Applied Geography 35 (2012) 235–246

Contents lists available at SciVerse ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Optimizing the location of stations in bike-sharing programs: A GIS approach

Juan Carlos García-Palomares*, Javier Gutiérrez, Marta Latorre

Departamento de Geografía Humana, Facultad de Geografía e Historia – Universidad Complutense de Madrid, C/Profesor Aranguren, s/n, 28040 Madrid, Spain

Keywords:
Bike-sharing programs
Bike-station location
Location–allocation models
GIS
Madrid

ABSTRACT

A growing number of cities are implementing bike-sharing programs to increase bicycle use. One of the key factors for the success of such programs is the location of bike stations in relation to potential demand (population, activities and public transport stations). This study proposes a GIS-based method to calculate the spatial distribution of the potential demand for trips, locate stations using location–allocation models, determine station capacity and define the characteristics of the demand for stations. The results obtained are compared with the most commonly used location–allocation modeling approaches: minimizing impedance and maximizing coverage. For the objective of this study, the latter approach is more useful. Diminishing returns are observed in both cases: as the number of stations increases, there is less improvement in the fraction of the population covered and accessibility to stations. Because the spatial structure of the proposed network also plays an important role in bike-station use, an additional accessibility analysis was carried out to calculate the volume of activity to which a station has access. With this analysis, stations that are relatively isolated, and therefore of little use to potential users, can be eliminated.

Introduction

In recent years, urban transport planners have focused much of their attention on policies promoting the use of bicycles as an alternative to intensive car use. Within the framework of sustainable mobility, bicycles are beneficial in a number of ways not only to society as a whole (with regard to environmental and economic sustainability and social equity) but also at the individual level. As well as being healthy and cheap, cycling is more efficient and quicker than using cars or public transport in congested town centers because traffic hold-ups can be avoided. Cycling also has its disadvantages, including a greater physical effort and the difficulty of carrying loads while cycling (Heinen, van Wee, & Maat, 2010).

The factors that increase bicycle use are currently being studied by policy makers and academic researchers in a search for measures to promote a modal shift from motorized transport to cycling. Numerous proposals have been put forward involving very different disciplines, ranging from urban and transportation planning to psychology. Urban planners try to redirect land-use distribution and urban form toward patterns that are more compact and diverse to facilitate shorter trips. Transportation planners invest in infrastructure geared to cycling, such as bike lanes or parking facilities; they give priority to cyclists over car drivers or facilitate bicycle use in conjunction with public transport. Psychologists aim to understand the effects of ability and behavior on bicycle use to be able to exert some influence over such effects (Dill & Voros, 2007).

One of the most prominent actions taken by transportation planners is the introduction of bike-sharing programs, also called "*rental bike*", "*public-use bicycles*" (PUBs), "*bicycle transit*" or "*smart bikes*" (Midgley, 2011). Bike-sharing programs are networks of public-use bicycles distributed around a city for use at low cost. The programs comprise short-term urban bicycle-rental schemes that enable bicycles to be picked up at any self-serve bicycle station and returned to any other bicycle station, which makes bicycle-sharing ideal for point-to-point trips (New York City Department of City Planning, 2009). The principle of bicycle sharing is simple: individuals use bicycles on an "as-needed" basis without the costs and responsibilities of bicycle ownership (Shaheen, Guzman, & Zhang, 2010).

The first public-use bicycles date back to 1968, with the famous "*White Bicycles*" system in Amsterdam. Since then, experiences have multiplied, and models have become increasingly more complex (Bonnette, 2007; DeMaio, 2009a). Today, there are an estimated 375 bicycle-sharing schemes operating in more than 30 countries in almost every region of the world, using approximately 240,000 bicycles (Midgley, 2011) (see bike-sharing world map at http://bike-sharing.blogspot.com, DeMaio, 2009a and 2009b).

One of the keys to the success of bike-sharing programs is the location of bike stations and their relation to trip demand (Lin & Yang, 2011). To gain user acceptance, the distance between stations and the origins and destinations of trips should be small, and the distance

* Corresponding author. Tel.: +34 91 3945949; fax: +34 91 3945960.
E-mail addresses: jcgarcia@ghis.ucm.es (J.C. García-Palomares), javiergutierrez@ghis.ucm.es (J. Gutiérrez), latorre_marta@hotmail.com (M. Latorre).

0143-6228/$ – see front matter
http://dx.doi.org/10.1016/j.apgeog.2012.07.002

between the stations themselves should be appropriate for transport by bicycle (Shu, Chou, Liu, Teo, & Wang, 2010).

This article proposes a GIS (Geographic Information System) based method to determine the optimal location for bike stations, identify their main characteristics and assess the accessibility of each station. The literature in this area is reviewed in Section 2 of the paper. Section 3 presents the scope of the study and the data, and Section 4 proposes the method. Section 5 shows the results, including the distribution of potential demand for bicycle trips, optimal station location in different scenarios and based on different models, characteristics of the stations proposed with respect to the areas served and accessibility from each station. Finally, the main conclusions are outlined in Section 6.

Background

The amount of literature available on bicycle use in cities is growing. In recent years, a number of reviews have been published with the aim of collating all of the contributions. Different studies are grouped according to their focus on factors that explain greater or lesser use of bicycles or the types of action or intervention that have taken place and their impact on mobility and access. Heinen et al. (2010), in a bibliographic review, defined large groups of factors affecting bicycle use. These factors range from the built environment (urban form, infrastructures, facilities at work, etc.) to factors related to the natural environment (topography, attractive built environments, seasons and climate or weather), socio-economic and psychological factors (attitudes and social norms, ecological beliefs, habits, etc.), and other factors related to utility theory (cost, travel time, effort and safety). Pucher, Dill and Handy, (2010) have comprehensively analyzed 139 studies and 14 case studies of cities that adopted multiple interventions. The studies were then broadly divided into the following three main groups of actions for promoting bicycle use:

a) *Travel-related infrastructure for bicycling*, distinguishing between infrastructure linked to the actual trip (e.g., bike lanes, signed bicycle routes, bicycle boulevards, colored lanes, bike boxes, bicycle phase traffic signals and facility maintenance) and that related to parking and services available at the end of the journey (e.g., parking facilities, bicycle stations and showers at workplaces);
b) *Measures for integrating bicycles with public transport* (e.g., parking at rail stations and bus stops, bike racks on buses and short-term rental bikes);
c) *Programs and legal interventions to promote cycling*, with consideration of programs to reduce trip distances in general and increase the safety of bike travel or bicycle-access programs (including bicycle-sharing programs).

Both Heinen et al. (2010) and Pucher et al. (2010) showed the importance of *bike-sharing programs* as one of the most common promotional measures taken and a key factor for fostering the use of bicycles in cities.

Bike-sharing programs

Bike sharing has generated a plethora of literature. Scientific studies and reports by planners prior to establishing programs in their cities frequently include a review of the experiences of other cities.[1] Such reviews analyze the evolution of bike-sharing programs and identify different generations (DeMaio, 2003; DeMaio & Gifford, 2004; Midgley, 2011). The first generation of public bicycles, based on civic and communal responsibility, lacked docking stations and control systems to deter theft. The second generation, dating from the 1990s, saw the introduction of the coin-operated loan of bicycles from different docking stations (the first scheme was Copenhagen's *Bycyklen* in 1995). The third generation introduced identification of both the user and bicycle. This system operates 24 h a day, using readings from either bankcards or cards specially designed for the system (Bonnette, 2007). Potential "fourth-generation" design innovations are already under development, including movable docking stations, solar-powered docking stations, electric bicycles and mobile phone and iPhone real-time availability applications. Of these innovations, the introduction of electric bicycles is likely to be the most significant in terms of attractiveness (Midgley, 2011).

Many studies have also analyzed the impact of bike-sharing programs on mobility in cities. The percentage of trips by bicycle increased from 0.75% in 2005 to 1.76% in 2007 in Barcelona (Romero, 2008), from 1.0% in 2001 to 2.5% in 2007 in Paris (Nadal, 2007; City of Paris, 2007) and from 0.5% in 1995 to 2% in 2006 in Lyon (Bonnette, 2007; Velo'v, 2009). Noland and Ishaque (2006), in a study of the OYBike in London, showed that 40% of users shifted from motorized modes. Nevertheless, the evidence of increases in bicycle mode share after the implementation of a bicycle-sharing program is confounded by improvements in bicycling facilities implemented at the same time as the bike-sharing program (Pucher et al., 2010).

