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Optimal location of bike-sharing stations: A built environment and accessibility approach

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A R T I C L E I N F O

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A B S T R A C T

Bike-sharing systems (BSS) have arisen worldwide as an attractive and sustainable travel alternative. As these systems have shown positive effects in reducing congestion and emissions, it is relevant to properly analyze their potential implementation in different contexts. Evidence has shown that BSS can only provide benefits when their network is adequately designed, in order to capture ridership and generate demand. This study proposes an integrated approach to model the demand of bike-sharing trips and the optimal location of stations in the system, based on built environment and accessibility-based variables. The methodology consists of two steps. On the first step, trip generation models are estimated through multiple regressions for different types of trips and periods of the week. On the second step, maximum demand coverage models are developed to allocate the BSS stations, according to the trip generation models and to different proposed scenarios. To test the proposed methodology, information from the BSS of Santiago de Chile is used. Results suggest a relationship between the built environment and the use of public bicycles, with a main effect of residential and office land uses, and the presence of long bicycle lanes near the stations. In addition, the presence of endogeneity, associated with the location of BSS stations and BSS demand generation, is confirmed and controlled using accessibility variables. As for the optimal location models, their outcomes differ significantly from the observed spatial distribution of stations in Santiago, with higher density in central areas and along corridors with cycling infrastructure. The forecasted demand level for the optimal distribution of stations is 64% higher than the observed demand. This study confirms the benefit of an integrated modelling of the trip generation and the station location to foster higher public bicycle usage, a relevant point for BSS decision planning and the promotion of a more sustainable mobility.

1. Introduction

Tackling traffic growth and encouraging public and non-motorized transport modes are actions that lead cities to a more sustainable and livable future (Banister, 2000; Kenworthy, 2006). In this context, evidence from multiple places around the world shows that Bike-Sharing Systems (BSS) contribute to a sustainable urban development by offering significant environmental and social benefits. For instance, the implementation of this kind of systems has reduced the emission of polluting gases and decreased congestion

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in some areas, especially in zones of high urban density and during rush hours (Hamilton & Wichman, 2018; Zhang & Mi, 2018). These effects are enhanced by the presence of robust public transport systems, offering more and better intermodal mobility options (Wang & Zhou, 2017). Other observed benefits of bike-sharing are an increase in the overall use of bicycle as a transport mode (Fuller et al., 2013; Vogel et al., 2014), shorter journey times than other transport modes (Bullock et al., 2017), a slight modal shift from cars to bicycles (Fishman et al., 2014), a lower accident rate compared to private bicycle users (Fishman & Schepers, 2016), a positive impact on urban landscape perception (Hurtubia et al., 2021), and positive effects on people's health in the long term (Otero et al., 2018; Woodcock et al., 2014).

Nevertheless, international experiences of different BSS have revealed a set of practical issues that may cause substantial difficulties for these services. Some of these issues are inadequate docking stations location and density (Conrow et al., 2018), limited bicycle availability (Kabra et al., 2018), insufficient cycling infrastructure and safety concerns (Fishman et al., 2012), theft and vandalism (Midgley, 2011), adverse geographical and climate factors (Sun et al., 2018), and financial difficulties (Audikana et al., 2017). Also, these systems face major challenges regarding the uncertainty of future demand and the long-term sustainability of their business models (S. Shaheen et al., 2010). Consequently, further research in the design and operations of BSS is still needed.

In recent years, dockless (or free-floating) BSS have gained attention because they allow the user to use the public bicycles without the restriction of movements given by the spatial distribution of stations, thus reducing the walking distance to their destination and eliminating the worry of finding no available docks to return the bike at the end of the trip (Pal & Zhang, 2017). Still, evidence shows that both types of systems may coexist in a city and recent studies suggest that their services may be complementary and suitable for different kinds of users and trips (Chen et al., 2018; Mckenzie, 2018). In fact, the experience from China in the past years indicates that station-based BSS can still be a better option for medium and small size cities to promote sustainable transport modes, especially among cities with low bicycle use levels (Gu et al., 2019). Accordingly, this research focuses on having a deeper understanding of station-based BSS to generate useful insights for the design of these systems.

The main objective of this study is to develop a methodology to support better planning and decision-making decisions regarding the location of BSS stations. This aim considers, first, the identification of built environment attributes and accessibility measures that are related to the generation of bike-sharing trips and the quantification of each effect. Second, the construction of an optimal location model to determine efficient spatial distributions of public bicycle stations, consistent with the previously selected built environment and accessibility variables and according to different operational scenarios. The proposed method departs from previous studies due to the use of accessibility measures to account for the endogeneity caused by the spatial distribution of stations in the demand for public bicycles and, therefore, in the optimal BSS network structure.

The methodology is applied to Bike Santiago, a BSS in Santiago de Chile. Analyses from Bike Santiago data motivated the exploration of different research paths that ended up shaping this research. In this regard, the proposed methodology combines both validated tools that can be found in the literature and novel ideas that emerged upon the observation of this case study. This study is consequently part of the few studies that analyze a station-based BSS operating in Latin American cities (Cerutti et al., 2019; Midgley, 2011; Shaheen et al., 2014).

This paper is organized as follows: Section 2 presents a literature review on demand and location optimization research on BSS. Section 3 describes the methods that are used in this investigation. Section 4 presents the case study. Section 5 shows and analyzes the results, and Section 6 concludes with final remarks.

