4 MET for each minute of that activity (Ainsworth et al., 2011).

During the analyzed period, the total cycled time in Milan was equal to 763.273 minutes. Since we don't have precise data of the number of the active users in that period, we considered the total amount of users with an annual subscription by January 2016, that were 45.300(2015 anno record per BikeMi: Toccata quota 45mila abbonati.2016). It has been suggested that each individual should achieved a minimum goal that should be in the range of 500–1,000 MET min/week. (De Hartog et al., 2010).In BikeMi, case the MET's value, calculated on a week base is 67 and it represents the 11% of the week requirement of physical activity on an average adult(De Hartog et al., 2010).

Cycled time [min/week]	763.273
Users	45.300
MET/week	**67**
% of weekly requirement	**11%**

Table 13. BikeMi MET

8. Conclusions

Mobility is a complex problem with many actors – both public and private – involved. During last years, with the introduction of flexible modes of transportation such as car and bike sharing, mobility offer has definitely increased in terms of option but, at the same time, the overall system has gained complexity. Sharing mobility has radically changed the concept of mobility as whole. Academic and practitioner studies on that topic are proliferating. Several researches focused on identify benefits, motivations and profile of the users of car sharing and bike sharing programmes. The impact of factors affecting the demand has been explored as the substitution rate in favour of the shared modes and the environmental impacts of the latter. Finally, efficiency problems such as service optimization and rebalancing have been treated. A dynamic data-driven approach, which is common in most of researches on traditional mobility, has not been totally explored. In particular, in sharing mobility field, there is an evident lack of studies relying on the theory of networks. Moreover, inter-modality characteristic of nowadays mobility claims for studies integrating different transportation modes. Since mobility is strongly attached to the contextual situation of the cities, ad hoc analyses are required. In the case of Milan no studies about the sharing mobility as a whole system have been delivered yet even if it is a good research scenario since the city represents 80% of Italian shared mobility market (Albè, 2016). For those reasons the paper has shown how bike sharing and car sharing systems are used within the city of Milan. Static and dynamic patterns in the displacement have been studied and interpreted. One of the main objects was to analyse the structure of the sharing mobility modes networks. This study has shown in which districts of the city the two services are more spread highlighting their differences. Bike sharing activity, as expected, is really concentrated in the city centre, the Duomo's location accounts for the 18% of the trips alone. Also car sharing is more used in the inner part of the city, but has a smoother decreasing moving outside the centre. The NIL (nucleo di indentità locale) Buenos Aires, which represents the area with the higher trip intensity, only allocates 5% of the trips. In terms of relative importance in fact CSPs (car sharing programs) gain relevance in the external NILs of the city and represent for some of them the only sharing mode alternative, covering 86 out of the 88 NILs. Bike sharing system covers just 39. Even if the program is having a geographic expansion its effectiveness in peripheral areas remains an open question. The usage in those zones could be boosted by an extension of the free cycle time span -that now amounts at 30 minutes- even if there are not studies that confirm that assumption yet. The analysis of networks' structures arose also a disparity in the purpose of the trips performed. Bike sharing's journeys appear strongly related to the average work habits while a similar pattern cannot be observed in car sharing's activity. Besides, the fact that a remarkable difference between week and weekend does not appear for this latter mode, confirms that the aim of the displacement is not related to people's occupations. This important result, that needs to be validated by further researches, has managerial implications related to communication strategy and brand positioning of the providers and to the main benefits offered to users. Groups of NILs stronger connected between each other were detected in the case of each of the two studied modes. The presence of clusters in the networks suggests a macro-areas division of the city that happens to coincide – with some exception in car sharing's network – with a geographical division, close NILs have higher interaction. Static analysis of networks' structure has been enriched by observing how that structure changes over time. The study of peak times and daily trip distributions within the networks reveals two opposite behaviours of NILs that led us to classify them into *working/school* and *residential/bridge* NILs. This division could be confirmed by other studies on the nature of Milano's districts.

Another aim of this work was to assess the impact that sharing mobility modes have on the city of Milan. Impact has been divided into three areas: efficiency, sustainability and health. One of the indicators used in this paper to measure efficiency impact is related to the velocity of the vehicles and to its reduction under congestion condition. The velocity has been measured for the two modes at each NIL. That measure, carries the limitation standing in the fact that we did not have information about the path – and thus about the actual travelled distance - of each trip performed by the car sharing programs. That has been highlighted as general limitation of the whole study. Nevertheless, the assumptions and considerations made a feasible scenario that gave some important estimations. Results tell that despite the car sharing trips, in the comparable locations have a higher velocity than the bike trips, these last ones are less variable in terms of velocity in both, from a general perspective and also considering the traffic pick time. For the rush hours, the velocity on a bike trip decreases only by 1,13% while this reduction reach almost 20% in the case of the car sharing trips. Also, involved with the mobility bottleneck, it was measured how much variability each system is handling. During the pick time, the congestion for bikes increases by a factor of 2,23, against only 1,68 of car sharing. Measures that are useful specially for the rebalancing of the system, a major access based consumption issue.

Finally, the sustainability and health impact, was evaluated respectively by the benefits involved with the CO2e reductions and the physical activity promoted by the modes. Both, with positive repercussions. In the sustainability scenario, encouraging either a better usage of the available resources or a direct diminution on the greenhouse gasses emissions and in the health one, fostering an adequate level of exercise correlated in several occasions with health risks reductions. These impacts, as done for other fields, could be further translate into public administration cost savings.

8.1 Limitations and future researches

The main limitation to our work is the dimension of the time span analysed that was 6-weeks-long. This is particularly restricting for a mode strongly influenced by the weather such as bike sharing. Results may change if the same analysis were performed in summer months instead of from January to March. Besides, expanding the time horizon seasonality pattern could be detected and studied. As mentioned information about the actual path or the kilometre travelled (as we had for BikeMi vehicles) for cars would provide more precise results for indicators such as *mode convenience*.) Other actions that could have led to biases are the aggregation of the trips by NILs and the screening of rebalancing trips in car sharing database. Some results of this study need to be validated or further explored and that by other researches. For example, the division in *working* and *residential* NILs can be studied and the result of hierarchical clustering tested with cross-validation or other validation methods.

Interesting developments of the study could consider, besides sharing mobility modes, also traditional mobility. CDR (call detail record) data for instance could be used to proxy the overall mobility within a city and used as a benchmark to assess which percentage of those journeys is covered by sharing modes. Moreover, other cities than Milan can be studied and the result could be compared to assess good practice in mobility. Finally, the relevance of actors such as Urbi – digital platform that gathers real-time data from mobility providers and make them easily accessible to users through a mobile app - and the possible impacts that they could have to the efficiency and the effectiveness of mobility services can be explored.

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