As promotion policies in general, studies of bike-sharing programs attempted to define and understand the factors that explain the greater or lesser degree of success of the programs. Curran (2008) described fourteen key factors, which he separates into two levels of importance. Factors external to the system appear once more, such as topography, weather, attitudes to cycling and the quality of public transport. However, these external factors, together with some internal ones, such as the type of bicycle, dockings, hours of service, safety and security and the technology support platform, are classified as being of secondary importance. Elements that gain more importance are maintenance, cost and, in particular, factors involving bike-station location, network structure and the cycling network infrastructure. It is also highly essential that the bicycle redistribution system is operated efficiently, which relates back to the bike-station location.

Bike-station location

In any bike-sharing program, one of the keys to success is the location and distribution of bike stations (Lin & Yang, 2011). However, most authors and preliminary studies tend to give only general recommendations regarding the station implementation.

The first of these recommendations concerns network coverage. In general, the distribution of stations is dependent on the size and configuration of the city. The methodological guide for introducing bike-sharing in Spain differentiates based on the size and density of the city and the type of loan system (IDAE, 2007). In high-density cities with more than 200,000 inhabitants, automatic stations distributed across the whole city are recommended, whereas in those cities where density is low, coverage with automatic stations is proposed only in city centers or higher-density areas. In most large cities, however, bike-sharing programs are usually limited to the city center. Only Paris has a program that covers the whole city. Some studies recommend initially introducing the system in zones with the highest density, which are usually the city centers, and gradually extending it to reach the peripheral areas (see, for example, IDAE 2007 and NYC Dept. City Planning, 2009).

[1] Experiences frequently referred to are those of Velib' Paris, Vélô Toulouse, Bicing in Barcelona, Bixi-Montreal, the Washington DC SmartBike, Copenhagen ByCylke and City Bikes of Helsinki.

Once the coverage area has been considered, the location of the bike-stations should be adapted to the objectives of the public bike program and the demand that it aims to satisfy. It is essential to differentiate between bike-sharing programs in general and recreational bicycle rentals. Recreational or tourist programs typically have only a few locations where bicycles can be rented and to which they must be returned. These locations are mostly found in major tourist areas, places of historical interest, or parks. In contrast, bike-sharing programs are aimed particularly at commuters. The stations must be located in close proximity to one another and to major transit hubs and are placed in both residential (origin) and commercial or manufacturing (destination) neighborhoods, which makes bike-shares ideal as a commuter transportation system (Midgley, 2011).

A key element is the location of the stations in relation to the public transport network (Martens, 2007). The bicycle becomes a complementary mode within the public transport system because it extends the radius of influence of transit stations and stops on movements related to both access and dispersion. In Europe and Japan, bike-parking facilities or bike stations are provided on a massive scale at most suburban rail stations and many Metro stations (DeMaio & Gifford, 2004; Holtzman, 2008; Litman, 2009; Martens, 2007; Pucher and Buehler, 2008 and 2009). However, bike parking at bus stops is less common (Pucher et al., 2010).

It is also important that the location of bike-stations is in accordance with the rest of the infrastructure for bicycles. Bike-sharing programs normally form part of cyclist mobility programs, which anticipate the construction or extension of a bicycle lane network together with other measures, such as restricted car use or traffic calming (Midgley, 2011).

The success of bike sharing as a public transport mode depends largely on how user demand is met. Various demand-based methods have been developed to predict non-motorized travel (Rybarczyk & Wu, 2011; Schwartz, 1999; Turner, Hotternstein, & Shunk, 1997) and have been applied to bicycle mobility planning. Landis (1996) proposed the latent demand score (LDS) model to estimate travel demand based on bicycle trip generators and attractors, such as employment, shopping centers, parks and schools. In the particular case of bike-sharing programs, the report on the introduction of a system in New York analyzes the distribution of potential user demand by integrating variables such as population density, worker density, facility services, proximity to cultural or recreational attractions, such as museums, theaters and concert halls, and proximity to retail shopping opportunities (NYC Dept. City Planning, 2009). Knowing the distribution of the potential demand and distinguishing areas that are trip generators from those that are trip attractors also makes it possible to anticipate the asymmetric travel demands of most large cities. This process is fundamental in the planning of bicycle-redistribution systems.

When selecting station locations, the distance between stations should be taken into consideration. Velib' bike-stations (Paris), for example, are located approximately every 4 blocks (300 m), which allows for easy access. The BIXI program has a station every 250–300 m throughout a 15 km^2 section of central Montreal. This density ensures that users can find a bicycle when they need one and return it easily when they are done. However, such a high density of stations requires substantial investment, and some authors have noted that overcoverage may be detrimental to the success of the system because it increases maintenance costs (Shu et al., 2010).

Bike stations, GIS and location–allocation models

Given the importance of station distribution for operating bike-sharing programs, it seems that the models needed are those that allow the location of stations to be optimized. In the same way, it is essential that different scenarios should be considered according to the area covered or the number of stations to be established. However, there is no experience of GIS models being used to optimize station location.

In Spain, the cycling mobility guide (IDAE-TRANSyT, 2010) proposes a model based on mobility matrices and user behavior, which has been tested in the town of Santander. This complex model requires detailed information on mobility, most of which has to be obtained through costly surveys.

Other studies are already making use of GIS as a support tool for assessing bicycle facility planning. Rybarczyk and Wu (2010) use GIS to evaluate supply- and demand-based models together in different territorial units (street segments and neighborhoods). These authors calculate the distribution of the latent demand score (Landis, 1996) while obtaining a bicycle level-of-service index (Harkey, Reinfurt & Knuiman, 1998). The results of both indicators are analyzed using exploratory spatial data analysis (ESDA) and Moran-I, with the aim of carrying out a joint evaluation. Larsen, Patterson, and El-Geneidy, (in press) propose a GIS methodology aimed at obtaining optimal locations for new routes, minor linkages and upgrades in the Montreal cycling network. The authors use multi-criteria methods to integrate information on current cyclist trips, short car trips (potential cycling), segments of bicycle paths suggested by survey respondents, bicycle crash data and dangling nodes on the existing bicycle network. Although the authors do not apply the method, they note that this same method could help identify areas in which to invest in bicycle parking spaces and/or public bicycle stations.

Optimal location tools for services (location–allocation models) have been implemented in a GIS environment, which may be of great use for locating bike stations with relation to the distribution of potential demand. This model consists of finding where facilities of a given type should be located and what their capacity should be to meet some predefined objective while satisfying demand from a given number of centers (Ribero & Pais, 2002).

Since the first studies of location–allocation were carried out (Cooper, 1963; Ghosh & Rushton, 1987; Hakimi, 1965; Rushton, 1979), different solutions for the optimal location of services have been proposed and applied in a number of fields. Initially, these models can be classified as continuous or discrete depending on whether the facilities can be located anywhere on the plane or at some points on the plane that are specified in advance (Yeh & Chow, 1996), although in practical applications, planners often resort to discrete-location models (Teixeira & Antunes, 2008). With respect to the solutions, a distinction can generally be made between efficient and equity-oriented models (Murray, 2010). Of the models proposed, the *p-median problem* (Hakimi, 1965) is the most common. The objective is to minimize the total demand-weighted travel to service facilities. Two other general approaches are center and covering. Hakimi (1964, 1965) described the *p-center* problem, with the intent of locating p facilities to minimize the maximum distance that a demand point was from its closest facility. Toregas, Swain, ReVelle, and Bergman (1971) formalized a location model in which the minimum number and location of facilities is to be found that guarantees a standard of service coverage or range in the context of central place theory. Service provision equates to the coverage of demand. A minimal set of facilities is sought such that demand points are responded to or served within a maximum travel time/distance. This model was called the location set covering problem (LSCP), although aspatial set covering problems were introduced earlier by Edmonds (1962). Recognizing practical limitations to the LSCP, Church and ReVelle (1974) formulated the maximal coverage location problem (MCLP), in which p facilities are to be sited to maximize demand served within the stipulated standard.