2. Literature review

There are several publications about public bicycle related topics that can be found in the literature. These cover sustainability and cycling promotion policies, bike and station technologies, benefits and impacts of the BSS, user preferences and user profiles, safety aspects, usage patterns and operational considerations, among others (Fishman, 2016; Fishman et al., 2013). The present study focuses on some previous investigations about demand and strategic aspects of these systems, topics that are briefly summarized in this section.

2.1. Bike-sharing demand modelling

BSS have special mobility patterns related to its stations network and to specific functional features. Therefore, BSS trips can be classified into different types, regarding the visited stations, the duration of the trips and the dwell time between trips (Bordagaray et al., 2016). Also, bike-sharing trips can be separated into simple and chain trips. (Zhao et al., 2015). Usually, BSS have a time threshold for trip duration to avoid the users from retaining the bikes for long periods. Trips longer than the threshold time are penalized by an additional cost. Thus, users can avoid this penalization by making consecutive trips in chain, not exceeding the time threshold in each stage. Additionally, BSS users can end a trip at any station they want if there is an available dock to return the bike at the destination. Consequently, trips can be divided into origin–destination (OD) trips and loop trips, depending on if the bike is returned to the station where the trip started or to a different station (Noland et al., 2016).

Other variations in bike-sharing mobility patterns have been identified for different travel purposes and socioeconomic characteristics of the users. For example, symmetrical patterns are frequent in commuting trips, while more heterogeneous and asymmetrical patterns are more frequent in casual trips (Bordagaray et al., 2016). Gender related differences have also been observed, such as the fact that women tend to cycle slower than men and the tendency of men to be more likely to make loop trips (Zhao et al., 2015). Likewise, other studies suggest that member users have a greater probability of commuting and casual users have a greater probability of using public bicycles for recreational purposes (Faghih-Imani & Eluru, 2015; Noland et al., 2019).

Data used in bike-sharing mobility analyses can come from passive or active sources. Passive data usually consists of records of the number of bicycles present at each station of the system and separated by a regular interval of time. In these cases, the modeling of bike-sharing demand is performed based on the changes observed between different periods and different spatial aggregations of stations (Faghih-Imani et al., 2014; Levy et al., 2017; Médard de Chardon & Caruso, 2015). On the other hand, active data is based on the record of every transaction that is generated in the system (Kaspi et al., 2016). This usually includes temporal information and identifications for the user, bicycle and stations that are involved in the transaction.

Bike-sharing trip generation has frequently been modelled using linear regressions (Duran-Rodas et al., 2019). Less frequent approaches include discrete choice models, such as Ordinal and Mixed Logit models (Faghih-Imani & Eluru, 2016a; Raux et al., 2017), and negative binomial models (Noland et al., 2019). When disaggregated data has been available, the models have been divided by season and by time-of-day intervals, which may be defined following peak and off-peak hours (Noland et al., 2019; Zhang et al., 2017) or by time intervals of the same length (Faghih-Imani et al., 2014; Faghih-Imani & Eluru, 2016b; Gebhart & Noland, 2014).

Built environment variables are amongst the most frequent variables that have been used to model bike-sharing trips. This type of variables includes aspects of the density and diversity of land uses around the stations, urban design, destination accessibility and distance to transit measurements (Ewing & Cervero, 2010). All of them have been included in previous publications via different measurements and data processing approaches. Some of the factors that have shown a positive effect in bike-sharing usage are the following: high values of residential and points of interest densities (Duran-Rodas et al., 2019; Faghih-Imani et al., 2017; Faghih-Imani & Eluru, 2016b); diverse land uses (Noland et al., 2019; Zhang et al., 2017); availability of cyclist infrastructure (El-Assi et al., 2017; Mateo-Babiano et al., 2016); accessibility to jobs (Faghih-Imani et al., 2014; Wang et al., 2015) and proximity to mass transit services (Nair et al., 2012; Noland et al., 2016).

In some cases, the models have been complemented with measurements of the network effect (Rixey, 2013), topographical measurements (Mateo-Babiano et al., 2016) or have been corrected by spatiotemporal aspects of the trips (Faghih-Imani & Eluru, 2016b). Other approaches have also considered logistic aspects of the system in modelling, such as the balance between more stations or larger stations based on higher levels of demand, which is linked to the effects of accessibility and availability of bicycles (Kabra et al., 2018).

2.1.1. *The role of cycling infrastructure*

The presence of bike lanes stands out as a key factor of bike-sharing success. For example, in Rossetti et al. (2018, 2019) the authors identify that public bicycle users are more likely to be very concerned about safety and to prefer highly segregated cycling infrastructure and even the sidewalk rather than riding on the streets, compared to cyclists who do not use these systems. Also, in Gutiérrez et al. (2020) the authors find that the presence of bicycle lanes increases the willingness of people to change their mode of transportation for commuting trips from motorized modes to the bicycle or public bicycle.

2.2. *Optimal location of BSS stations*

In relation to the second part of this study, there are a few publications that have covered the modelling of optimal location of BSS stations. Within the purely deterministic approaches, minimum impedance (p-median) and maximum coverage models have been considered, most of them inspired in the work on location modelling presented in Church and ReVelle (1974) and other previous publications. In the first type of models the average distance to the demand points covered from the stations to be allocated is minimized. On the other hand, in the second type of models the amount of reachable demand within a certain coverage area is maximized (Conrow et al., 2018; Frade & Ribeiro, 2015). In particular, some publications have compared these approaches, obtaining greater spatial coverage, and spacing between stations with the use of the minimum impedance models, while a higher level of covered demand and a higher density of stations in certain important areas with the use of maximum coverage models (García-Palomares et al., 2012; Park & Sohn, 2017).