There are numerous examples of GIS-based applications of location–allocation models in a range of public and private sector contexts (see Church, 1999; Drezne & Hamacher, 2002; or reviews by Church, 2002; Church & Murray, 2009; Murray, 2010). The simplest approach consists of using the built-in commands included in some GIS packages (for instance, ArcGIS, MapInfo and TransCad). With respect to public services, the most frequent applications are for health care facilities (Murawski & Church, 2009; Møller-Jensen & Kofie, 2006; Verter & Lapierre, 2002), fire stations (Liu, Huang, & Chandramouli, 2006; Murray & Tong, 2009; ReVelle, 1991), schools (Teixeira, Paes, & Peeters, 2007), recycling depot planning (Valeo, Baetz, & Tsanis, 1998), incinerators (Almeida, Coutinho-Rodrigues, & Current, 2009), open-space planning (Yeh & Chow, 1996), waste disposal (List & Mirchandani, 1991) and conservation-reserve planning (Gerrard, Church, Stoms, & Davis, 1997), etc. In private sector contexts, the models have been applied in banking (Min & Melachrinoudis, 2001), franchise establishments (such as fast food establishments) and the placement of cellular towers and locating equipment for wireless broadband access (Grubesic & Murray, 2002; Kalvenes, Kennington, & Olinick, 2005), etc.

In sum, previous studies have identified the key elements for success in bike-sharing programs. One of the most important of these elements is station location. Locations must be related to the proximity of population, activities and the public transport network and allow for the configuration of a network with distances between stations that are suitable for bicycle trips. Some studies take advantage of the possibilities of spatial analysis offered by GIS for evaluating bike-sharing programs. Nevertheless, to date, no study has used location–allocation models to establish optimal station location, identify the stations' main characteristics and assess the utility (accessibility to potential destinations) of each station in the network as a whole.

Area of study and data

The proposed method has been applied in central Madrid (Fig. 1). In recent years, local planners in this city have shown a growing interest in promoting the use of bicycles. In 2009, the Madrid city council presented the *MyBici* project for public bicycle hire, although this program has still not been implemented.

The center of Madrid is an area with a great diversity of land use and a high density of population and employment. It is home to 1.1 million inhabitants and provides 0.93 million jobs. At the present time, only 0.1% of trips are made by bicycle. Nevertheless, mobility data show that the number of trips that could be made by bicycle is considerable: approximately 54% of motorized trips cover distances of less than 3 km (Vega, 2006) and approximately 15% of the trips currently made by car could be made by cycling within the same trip time and without affecting their characteristics (Monzón, Vega, & López-Lambas, 2007).

The following mapping and statistical information has been used to apply the proposed method:

- *Street network* (from the Madrid Regional Statistics Office [*Instituto de Estadística de la Comunidad de Madrid*], 2010). This network has full connectivity and allows a simulation of the mobility of pedestrians (access/egress to/from bike-stations) and cyclists (trips between stations). To calculate bicycle

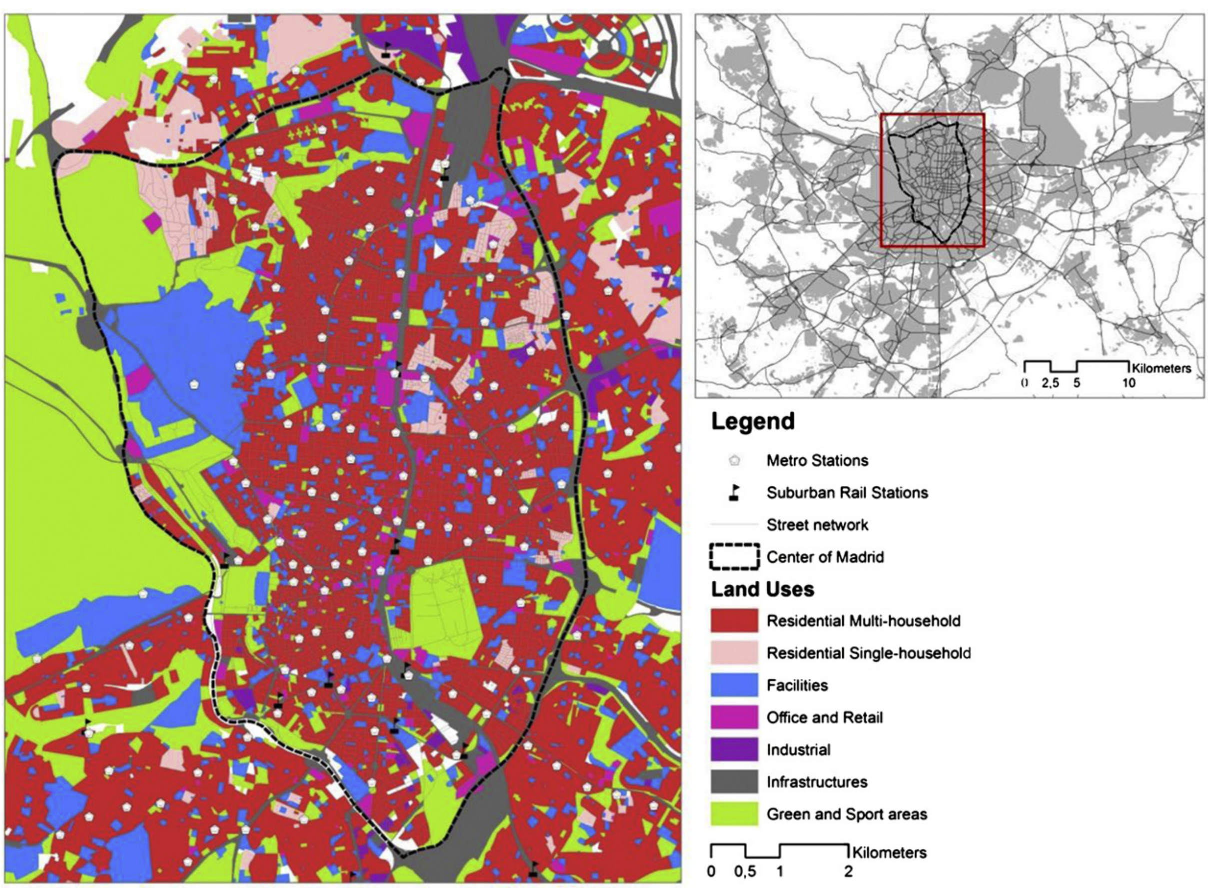

Fig. 1. Study area.

times over the network, information on the slopes and speeds was included in each arc.

– *Buildings* (Cartociudad-National Geographical Institute [*Instituto Geográfico Nacional*], 2010). The population and number of jobs are available at the building level (represented as points).
– *Transport zones*. The 2004 mobility survey provides information on generated and attracted trips at the transport zone level. This information has been taken into account to calculate the potential demand for bicycle trips.
– *Stations and stops in the public transport network (2011)*. GIS layers containing Metro and suburban rail stations were used for locating requested stations.

The ArcGIS-ArcINFO 10 program (Environmental Systems Research Institute, ESRI) and its network analyst module were used for treating the information and applying location–allocation models.

Methodology

There are four stages to the method proposed for optimal station location in a bike-sharing program. First, it is necessary to know the distribution of the potential user demand. The location–allocation models are then applied, defining obligatory bike-stations, candidate locations, the number of stations to be located and the type of solution chosen. Once bike-station location has been obtained, the station characteristics are described. The final stage is the analysis of station use in terms of accessibility to potential destinations.

Distribution of potential demand

The spatial distribution of demand is a fundamental element in optimal location models. Obtaining potential station demand starts with the creation a layer of points containing the population and employment associated with each building number and a layer of polygons containing the number of trips generated and attracted for each transport zone. Multiplying the number of inhabitants in each building by the ratio of trips generated per inhabitant in the building's transport zone will give the number of trips generated by each building. In the same way, by multiplying the number of jobs in each building by the ratio of trips attracted by employment in the building's transport zone, the number of attracted trips per building can be obtained. This way, zones specializing in activities that attract a high number of trips per job (for example, commercial, educational, etc.) can be differentiated from those with activities that attract a low number of trips per job (for example, industrial, office jobs, etc.). The total number of trips is calculated by adding the data of trips generated and attracted for each building. Using these data, kernel density maps have been calculated to show the spatial distribution of the demand for bike-stations.

Location–allocation models

Location–allocation models have been calculated using discrete data both for candidate locations for bike-stations and at the demand points. Of the solutions proposed in ArcGIS 10, the ones that have been applied are *minimize impedance (P-Median)* and *maximize coverage*. In P-median, the stations are located such that the sum of all of the weighted costs between demand points and solution facilities is minimized, while to maximize coverage, the stations are located such that as many demand points as possible are allocated to solution facilities within the impedance cutoff. In the 'maximize coverage' model, the impedance cutoff considered was 200 m, deemed to be a suitable distance for pedestrian access to bicycles.[2]

Scenarios

Five different scenarios are considered, based on the total number of stations: 100, 200, 300, 400 and 500. These values were fixed according to the ratios of bicycles per 1000 inhabitants and the average number of bicycles per station in other European cities (see below). Other studies, such as the one carried out in New York, also define different scenarios based on the total number of stations or the extent of the area to be covered by the system (see NYC Dept. City Planning, 2009). In our study, the area covered by the program was fixed to test differences in the location of stations as the number of stations increase. The volume of bicycles set by most programs is based on the total number of inhabitants. The scale of bicycle-sharing network coverage is relatively dense in French cities, such as Paris (9.6 bicycles per 1000 inhabitants), Lyon (6.4/1000) and Rennes (4.8/1000), compared with other European cities, such as Copenhagen and Stockholm (both 4.0/1000), Barcelona (3.7/1000), Brussels or Frankfurt (both 1.1/1000), Oslo (0.5/1000) and Vienna (0.4/1000) (Midgley, 2011). In accordance with the data in Table 1 and assuming a number of docks double that of bicycles (Madrid City Council [*Ayuntamiento de Madrid*], 2009), the number of bicycles and docks per station is approximately 12 and 24, respectively. Applying these average values for future stations in Madrid, the number of bicycles needed would range from 1200 (1.1 bicycles per 1000 inhabitants) in the first scenario to 6000 in the fifth (5.5 bicycles per 1000 inhabitants) and the number of docks would range from 2400 to 12,000 (Table 2).

Table 1
Fleet size, stations and bike/station in selected cities.

City (system)	Fleet size	Stations	Bikes/station
Rio de Janeiro (PedalaRio)	250	19	13.2
Montreal (BIXI)	5000	400	12.5
Milan (BikeMi)	1400	104	13.5
Lyon (Vélo'v)	4000	343	11.7
Daejon (Ta-shu)	224	18	12.4
Oslo (Bysykkel)	1200	120	10.0
Krakow (BikeOne)	155	13	11.9
Barcelona (Bicing)	6000	400	15.0
Stockholm (City Bikes)	2000	180	11.1
Reading (OYBike)	21	3	7.0
Denver (Denver B-cycle)	500	50	10.0

Source: Midgley, 2011.

Table 2
Estimated number of bikes and docks in future bike-stations in Madrid.

Scenarios (number of bike-stations)	Bikes	Docks	Bikes/1000 inhabitants
100	1200	2400	1.1
200	2400	4800	2.2
300	3600	7200	3.3
400	4800	9600	4.4
500	6000	12,000	5.5

Source: Calculations by author.

[2] In coverage analyses, transport planners tend to assume certain walking distance limits as the thresholds that people are willing to walk to access transport facilities. This distance limit depends on the facility to be reached. Most studies use distance thresholds of 0.25 miles (400 m) for access to bus stops and 0.50 miles (800 m) for metro or railway stations. Unfortunately, there is not a standard distance limit for access bike-sharing stations. Because people are willing to walk longer distances for access transport facilities for long trips and the average distance for bike trips is very short, the impedance threshold for accessing bike-sharing stations should be lower than that used for public transport facilities.

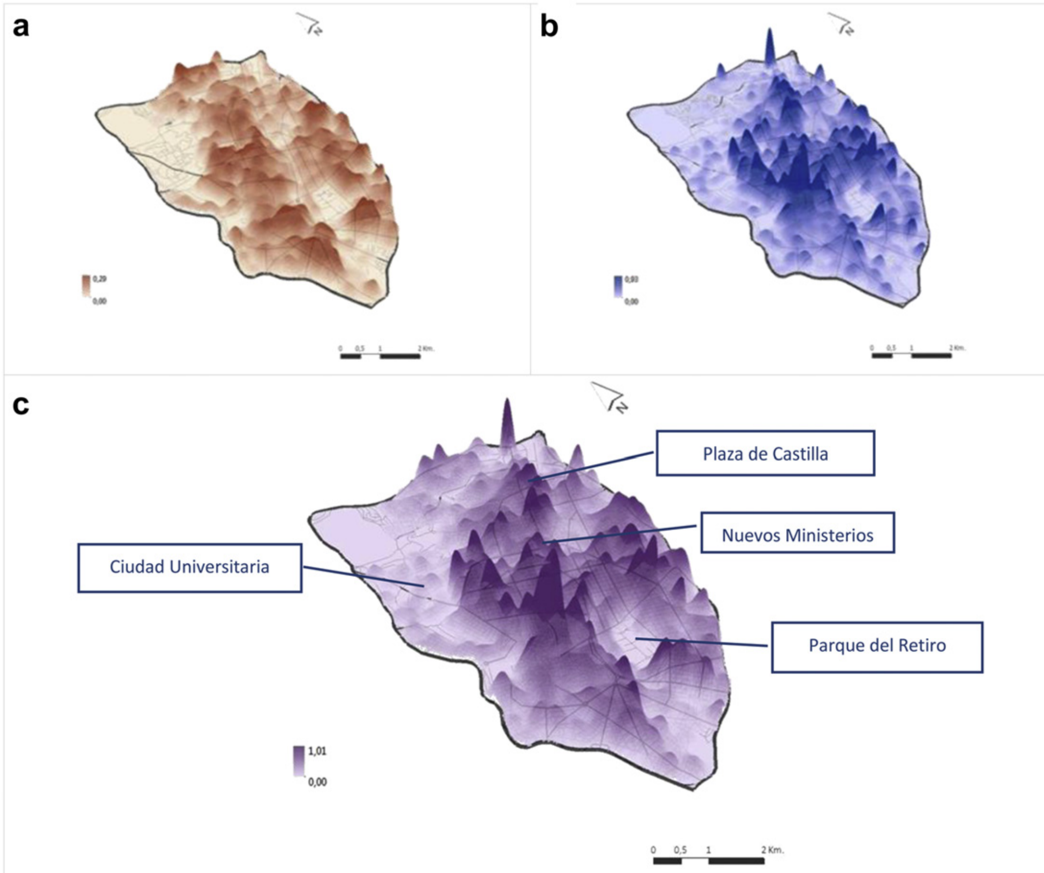

Fig. 2. Density of generated trips (a), attracted trips (b) and total trips (potential demand) (c) in the study area (trips/m^2).

Following recommendations from existing experiences, it was decided to locate the required bike stations in all suburban train stations and in Metro stations with more than 10,000 travelers per day. These total 52 required bike-stations are fixed in all of the scenarios.

Station capacity

In the previous subsection, it was assumed that the average number of bicycles and docks per station is 12 and 24, respectively. However, there are spatial variations in station capacity depending on the characteristics of the area covered (potential demand). For example, in the New York bike-sharing program, the stations range in size from approximately 12 docks/station in less highly trafficked areas to up to 70 docks/station around major tourist attractions. Bike-station density typically increases around commercial/transit hubs, although individual bike-stations are often smaller (15–25 docks/station) (NYC Dept. City Planning, 2009).

Location–allocation models give the amount of potential demand allocated to each bike station. Converting the amount of each station's potential demand into the number docks is very simple. The total number of docks in each scenario must simply be distributed among the different stations in proportion to the demand allocated to each station.

Station characterization

It is necessary to know not only the capacity (number of docks) of the stations but also the distribution of bicycles at each station in relation to the asymmetric travel demand throughout the day. With GIS, it is possible to relate the location of each station with the type of allocated demand. Location determines the characteristics of each base, either as a trip generator or attractor, depending on whether its potential demand comes from residential areas or areas of economic activity. This characterization makes it possible to vary the number of bicycles or free docks at the stations according to the time of day, leading to more efficient bicycle redistribution systems. The number of bicycles and free docks at the beginning of the day is obtained by distributing the total number of free docks in proportion to the number of trips generated and attracted by each station. This means, for example, that at that time of day, a 12-dock station with 75% of its demand made up of generated trips and 25% of attracted trips would require 9 bicycles and 3 free docks because it is in what is predominantly a generator zone.[3]

To show the spatial variation in station characteristics based on data for potential demand, four different types of bike station are distinguished:

- *Generators*: Attracted trip/total trip ratio of less than 40%. Most of the trips using these stations are generated by people living in the surrounding areas. The stations need to have bicycles in most of their docks during the morning rush hour and a sizable number of free docks in the evening.

[3] The case of required bike stations at Metro and suburban rail stations is rather different: the number of free docks and bicycles should also be adapted to the daily rate of passenger ingress and egress. Because most of the trips to the center of Madrid are made by public transport, it is logical that in the morning, bike stations located at the busiest Metro and suburban rail stations should have more bicycles than free docks.