On the other hand, some studies have taken stochastic approaches. For example, bi-objective modeling, which considers both the minimization of social transport costs and the maximization of the modal partition of public bicycle trips (Romero et al., 2012). Minimizing unmet demand has also been to the station allocation modelling approach (Çelebi et al., 2018). Also, the use of minimum cost models has been considered, which establish a value for different elements related to the use and implementation of a SBP and have the objective of minimizing the total cost of the system (Lin et al., 2013; Lin & Yang, 2011). However, modeling schemes with high stochastic components are more frequent in modeling the use and redistribution of public bicycles (Shu et al., 2013).

A similar problem regarding location decisions for shared transportation services can be found in carsharing systems literature (Correia & Antunes, 2012; Boyacı et al., 2015). Despite the differences in the transportation mode that is modelled, the average distance of the trips and other particularities about the use of the system, an important part of the principles behind the models coincide.

The methodology that is proposed in this research considers some aspects present in the literature and proposes new considerations. Previously developed optimization models for BSS have considered demand and accessibility aspects regarding the use of public bicycles using simplified networks and variables. This study contributes to the design of optimization models for BSS stations that comprehensively consider the complexity of the BSS trip demand in its relation to the built environment, to the network structure and to its variations across different spatial and temporal conditions. Nevertheless, some of the mentioned aspects, such as socio-economic characteristics of users and bicycle relocation aspects are not incorporated due to the limitation in the available data.

3. Methodology

This section presents the methodological approach that is considered to identify significant built environment and accessibility variables that can explain the generation of trips in a BSS and to determine an optimal location for BSS stations, with focus on the maximization of the covered demand. This process consists of two parts. First, the estimation and calibration of BSS demand generation models using data from an observed BSS system and its urban context. Second, a model for the optimal location of public bicycle stations, based on parameters associated with the previously calibrated trip generation models and using built environment information from a selected urban scenario.

3.1. Bike-sharing trip generation modelling

To model the BSS trip generation, a multiple linear regression structure is used. On the one hand, this step considers the use of actively generated transaction records from an observed BSS, with spatial and temporal references. These transactions are processed to obtain complete trips information, binding consecutive trip segments that are part of a trip chain and eliminating short trips that may indicate a malfunction in the bicycle or another practical inconvenience that produced an unfinished trip (Bordagaray et al., 2016; Kaspi et al., 2016). The trips corresponding to redistributions of bicycles made by the system operator are also not considered. Then, a set of trip categories is selected, each category considering specific days of the week, periods of the day, and one type of trips (OD trips or loop trips). Consequently, the dependent variables for the models are constructed as the average daily trip generation at each station for each trip category. On the other hand, different built environment attributes are processed to create the local and accessibility variables that compose the set of independent variables for the models.

3.1.1. Local built environment variables

Local variables incorporate built environment features present within an area of influence surrounding each BSS station. The area of influence of an observed station is defined in this work as a circular buffer around it, whose radius is associated with a walk access distance determined for the city where the observed BSS operates. If an element of the built environment is covered by two or more areas of influence of different stations, its information will be assigned either to the area of influence of the closest station or distributed between the areas of influence, depending on if the attribute that is considered is cumulative or non-cumulative. Cumulative attributes consist of amounts that can be added, such as the square meters of a type of land use, while non-cumulative attributes consist of non-summable values, such as average or binary values. Thus, Thiessen polygons are used to shape the areas of influence to avoid double counts on the cumulative variables (Duran-Rodas et al., 2019; Noland et al., 2019). This is shown in Fig. 1.

Fig. 1. Area of influence for non-cumulative (left) and cumulative variables (right).

3.1.2. Accessibility variables

Accessibility variables consist of integral distance-weighted measures of built environment features present in the surroundings of each one of the BSS stations that are reachable from the station in the origin of a trip. These variables incorporate information about the built environment at the possible destinations of a trip and about the spatial distribution of the stations, features that capture part of the endogeneity that is present in the public bicycles travel demand, as trips are only allowed to start and finish in an operating station of the system.

The accessibility variables considered in this investigation are of the integral type, since they are calculated as the sum of the relative accessibility values between a station in the origin of a trip and each of the possible destination stations located within a distance range. For each pair of stations, the relative accessibility value consists of the amount of a built environment attribute present in the vicinity of the destination station, weighted by the value that an empirical accessibility function takes for the shortest path distance between the two stations, considering the network of streets and bike lanes. Here, a distance measurement is used instead of a time measurement because the duration of the shared bicycle trip may vary significantly between users and in relation to weather effects (Gebhart & Noland, 2014). Although users are likely to take longer routes than the shortest route between two stations, this minimum distance measurement is independent of user behavior and is comparable between different cities and systems, while the minimum or average time measurements depend on the speed of the cyclists and other factors.

The empirical accessibility function that is used to measure accessibility in this methodology considers that the BSS trips distance follow a log-normal distribution. This distribution has previously been proposed for modelling both travel times and travelled distance for bike-sharing trips and has shown satisfactory results, especially for large-scale cities where the routes that users choose are not restricted by the city limits or a reduced set of route options (Kou & Cai, 2019; Li et al., 2015). Also, this functional form is better adapted to the observed OD-type trips than the negative exponential forms commonly used for accessibility measures in the literature. This is due to the rapid growth in the number of trips observed as the distance increases from zero to medium distance values, followed by a less pronounced decrease in trips as the distance increases beyond that point. This means that maximum accessibility for public bicycles is not necessarily achieved at the shortest distance but, instead, at a “too long to walk” but “short enough to cycle” one. In practical terms, this responds to the fact that the public bicycle competes more directly with (and is dominated by) walking on shorter trips and then with motorized modes of transport for longer trips. Other successful applications of log-normal distribution in transport modelling include travel times in private vehicles and public transport (Arezoumandi, 2011; Kieu et al., 2015).