- *Mixed*: Attracted trip/total trip ratio of between 40 and 60%, in zones with mixed land use. The bike-stations are restocked with bicycles throughout the day.
- *Attractors*: Attracted trip/total trip ratio of between 60 and 80%. Commercial and business zones are the destination for many of the trips. In the morning rush hour, there should be more free docks than occupied ones, with this situation reversed in the evening.
- *High attractors*: Attracted trip/total trip ratio of over 80%. Almost all of the docks at such stations should be free in the morning rush hour.

Accessibility from bike stations

Measurements of station usefulness have been based on the potential accessibility indicator, which is widely used in different spatial contexts (see, for example, Bruinsma & Rietveld, 1998; Muhammad, de Jong, & Ottens, 2008). This indicator relates the accessibility of a location directly with the number of opportunities available and inversely with the distance needed for those opportunities to be taken. It is formulated as follows:

$$P_i = \sum_{j=1}^{n} M_j d_{ij} / t_{ij}^{\alpha} \tag{1}$$

where P_i is the potential accessibility of the station i, M_j is the mass, that is, the opportunities available, together with the destination station j (trips attracted by the area allocated to each station), d_{ij} takes the value of 1 if the distance between i and j is less than 5 km and is 0 otherwise (according to Jensen, Rouquier, Ovtracht, & Robardet, 2010), t_{ij} is the bicycle trip time between station i and destination station j and α is a parameter reflecting the rate of increase of the friction of distance (distance decay), which is considered here to be equal to 2 (reflecting the high distance decay in the case of bicycle trips).

This indicator should be interpreted as the volume of activity to which a station has access, after accounting for the time to cover the distance to the destination stations. It is therefore to be expected that the use of each station depends not only on the amount of demand allocated by the location-allocation models but also on its accessibility in the network as a whole. This way, it is possible to prioritize stations within the bike-sharing program (eliminating those with poor accessibility) and identify those stations requiring greater attention with respect to management (those with very high accessibility).

Results

Distribution of potential demand

Fig. 2 shows the density of potential bicycle trips in the center of Madrid, with potential trips generated (Fig. 2a) distinguished from those that are attracted (Fig. 2b). Given the characteristics of the city center, which has a large number of workplaces, there are more attracted trips than generated ones. The way in which the densities are distributed reflects

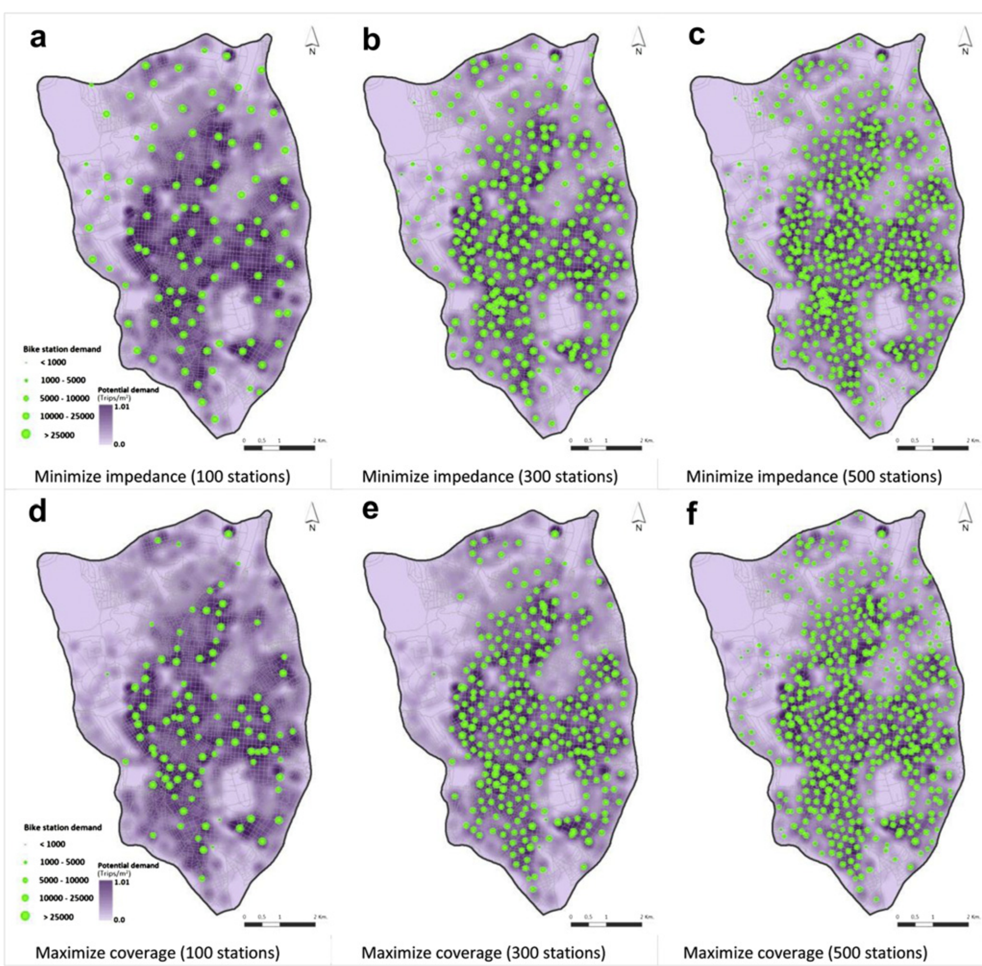

Fig. 3. Results from the location–allocation models.

differences in the location of population (more homogeneous) and activities (more concentrated). The sum of the potential demand from generated and attracted trips gives the total potential trip demand (Fig. 2c).

Station location

Fig. 3 shows the results from the location-allocation models. The distributions are very different, both with regard to the solution used and the number of stations considered in each scenario. Using the *minimize impedance (P-median)* solution, the stations are dispersed over the whole area, whereas with *maximize coverage*, the stations are concentrated in the most central areas (with greater density of demand).

When the number of stations is increased, the minimize-impedance solution gives a uniform increase in station density in all of the scenarios. With the maximize-coverage model, there is an initial increase in the number of stations in areas with greater density of demand (scenarios with 200 or 300 stations), thus reinforcing concentration. It is only when zones with high density of demand have been covered that new stations tend to be located in more outlying areas as well (scenarios with 500 stations). The scenarios with 500 stations are therefore relatively similar for both of the solutions.

Table 3 shows the maximum and minimum distances from the demand points to the stations, weighted by demand. With the *minimize-impedance* model, all of the demand is allocated to the stations. The maximum distance in all of the scenarios is somewhat less than 800 m. If the number of stations is increased, there is a notable reduction in average demand distances, ranging from 337 m with 100 bike stations to 124 m with 500. With the *maximize-coverage* model, location is determined by maximizing the demand covered at 200 m (the impedance cut-off considered) and leaving out the rest of the demand. If the rest of the demand is allocated to the nearest station, there is a dramatic rise in the maximum distance (3700 m in the scenario with 100 bike-stations and 2800 m with 500). Naturally, average distances are also higher with the maximize-coverage solution, but they decrease more strongly in the different scenarios in such a way that, with 500 bike-stations, they tend to converge. Decreasing returns are found with both of the solutions, with markedly reduced distances between demand and bike stations in the first scenarios and less reduction in the later ones.

Logically, a greater amount of demand covered at a suitable distance for pedestrian trips to stations (200 m) is found with the maximize-coverage solution (Table 4). The differences are greater in scenarios with fewer stations and decrease as the number of stations and total network coverage increase. Both solutions show diminishing returns with an increase in the number of stations (Fig. 4). In both of the solutions, an increase of 100 bike stations in the first scenarios means a marked rise in demand covered (26% and 24.1% between 100 and 200 stations, respectively). However, increases in the demand covered are much lower as the number of stations increases. Therefore, going from 400 to 500 stations means an increase in demand covered of only 8.1% and 7.2% (Table 4 and Fig. 4).

To obtain an idea of the spacing between stations, the average distance from each station to the next station and the five nearest stations was calculated. As was to be expected, these average distances are greater in the minimize-impedance model, which tends to disperse the stations, than in the maximize-coverage model, which has more concentrated distributions (Fig. 3 and Table 5). However, with maximal coverage in scenarios with fewer stations, the few stations that appear on the periphery are isolated from the rest of the network, reducing their usefulness (see subsection 5.4). Scenarios with a high number of stations not only reduce the average distances between stations but also give much more uniform distributions within both of the solutions.