The parameters of the log-normal accessibility function (μ,σ) are calibrated using the trip data of the observed BSS. Then, for each pair of stations (i,j) of the observed system the empirical accessibility density value $f_{i,j}$ is calculated based on the distance between both stations $(d_{i,j})$ and according to the following expression, corresponding to the log-normal probability density function:

$$f_{i,j} = \frac{1}{d_{i,j}} \frac{1}{\sigma\sqrt{2\pi}} exp\left(- \frac{\left(\ln\left(d_{i,j}\right) - \mu\right)^2}{2\sigma^2} \right), \forall i,j \tag{1}$$

Once the empirical accessibility function is calibrated, it is possible to calculate the value of the integral accessibility measures to be considered in the econometric analysis. For each *i* station and for each *k* attribute of the built environment (e.g. a density, diversity, or design element), the accessibility variable Acc_i^k is then constructed as the weighted sum of the attributes of the built environment N_j^k and the values of the accessibility density function $f_{i,j}$ for the *j* stations present in the set of S_i stations located within a cut-off distance (at which the relation between stations becomes neglectable) relative to station i :

$$Acc_i^k = \sum_{j,j\neq i}^{S_i} \left(f_{i,j} \bullet \mathrm{N}_\mathrm{j}^\mathrm{k} \right), \forall \mathrm{i}, \mathrm{k} \tag{2}$$

For greater flexibility in the design of accessibility variables, it is also possible to add information about the built environment in the proximity of the station in the origin. This can be incorporated by weighing the expression present in equation (2) by a factor related to an attribute of the built environment present in the vicinity of station *i*. For example, a binary factor can be used to consider a non-zero value of accessibility just for the BSS stations that have a subway station nearby.

It is important to indicate that, given the characteristics of loop trips, they do not necessarily interact with stations other than the one where the trip started. For this reason, loop trips are modelled only using local variables.

3.1.3. Models selection

An independent trip generation model is estimated for each trip category. These models are calibrated using Ordinary Least Squares. The model selection is performed iteratively, a process in which independent variables are added and omitted based on achieving a better fit, getting the expected signs for the parameters, and obtaining a statistical confidence level (*t*-test) of at least 90% for each regressor. In addition, models that can more easily be related to the probable trip purpose for the selected category are preferred.

3.2. Optimal BSS stations location models

To model the optimal location for BSS stations, a maximal demand covering approach is taken. As bike-sharing travel demand does not only depend on spatially distributed independent variables but also on endogeneity associated with the location of the BSS stations, this model considers both decision variables related to possible station locations and auxiliary variables related to elements of the built environment present in the surroundings of these possible station locations. Together, these variables

Fig. 2. A possible station location and its area of influence within an equilateral triangle space tessellation.

incorporate the effects of the local and the bike-accessible built environment that were previously considered in the trip generation models.

To build the model, a target urban area is selected and divided into a set of T equilateral triangles that tessellate the study area. This geometrical form has been selected because of its flexibility linking possible station locations with their area of influence, without generating multiple counts of the elements in the area that is covered by two or more near station locations. The size of each triangle t is such that the surface of 6 triangles is equal to the surface of the circular area of influence that was previously estimated for the stations in the observed city. A set of I possible station locations is then created, based on every point of intersection of triangle vertices that is surrounded by 6 equilateral triangles in the tessellation. Then, a circular buffer is also created around each possible station location to incorporate the built environment attributes in the surroundings that are not cumulative. Fig. 2 shows a possible station location, surrounded by a circular buffer and its 6 adjacent equilateral triangles.

The built environment attributes are then linked to the spatial items in the optimization model, following the previously estimated travel demand models. Attributes related to cumulative variables are calculated within each equilateral triangle t, while attributes related to non-cumulative variables are calculated within the circular buffers and assigned each of to the respective possible station locations i. To incorporate the effect of the selected accessibility variables, the distance of the shortest path between every couple of possible station locations is measured and the accessibility weights $(f_{i,j})$ are calculated. Then, accessibility weights between the possible station locations and the triangles $(f_{i,t})$ are also calculated, a value that is determined as the mean of the accessibility weights from the location in the origin to the locations at the vertices of the triangle.

The mathematical formulation of the problem is structured as shown in Table 1 and in the following equations (3) to (13).

Table 1
Maximum coverage optimization model: subscripts, sets, parameters and variables.