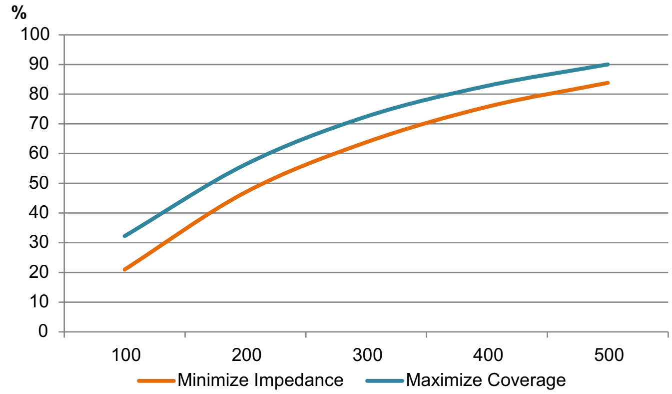

Fig. 4. Percentage of demand covered by bike-stations at 200 m on foot.

Table 3
Distances from demand points to the stations.

Scenarios (number of stations)	Minimize impedance (P-median)			Maximize coverage		
	Average distance (m) weighted demand		Maximum distance (m)	Average distance (m) weighted demand		Maximum distance (m)
	Average	Std. dev.		Average	Std. dev.	
100	336.8	156.7	794	455.2	327.2	3728
200	214.0	118.0	799	274.9	264.0	3415
300	169.1	98.8	797	208.2	195.7	3124
400	142.4	88.6	798	170.4	147.9	3018
500	123.7	80.4	796	145.0	96.0	2816

Source: Calculations by author.

Table 4
Potential demand covered at less than 200 m from stations.

Scenarios (number of stations)	Minimize impedance (P-median)				Maximize coverage			
	Demand covered at 200 m				Demand covered at 200 m			
	Total	%	Increment	Increment %	Total	%	Increment	Increment %
100	1,675,270	21.0	–	–	2,575,828	32.2	–	–
200	3,754,765	47.0	2,079,495	26.0	4,503,626	56.3	1,927,798	24.1
300	5,100,530	63.8	1,345,765	16.8	5,791,870	72.5	1,288,244	16.2
400	6,053,825	75.7	953,295	11.9	6,617,587	82.8	825,717	10.3
500	6,699,270	83.8	645,445	8.1	7,194,755	90.0	577,168	7.2

Source: Calculations by author.

Table 5
Distances between stations (in meters).

Scenarios (number of stations)	Minimize impedance (P-median)				Maximize coverage			
	Average distance to the nearest station	Std. dev.	Average distance from the 5 nearest stations	Std. dev.	Average distance to the nearest station	Std. dev.	Average distance from the 5 nearest stations	Std. dev.
100	655.5	207.3	997.4	288.5	478.7	209.0	740.4	317.1
200	474.6	157.7	677.8	228.1	381.4	145.1	537.0	216.5
300	396.0	165.4	559.6	225.7	350.1	124.5	472.5	162.5
400	343.5	145.5	484.9	200.0	321.3	98.0	436.5	154.4
500	311.3	127.8	436.3	173.6	301.7	82.3	420.0	120.3

Source: Calculations by author.

Station characterization

Fig. 5 shows the distribution of bike stations according to their classification as generators, mixed, attractors or high attractors (see Section 4.3), for the maximize-coverage model only (for reasons of space). Leaving required bases aside, in the 100-station scenario, most of the stations (39%) are attractors or high attractors, while scarcely 2% are generators (Table 6). Nevertheless, as the number of stations increases, so does the percentage of generator stations. In the 300-station scenario, generator stations represent 18%, while in that of 500 stations, they represent 28%. The percentage of mixed stations also increases, while the weight of those located in high attractor zones diminishes. This shift is because the center of Madrid attracts more trips than it generates, so that places with the greatest density of potential trips have a clear attractor component (areas of activity). It is only when the number of stations increases that station in trip-generator areas (residential areas) appear more frequently. These stations should have more bicycles than free docks available first thing in the morning, while the situation for attractor stations is exactly the opposite. The case of required bike stations (located at Metro and suburban rail stations) is a special one because the availability of bicycles and free docks depends not only on the characteristics of the allocated areas but also on the daily rate of passenger ingress and egress at the station.

Accessibility from the stations

Fig. 6 shows accessibility from the stations to potential destinations in the maximize-coverage model. The stations with a greater level of accessibility are the most central ones, close to zones of activity where other high attractor stations are located. Some peripheral or isolated stations located in residential areas (generators) have poor accessibility and could therefore be disregarded.

Table 6
Number of stations according to their typology (Maximize Coverage).

Scenarios	Generators		Mixed		Attractors		High attractors		Required	
	Total	%	Total	%	Total	%	Total	%	Total	%
100	2	2.0	7	7.0	19	19.0	20	20.0	52	52.0
200	23	11.5	48	24.0	47	23.5	30	15.0	52	26.0
300	54	18.0	72	24.0	80	26.7	42	14.0	52	17.3
400	93	23.3	107	26.8	93	23.3	55	13.8	52	13.0
500	140	28.0	128	25.6	120	24.0	60	12.0	52	10.4

Source: Calculations by author.

An increase in the number of stations leads to general increases in accessibility, and stations with high accessibility tend to spread out from the more central areas to the periphery (Fig. 6b and c). The accessibility of each station increases as the number of stations in the immediate vicinity increases, which increases the accessibility of the network as a whole (Table 7). This pattern is a well-known fact in transport literature. As a transport network is expanded, more opportunities become available at a given travel time or generalized cost. This will lead to positive consumption externalities and these are a source of network effects (Laird, Nellthorp, & Mackie, 2005). Once again, however, returns diminish: between the 100 and 200 bike-station scenarios, the average accessibility to the network increases by 59.8%, but the accessibility only increases by 6.2% between the 400- and 500-station scenarios (Table 7).

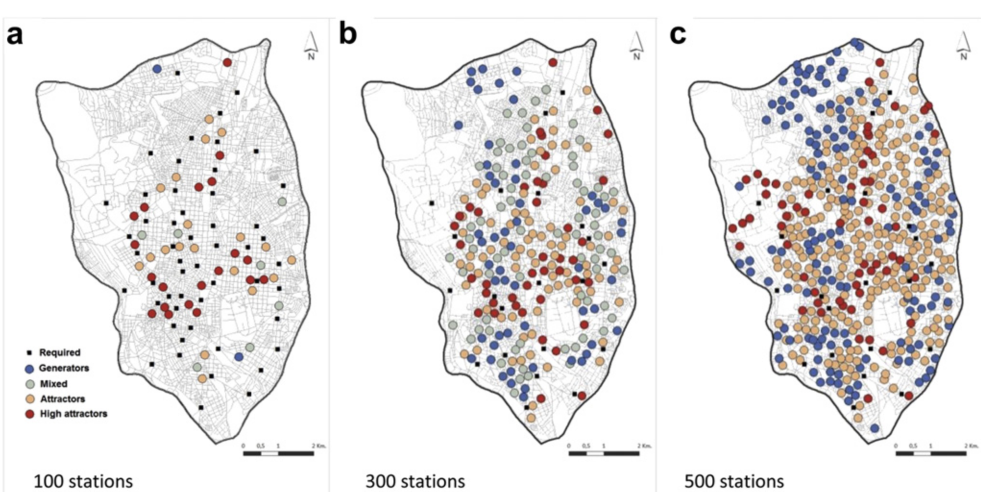

Fig. 5. Station typology (with Maximize Coverage solution).

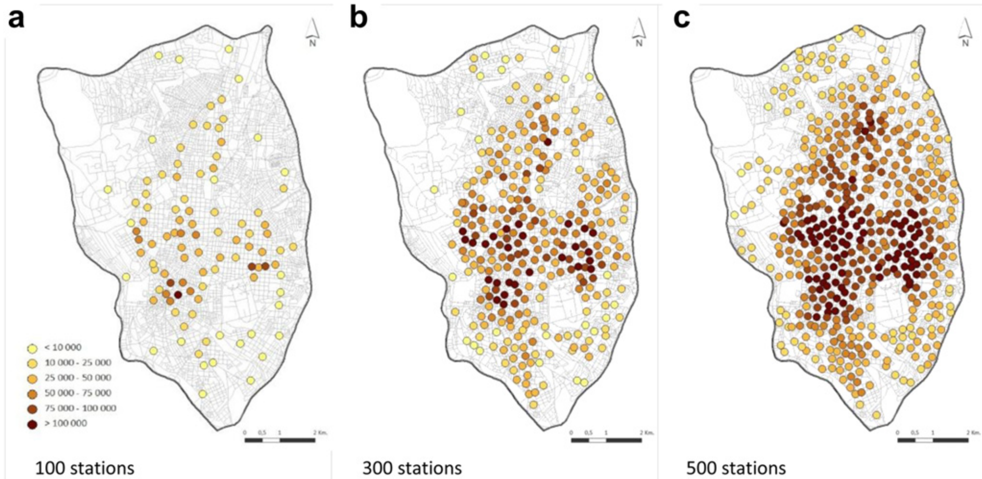

Fig. 6. Accessibility from the stations (Maximize Coverage solution).

Table 7
Average accessibility to the stations (in units of potential).

Scenarios (number of stations)	Average	Increment	Increment %	Std. dev.
100	25689.1	–	–	21523.9
200	41054.4	15365	59.8	20304.9
300	50339.6	9285	22.6	36869.0
400	58508.8	8169	16.2	29950.6
500	62154.6	3646	6.2	33875.4

Source: Calculations by author.

Conclusions

Bike-sharing programs have become one of the most frequent actions taken to promote the use of bicycles in cities. Numerous experiences demonstrate that the implementation of such programs produces a significant increase in bicycle use. Given the program's importance, many studies analyze the keys to the degree of success of the programs, investigating factors such as cost, type of bicycle, weather, topography (e.g., Curran, 2008) and the urgent need for guidelines and manuals for introducing bike-sharing programs (Midgley, 2011).

One key to the success of bike-sharing programs is the location of the bike stations, their relation with demand and the public transport system and the way the network is structured (distribution of stations in the urban area). However, as with all other infrastructures linked to bicycles, hardly any methods for locating new facilities have been developed to date. In the absence of such a methodology, new facilities are often built with a view toward recreational cycling or keeping bicycles "out of the way" of motorized traffic. However, to best serve, methods must be developed to objectively determine how to optimally locate bike facilities (Larsen et al., in press).

GIS is a highly useful tool for developing methods for bike-station location. Some studies have used GIS-based multi-criteria analysis tools both to evaluate bicycle infrastructures and analyze the distribution of potential demand (see, for example, Rybarczyk & Wu, 2010; or Larsen et al., in press). However, no optimal location model for bike-sharing stations has been developed that makes use of the tools for optimal service location.

In this study, we have shown the possibilities for location-allocation models integrated with one of the most commonly used commercial GIS and applied to a proposal for the optimal location of bike-sharing stations in the city center of Madrid. Different scenarios were evaluated with variations in the number of stations to be introduced. To this end, the potential demand for bike trips based on addresses available for residential or commercial activity was identified, differentiating between generated trips (from home) and attracted trips (to activities). By treating demand in this way, not only can bike-station capacity (number of docks) be determined but also stations can be characterized according to their daily asymmetric travel demands (to calculate the number of docks and bicycles at each station). This information is of great use for managing the redistribution of bicycles among the stations (Curran, 2008).

Two of the most common solutions in location-allocation models have been tested: minimizing impedance and maximizing coverage. The first approach allows station location to be optimized as it minimizes the distance between supply and demand, giving a station distribution that covers the whole area relatively uniformly. The second approach attempts to optimize the total population covered within a particular radius (here 200 m) in such a way that the stations are concentrated in the zones with greatest potential demand. The maximize-coverage solution is clearly more interesting in Madrid in terms of efficiency because it maximizes the potential demand covered by the stations. The minimize-impedance solution seems to be more advantageous in terms of spatial equity because it generates a more uniform coverage, helping to increase bicycling as a whole, but in some peripheral areas, it would be inefficient because of low potential demand.

The results offered by the proposed methodology are of great use for bike-station location. Nevertheless, it is also clear there are some limitations. Firstly, the program is aimed at serving the local population on workdays; in other words, it is a bike-sharing program for the general public. Recreational or tourist programs require a different methodology. The second limitation is that certain places in the city (e.g., large parks) have neither population nor jobs and yet may attract a considerable number of trips, while other places (e.g., museums) may have a ratio of attraction per job that is far higher than that of their transport zone, meaning that more trips will be attracted in reality than predicted by the model. A third limitation is related to the presence of relatively isolated stations, particularly in the maximize-coverage model. However, these stations can easily be identified and eliminated after the accessibility analysis is carried out (the scant number of destinations reached from them makes their viability very questionable). Finally, given the scale of the study, it is only logical that detailed studies are required to determine the exact location of each station.

The results obtained are therefore useful for decision making but should be complemented with other criteria and more detailed studies to determine the exact location of each station.

The evaluation of different scenarios has made it possible to confirm that an increment in the number of stations logically leads to an increase in both the demand covered and the accessibility of stations to potential destinations, but with diminishing returns. As Shu et al. (2010) note, a very high number of stations may produce an excessive increase in the cost of the system without bringing about any substantial improvement.

Acknowledgments

This research was financed by the Spanish Ministerio de Economía y Competitividad (Projects TRA2008-06682/MODAL and TRANSBIC-TRA2010-17035).