Subscripts and sets	
$i,j \in I$	denote the possible station locations
$t \in T$	denotes the triangles that define the modelled urban area
$i \in \delta_t$	denote the locations present at the edges of the triangle t
$j \in \delta_i^I$	denote the locations present within the distance cutoff from the location i
$t \in \delta_i^T$	denote the triangles present within the distance cutoff from the location i
$k,l \in K_I, K_T$	denote the attributes of the local built environment, related to a location or a triangle, respectively
$k,l \in K_{II}, K_{IT}$	denote the attributes of the built environment for accessibility variables, between two locations or between one location and a triangle
$p \in P$	denotes the trip category
Parameters	
α_p	is the weight in the model for the p trip category (it depends on its frequency within the modeled month)
$\beta^{k,p}$, $\beta^{(k,l),p}$	are the coefficients related to the trip generation models
c_i^k, c_j^l	are the value of a built environment attribute for a station location
q_t^k, q_t^l	are the value of a built environment attribute for a triangle
$f_{i,j}, f_{i,t}$	are the empirical accessibility density function values between two station locations or between a station location and a triangle, respectively
N	is the maximum amount of BSS stations to be allocated (budget)
Variables	
x_i	equals 1 if a station is installed in the location i, 0 if not
g_t	equals 1 if a station is installed in at least one of the locations present in the edges of triangle t, 0 if not. This variable activates triangle t
$m_{i,j}$	equals 1 if both locations i and j have a station installed, 0 if not
$y_{i,t}$	equals 1 if location i has a station installed and triangle t is active, 0 if not

Optimization model

$$Max\sum_{p}^{P}\alpha_p\left[\overbrace{\sum_{k\in K_I}\sum_{i}^{I}\left(\beta^{k,p}\cdot c_i^k\cdot x_i\right)}^{\text{trips generated for station (noncumulative variables)}}+\overbrace{\sum_{k\in K_T}\sum_{t}^{T}\left(\beta^{k,p}\cdot q_t^k\cdot g_t\right)}^{\text{trips generated for triangle (cumulative variables)}}+\sum_{(k,l)\in K_{II}}\sum_{i}^{I}\sum_{j\in\delta_i^I}\left(\beta^{(k,l),p}\cdot f_{i,j}\cdot c_i^k\cdot c_j^l\cdot m_{i,j}\right)\right.$$
$$\left.+\sum_{(k,l)\in K_{IT}}\sum_{i}^{I}\sum_{t\in\delta_i^T}\left(\beta^{(k,l),p}\cdot f_{i,t}\cdot c_i^k\cdot q_t^l\cdot y_{i,t}\right)\right] \tag{3}$$

such that

$$\sum_{i}^{I}x_i\leq N \tag{4}$$

$$g_t\leq\sum_{i\in\delta_t}x_i,\forall t\in T \tag{5}$$

$$g_t\geq x_i,\forall t\in T,\forall i\in\delta_t \tag{6}$$

$$m_{i,j}\leq x_i,\forall i\in I,\forall j\in\delta_i^I \tag{7}$$

$$m_{i,j}\leq x_j,\forall i\in I,\forall j\in\delta_i^I \tag{8}$$

$$m_{i,j}\geq x_i+x_j-1,\forall i\in I,\forall j\in\delta_i^I \tag{9}$$

$$y_{i,t}\leq x_i,\forall i\in I,\forall t\in\delta_i^T \tag{10}$$

$$y_{i,t}\leq g_t,\forall i\in I,\forall t\in\delta_i^T \tag{11}$$

$$y_{i,t}\geq x_i+g_t-1,\forall i\in I,\forall t\in\delta_i^T \tag{12}$$

$$x_i,g_t,m_{i,j},y_{i,j}\in\{0,1\} \tag{13}$$

First, the objective function (3) is presented as a sum of the generated travel demand in each of the P categories that are considered, weighted by a value (α_p) that represents the frequency of the category in the modelled period. Then, the generated travelled demand for each P category is modelled according to four terms. Following the same order presented in (3), these terms represent: i) local

Fig. 3. A Bike Santiago public bicycle station. Source: Bicicultura.cl.

generation by non-cumulative variables, ii) local generation by cumulative variables, iii) accessibility-based generation by non-cumulative variables and iv) accessibility-based generation by accessibility cumulative variables. Each of the terms considers, at least, a variable related to the activation of stations locations (x_i) or triangular sections (g_t) of the built environment, multiplied by the value of a build environment attribute present in that circular buffer (c_i^k) or triangular buffer (q_t^k) and weighted by the trip generation coefficient related to that attribute ($\beta^{k,p}$ or $\beta^{(k,l),p}$). As the last two terms are related to accessibility variables, these terms include the empirical accessibility density function values ($f_{i,j}$ or $f_{i,t}$) and a parameter c_i^k. This last parameter is used for accessibility variables that also consider non-cumulative attributes of the station of origin i, such as the presence of a subway in its surroundings, for example. In other cases, this parameter is replaced by a constant equal to 1.

Second, the set of the model constraints is presented. The first constraint considers the number of stations to be allocated (4), while the following constraints are used to activate the auxiliary variables and to define their minimum and maximum levels. These are used for the triangle activation (5 and 6), accessibility activation for non-cumulative variables (7, 8 and 9) and accessibility activation for cumulative variables (10, 11 and 12). Lastly, the nature of the variables is presented (13).

Different scenarios for BSS planning can be tested with this formulation, by changing the distribution of the built environment variables that are used as the input of the problem and by relaxing the budget restriction. Additionally, the allocation of some of the stations can be previously fixed in the model (e.g. having stations close to attractive places) and the allocation of isolated stations far from the main clusters or in places that are not feasible in practice can also be controlled by additional constraints to the model.

All the spatial treatment of the attributes of the built environment can be performed through the QGIS platform. The optimization model is written in Python and it uses libraries associated with the GUROBI optimizer to solve the different scenarios that are evaluated.

4. Case study

To test the proposed methodology, this study focuses on the case of Bike Santiago, a station-based BSS that operates in Santiago, the capital, principal financial center, and largest city of Chile, with an area of approximately 640 km^2 and over 7 million inhabitants.

4.1. Bike Santiago

The operational information used in this study comes from the observed transactions in the Bike Santiago system during March 2016. It considers a network of 168 public bicycle stations distributed across 14 municipalities, yet mainly located within the central and northeast areas of the city, in high-income districts. Back then the stations looked like the one showed in Fig. 3 and included between 7 and 35 docks each. The transactions were associated with the individual key cards that allowed the use of the bicycles according to one of the more than 20 different subscription options. These plans were paid in advance and varied in price, available ride time (30, 60 or 90 min) and subscription period (from a daily pass to an annual membership). Later, in 2018, the system was acquired by the Brazilian bike-sharing operator Tembici.

4.1.1. Trips

After processing the observed transactions of the system, a total of 170,536 trips are considered valid for this study. Of this total, 8.77% is related to chained trips that have 2 or more linked stages. The trips are distributed over a total of 22 business days and 9 non-business days in the month observed. Within non-business days there are 8 weekend days and a holiday, date on which the trips observed are similar to those of a weekend day. On average, there are 6,852 trips generated on a business day and 2,198 trips generated on a non-business day. Regarding the type of trips, 96.6% of the total corresponds to OD trips and the remaining 3.4% corresponds to loop trips. The distribution of trips throughout a day can be seen in Fig. 4, where the different trip patterns between business and non-business can be observed. This heterogeneous behavior leads to categorizations to analyze the travel demand.

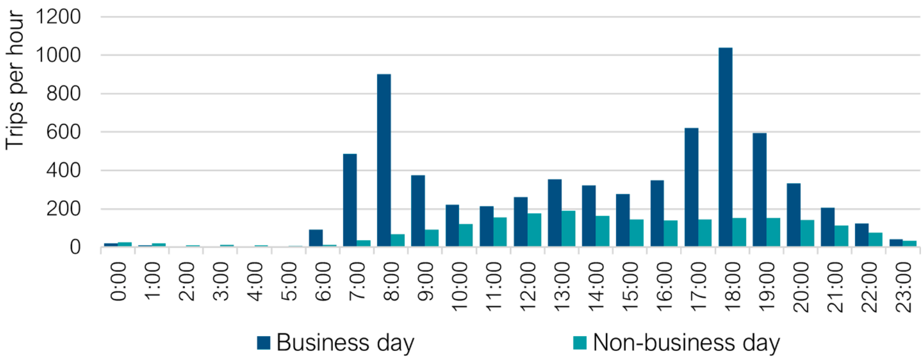

Fig. 4. Average daily bike-sharing trips in Bike Santiago BSS.

Table 2
Selected trip categories for Bike Santiago BSS.

Category	Type of day	Period of the day	Type of trip	Number of observed monthly trips
Morning Peak	Business day	7:20 – 9:20	OD	31,942
Evening Peak	Business day	17:30 – 20:00	OD	43,062
Off-peak	Business day	6:30 – 7:20 /9:20 – 17:30 /20:00 – 23:00	OD	69,075
Non-business day	Non-business day	6:30 – 23:00	OD	4,315
Business day loop	Business day	6:30 – 23:00	loop	17,374
Non-business day loop	Non-business day	6:30 – 23:00	loop	1,301

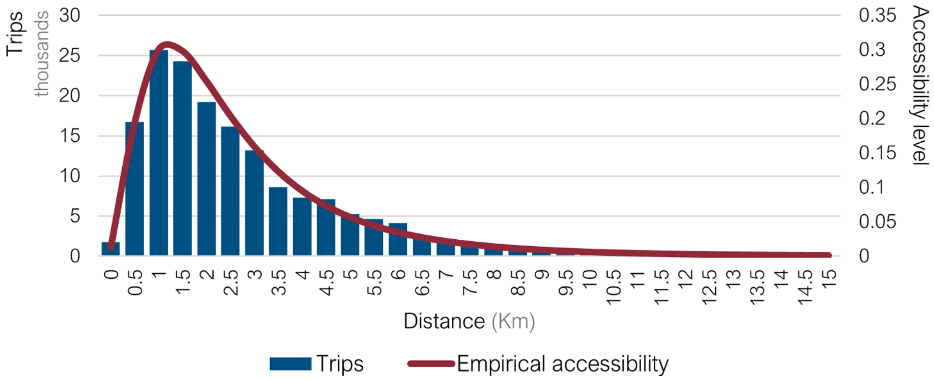

Fig. 5. Trip distribution and accessibility level based on the shortest path distance for the observed trips in Bike Santiago.

4.1.2. *Trip categories*

To study the trips in this BSS, 6 different independent trip categories have been determined, following the literature review of section 2.1. In total, these categories account for 97.97% of the trips, leaving only night trips aside. These categories are presented in Table 2.

4.1.3. *Trip spatial distribution*

To calibrate the empirical accessibility function for Bike Santiago, the shortest path length between the stations in the system is calculated, taking the network of streets that can be used by cyclists in Santiago, that is, every bike lane and street, excepting pedestrian streets and motorways. This distance was measured with graph libraries and Open Street Map for Python (Boeing, 2017). To reduce the computational cost of this calculation, only pairs of stations separated by less than 10 km of Euclidean distance are considered, since farther distanced pairs represent just 2% of the trips and do not contribute significantly to the accessibility analysis.

Then, using the trip data information and the shortest path distance matrix the empirical accessibility curve for the system is calibrated. The estimated parameters for this curve are $\mu = 0.86$ and $\sigma = 0.69$, corresponding to the mean and standard deviation of the logarithm of the distance in kilometers, respectively. The distribution of trips according to the estimated distance and the calibrated accessibility level curve, as described by equation (1), can be seen in Fig. 5. Maximum accessibility (and number of trips) is achieved around 1.5 km while trips longer than 7 km provide very low accessibility (below 2%).