References

Almeida, L. A., Coutinho-Rodrigues, J., & Current, J. (2009). A multiobjective modeling approach to locating incinerators. *Socio-Economic Planning Sciences, 43*, 111–120.
Bonnette, B. (2007). *The implementation of a Public-Use Bicycle Program in Philadelphia*. Urban Studies Program. Senior Seminar Papers. Pennsylvania University.
Bruinsma, F., & Rietveld, P. (1998). The accessibility of European cities: theoretical framework and comparison of approaches. *Environment and Planning A, 30*, 499–521.
Church, R. L. (1999). Location modelling and GIS. In P. A. Longley, M. F. Goodchild, D. J. Maguire, & D. W. Rhind (Eds.), *Geographical information systems*. New York: Wiley.
Church, R. L. (2002). Geographic information systems and location science. *Computers & Operations Research, 29*, 541–562.
Church, R. L., & Murray, A. T. (2009). *Business site selection, location analysis and GIS*. New York: Wiley.
Church, R. L., & ReVelle, C. (1974). The maximal covering location problem. *Papers in Regional Science, 32*, 101–118.
City of Paris. (2007). *Le bilan des deplacements en 2007 a Paris*. Paris, France: La Mairie de Paris, L'Observatoire de Deplacements.
Cooper, L. (1963). Location–allocation problems. *Operations Research, 11*, 331–343.
Curran, A. (2008). *Translink public bike system feasibility study*. Vancouver: Quay Communications Inc.
DeMaio, P. (2003). Smart bikes: public transportation for the 21st century. *Transportation Quarterly, 57*(1), 9–11.
DeMaio, P. (2009a). *The bike-sharing blog*. Accessible at http://bike-sharing.blogspot.com.
DeMaio, P. (2009b). *The bike-sharing map*. Accessible at http://maps.google.com/maps/ms?ie=UTF8&hl=en&msa=0&msid=104227318304000014160.00043d80f9456b3416ced&z=2.
DeMaio, P., & Gifford, J. (2004). Will smart bikes succeed as public transportation in the United States? *Journal of Public Transport, 7*(2), 1–14. http://www.nctr.usf.edu/jpt/pdf/JPT%207-2%20DeMaio.pdf.
Dill, J., & Voros, K. (2007). *Factors affecting bicycling demand: Initial survey findings from the Portland region*. Washington, DC: Transportation Research Board.
Drezne, Z., & Hamacher, H. (Eds.), (2002). *Facility location: Applications and theory*. New York: Springer.
Edmonds, J. (1962). Covers and packings in a family of sets. *Bulletin of the American Mathematical Society, 68*, 494–499.
Gerrard, R. A., Church, R. L., Stoms, D. M., & Davis, F. W. (1997). Selecting conservation reserves using speciescovering models: adapting the ARC/INFO GIS. *Transactions in GIS, 2*, 45–60.
Ghosh, A., & Rushton, G. (1987). *Spatial analysis and location-allocation models*. New York: Van Nostrand Reinhold.
Grubesic, T. H., & Murray, A. T. (2002). Constructing the divide: spatial disparities in broadband access. *Papers in Regional Science, 81*, 197–221.
Hakimi, L. (1964). Optimum locations of switching centers and the absolute centers and medians of a graph. *Operations Research, 12*, 450–459.
Hakimi, L. (1965). Optimum distribution of switching centers in a communication network and some related graph theoretic problems. *Operations Research, 13*, 462–475.
Harkey, D. L., Reinfurt, D. W., & Knuiman, M. (1998). Development of the bicycle compatibility index. *Journal of the Transportation Research Board, 1636*, 13–20.
Heinen, E., van Wee, B., & Maat, K. (2010). Commuting by bicycle: an overview of the literature. *Transport Reviews, 30*(1), 59–96.
Holtzman, D. (2008). Share a bike. *Planning, 74*(5), 20–23.
IDAE. (2007). *Guía metodológica para la implantación de sistemas de bicicletas públicas en España*. Madrid: Instituto para la Diversificación y Ahorro de la Energía.
IDAE-TRANSyT. (2010). *PROBICI. Guía de la movilidad ciclista. Métodos y Técnicas para el fomento de la bicicleta en áreas urbanas*. Madrid: Instituto para la Diversificación y Ahorro de Energía y TRANSyT.
Jensen, P., Rouquier, J. B., Ovtracht, N., & Robardet, C. (2010). Characterizing the speed and paths of shared bicycles in Lyon. *Transportation Research D, 15*(8), 522–524.
Kalvenes, J., Kennington, J., & Olinick, E. (2005). Hierarchical cellular network design with channel allocation. *European Journal of Operational Research, 160*, 3–18.
Laird, J., Nellthorp, J., & Mackie, P. (2005). Network effects and total economic impact in transport appraisal. *Transport Policy, 12*, 537–544.
Landis, B. W. (1996). Bicycle system performance measures. *ITE Journal, 66*(2), 18–26.
Larsen, J., Patterson, Z., & El-Geneidy, A. Build it. But where? The use of geographic information systems in identifying locations for new cycling infrastructure. *International Journal of Sustainable Transportation,* in press.
Lin, J. R., & Yang, T. H. (2011). Strategic design of public bicycle sharing systems with service level constraints. *Transportation Research E, 47*, 284–294.
List, G., & Mirchandani, P. (1991). Integrated network/planar multiobjective model for routing and siting for hazardous materials and wastes. *Transportation Science, 25*, 146–156.
Litman, T. (2009). *Bicycle parking, storage, and changing facilities*. Accessible at http://www.vtpi.org/tdm/tdm85.htm.
Liu, N., Huang, B., & Chandramouli, M. (2006). Optimal siting of fire stations using GIS and ANT algorithm. *Journal of Computing in Civil Engineering, 20*, 361–369.
Martens, K. (2007). Promoting bike and ride: the Dutch experience. *Transportation Research A, 41*, 326–338.
Midgley, P. (2011). *Bicycle-sharing schemes: Enhancing sustainable mobility in urban areas*. Background Paper No. 8, CSD19/2011/BP8, Commission on Sustainable Development. United Nations.
Min, H., & Melachrinoudis, E. (2001). The three-hierarchical location–allocation of banking facilities with risk and uncertainty. *International Transactions in Operational Research, 8*, 381–401.
Møller-Jensen, L., & Kofie, R. Y. (2006). Exploiting available data sources: location/allocation modeling for health service planning in rural Ghana. *Geografisk Tidsskrift, Danish Journal of Geography, 101*, 145–153.
Monzón, A., Vega, L., & López-Lambas, M. E. (2007). Potential to attract drivers out of their cars in dense urban areas. TRB 2007 Annual Meeting.
Muhammad, S., de Jong, T., & Ottens, H. F. L. (2008). Job accessibility under the influence of information and communication technologies in the Netherlands. *Journal of Transport Geography, 16*, 203–216.
Murawski, L., & Church, R. L. (2009). Improving accessibility to rural health services: the maximal covering network improvement problem. *Socio-Economic Planning Sciences, 43*, 101–110.
Murray, A. T. (2010). Advances in location modeling: GIS linkages and contributions. *Journal of Geographycal Systems, 12*, 335–354.
Murray, A. T., & Tong, D. (2009). GIS and spatial analysis in the media. *Applied Geography, 29*, 250–259.
Nadal, L. (2007). Bike sharing sweeps Paris off its feet. *Sustainable Transport, 19*, 8–12.
Noland, R. B., & Ishaque, M. M. (2006). Smart bicycles in an urban area: Evaluation of a pilot scheme in London. *Journal of Public Transportation, 9*(5), 71–95.
NYC Dept. City Planning. (2009). *Bike-share. Opportunities in New York city*. http://www.nyc.gov/html/dcp/html/transportation/td_bike_share.shtml.
Pucher, J., & Buehler, R. (2008). Making cycling irresistible: lessons from the Netherlands, Denmark, and Germany. *Transport Reviews, 28*(4), 495–528.
Pucher, J., & Buehler, R. (2009). Integration of bicycling with public transport in North America. *Journal of Public Transport, 12*(3), 79–104.
Pucher, J., Dill, J., & Handy, S. (2010). Infrastructure, programs, and policies to increase bicycling: an international review. *Preventive Medicine, 50*, 106–125.
ReVelle, C. (1991). Siting ambulances and fire companies: new tools for planners. *Journal of the American Planning Association, 57*, 471–485.
Ribero, A., & Pais, A. (2002). A GIS-based decision-support tool for public facility planning. *Environment and Planning B: Planning and Design, 29*, 553–569.
Romero, C. (2008). Spicycles in Barcelona. PowerPoint Presentation by City of Barcelona at the Spicycles Conference, Bucharest, Romania, December 2008. Accessible at: http://spicycles.velo.info/Portals/0/FinalReports/Barcelona_Final_Report.ppt.
Rushton, G. (1979). *Optimal location of facilities*. Wentworth, NH: COMPress.
Rybarczyk, G., & Wu, C. (2010). Bicycle facility planning using GIS and multi-criteria decision analysis. *Applied Geography, 30*, 282–293.
Shaheen, S., Guzman, S., & Zhang, H. (2010). Bikesharing in Europe, the Americas, an Asia: past, present, and future (Washington D.C). *Transportation Research Board Annual Meeting*.
Schwartz, W. L. (1999). *Guidebook on methods to estimate non-motorized travel: Supporting documentation*. US Dept. of Transportation, Federal Highway Administration, Research and Development, Turner-Fairbank Highway Research Center. http://safety.fhwa.dot.gov/ped_bike/docs/guidebook2.pdf.
Shu, J., Chou, M., Liu, Q., Teo, C. P., & Wang, I. L. (2010). *Bicycle-sharing system: Deployment, utilization and the value of re-distribution*. Singapore: National University of Singapore- NUS Business School. http://www.bschool.nus.edu.sg/Staff/bizteocp/BS2010.pdf.
Teixeira, J., Paes, A., & Peeters, D. (2007). An optimization-based study on the redevelopment of a secondary school network. *Environment and Planning B, 34*, 296–315.
Teixeira, J., & Antunes, A. (2008). A hierarchical location model for public facility planning. *European Journal of Operational Research, 185*, 92–104.

Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. *Operations Research, 19*, 1363–1373.
Turner, S., Hotternstein, A., & Shunk, G. (1997). *Bicycle and pedestrian travel demand forecasting: Literature review*. Texas Transportation Institute, Texas A & M University System, Available through National Technical Information Service. http://safety.fhwa.dot.gov/ped_bike/docs/txdot_3988s.pdf.
Valeo, C., Baetz, B. W., & Tsanis, I. K. (1998). Location of recycling depots with GIS. *Journal of Urban Planning and Development, 124*(2), 93–99.
Vega, L. A. (2006). *Beneficios socio-ambientales de estrategias de movilidad sostenible en el centro de las ciudades: aplicación al caso de Madrid*. PhD Thesis, E.T.S.I. Caminos, Canales y Puertos, Universidad Politécnica de Madrid. http://oa.upm.es/894/1/BENEFICIOS_SOCIO-AMBIENTALES_DE_ESTRATEGIAS_DE_MOVILIDAD_SOSTENIBLE.pdf.
Verter, V., & Lapierre, S. D. (2002). Location of preventive health care facilities. *Annals of Operations Research, 110*, 123–132.
Velo'v. (2009). *Velo'v information website*. Accessible at http://www.velov.grandlyon.com/Archives-Velo-V.63.0.html.
Yeh, A. G. O., & Chow, M. H. (1996). An integrated GIS and location–allocation approach to public facilities planning–an example of open space planning. *Computers, Environment and Urban Systems, 20*, 339–350.