4.2. *Built environment attributes*

The attributes of the built environment that are considered in this study come from different georeferenced data sources of the city of Santiago, such as the Chilean Internal Revenue Service (SII, 2014), the Chilean National Statistics Institute (INE, 2011) and Open Street Maps. These datasets include multiple measures of land uses, streets and sites design, the transit network, and the topology of the city, among others. In total, more than 100 measurements of built environment attributes are considered in this study.

The construction of variables of the built environment in this case responds to the categories previously considered in the literature, that is, variables of density, diversity, design, accessibility to destinations and distances to public transport (Ewing & Cervero, 2010). This process is carried out using the QGIS platform (QGIS.org, 2018), with small differences depending on the type of variable (accumulative or non-accumulative) and the model for which it is used, either a demand model or an optimal location model. A 500-meter buffer radius is considered as the reference area of influence, value that has previously been used in studies of bicycle trips in Santiago (Oliva et al., 2018) and that is within the ranges reported in the literature (García-Palomares et al., 2012; ITDP, 2013; Noland et al., 2019). Consequently, the side length of the equilateral triangles that are used in the optimal location model is set to 550 m, so the surface of 6 triangles matches with the surface of the circular buffer, as shown in Fig. 2. The spatial distribution of Bike Santiago stations, the bikeway network in Santiago and the spatial division of Santiago for the optimal demand model, with a total of 2,780 possible station locations and 5,220 covering triangles, are shown in Fig. 6.

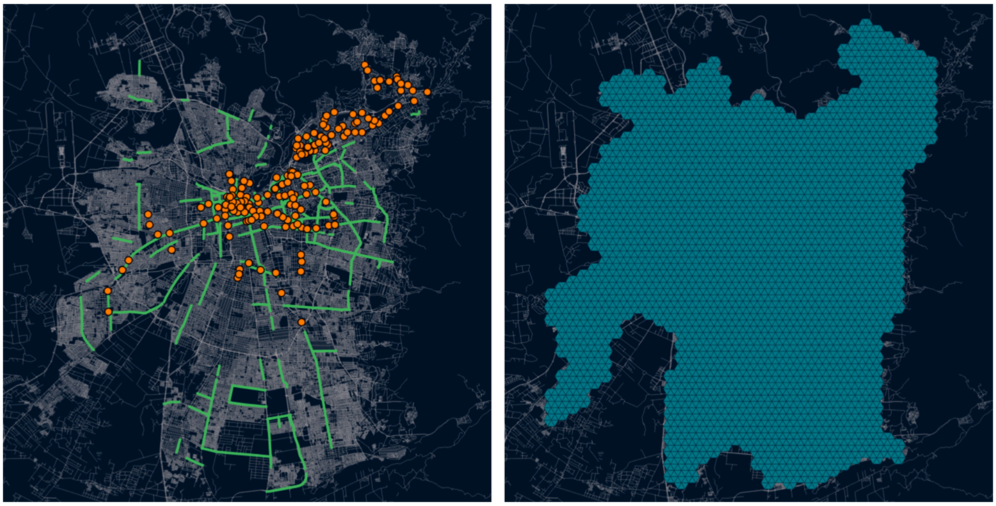

Fig. 6. Spatial distribution of Bike Santiago stations and the bikeway network in Santiago (left). Spatial division for the optimal location model (right).

5. Results

The main results of the application of the proposed methodology in the case study are presented in this section. Also, some general lines of discussion about public policies related to PBS are mentioned.

5.1. Bike Santiago trip generation models

The selected demand models for the 6 categories of bike-sharing trips that are considered for the Bike Santiago BSS are presented in Table 3. These models have been calculated for daily trip generations in a station and for the period of the day that corresponds to each trip category. Finally, only 11 of the more than 100 available variables were selected. All the estimated coefficients for the chosen

Table 3
Calibrated daily trip generation models for Bike Santiago BSS.

	Morning Peak	Evening Peak	Off-peak	Non-business day	Business day loop	Non-business day loop
Intercept	−5.25 (−2.82)	−2.39 (−0.99)	1.05 (0.5)	−3.67 (−2.12)	−0.06 (−0.29)	−0.66 (−3.61)
Cumulative variables						
Empty lots (tens of units)	−0.56 (−3.69)	−0.75 (−3.43)	−0.66 (−2.92)	−0.38 (−2.36)	−0.07 (−4.28)	−0.06 (−4.21)
Dwellings (thousands of units)	2.31 (4.52)	–	–	2.08 (3.94)	0.19 (3.23)	0.36 (6.98)
Offices (ha)	–	0.98 (5.42)	1.44 (9.21)	–	0.12 (10.31)	–
Urban parks (ha)	–	–	–	–	–	0.03 (2.33)
Local non-cumulative variables						
Average street length (hundreds of meters)	1.26 (3.03)	–	–	–	0.11 (2.11)	0.2 (4.48)
Total bike lanes length (km)	1.54 (5.21)	1.83 (4.16)	2.38 (5.0)	1.95 (6.52)	0.16 (4.89)	0.14 (5.13)
Street intersections (hundreds of units)	–	5.47 (3.39)	–	–	–	–
Accessibility variables						
Accessibility to dwellings from a subway station (accessibility units every ten thousand dwellings)	–	2.49 (2.79)	–	–	–	–
Accessibility to offices (accessibility units every ten hectares of offices)	0.65 (3.02)	–	2.1 (6.06)	–	–	–
Accessibility to commerce (accessibility units every ten hectares of commerce)	–	–	–	1.52 (6.42)	–	–
Accessibility to the subway (accessibility units)	0.6 (2.81)	–	–	–	–	–
Adjusted R^2	**0.6**	**0.52**	**0.71**	**0.62**	**0.59**	**0.51**

Hyphen "–" shows that the variable was not included in the respective model.

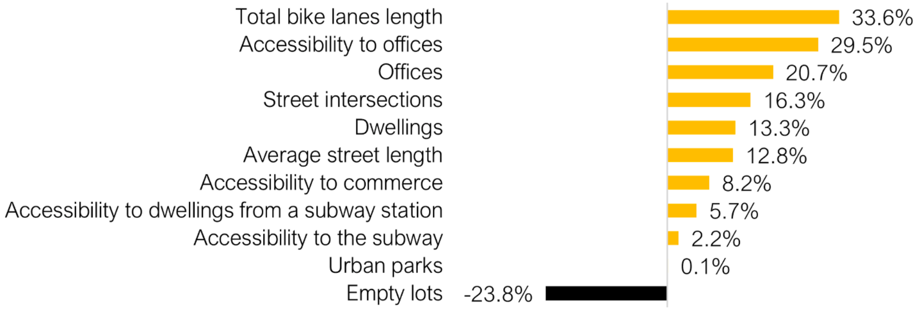

Fig. 7. Variable elasticities for a month of trip generation in Bike Santiago.

variables meet a statistical confidence level higher than 90%; their *t*-test values are shown in parenthesis in the table. Additionally, the values of elasticity for the different variables, considering the trip generation models for a reference month of 22 working days and 9 non-working days in the studied BSS, are shown in Fig. 7.

In general terms, the travel structure is confirmed to be highly associated with commuting trips, going from areas of residential use (dwellings) to areas with higher presence of jobs (offices) in the morning peak and the other way around in the evening peak. During off-peak periods on business days, trips are predominantly generated in areas with higher presence of (and access to) business activities (office land use). The relevance of work and residential land uses is also confirmed by the high elasticity of their related variables. In total, variables related to office surface explain 50.2% of the trips while variables related to dwellings explain 19% of the trips, considering local and accessibility variables.

For OD trips made on non-business days, the results suggest a higher generation of trips to access commerce land uses and originated in residential areas. In this case, users may possibly prefer to change their mode of transportation to return home after reaching their destination, because trips from commerce areas with higher access to residential areas were not significant for this trip category. In contrast, loop trips on non-business days are mostly generated in areas with a high presence of urban parks surfaces. This is possibly related to a recreational use of public bicycles around areas where users can rent a bike, use it to move around the park and return it to the same station where they took it from.

As for the transport infrastructure variables, a greater generation of trips is shown in areas with more street intersections and with longer average street length. The values of elasticities for these variables are 16.3% and 12.8%, respectively. These measures can be interpreted as proxies of zones that are more permeable by the cyclist and that offer more direct paths both to reach the stations and to move on the bicycle from the station at the origin of the trip to any other station in the destination.

As in previous studies, the results for this research highlight the presence of more and longer bike lanes as one of the most relevant factors of trip generation in BSS systems. The variable related to this effect, measured as the total length of bike lanes that cross the area of influence of a station, is transversely considered in the models and has an elasticity of 33.6%, the highest amongst the regressors.

Also, the results suggest that a minor part of the trips include a modal change from the public bicycle to the subway in the morning peak and from the subway to the public bicycle in evening peak. The first effect is incorporated by the variable of accessibility to the subway, measurement that is only calculated for BSS stations that do not have a subway station within its local area of influence. In contrast, the second effect is incorporated by the variable of accessibility to dwellings from a subway station, measurement that is only calculated for BSS stations that have a subway station within its area of influence.

Only the presence of empty lots is related to a negative effect in the generation of bike-sharing trips and stands as a control variable of all the other regressors. This variable is linked to less urbanized areas and thus fewer activities around the stations.

Lastly, other variables like the topographical elevation, the presence of other transport modes in the surroundings and the presence of educational buildings, among other built environment measures, were not significant and therefore not selected in the models.

5.1.1. Spatial autocorrelation

When dealing with data that have a direct relationship with the use of space, it is frequent that elements that are closer to each other have a greater relationship than elements that are further away from each other; this effect is called spatial autocorrelation (Anselin & Kelejian, 1997; Legendre, 1993). Even though this study is not focused on controlling the spatial autocorrelation effect for the estimated demand models, the empirical accessibility curve used to calibrate part of the selected variables provides higher values for stations that are closer to each other and thus controls for part of this effect. This is evident in the case of the variables related to the presence of offices and dwellings because the presence of these attributes of the built environment is considered in the model both locally and within the other stations in the surroundings.

Notwithstanding the above, the Moran's I test for the residuals of the selected trip generation regressions has been calculated as an exercise to have a notion of the magnitude of the spatial autocorrelation in the models. This is one of the spatial statistics tests that has been designed to verify the intensity of the relationships between close data units (Bivand & Wong, 2018). In this case, a neighborhood of the 5 closest stations for each BSS station is considered for this calculation, using equal weights for each neighbor station. The results are presented in Table 4.

Table 4
Moran's I for the selected trip generation models.

Category	Observed Moran's I	z
Morning Peak	0.218	5.62
Evening Peak	0.045	1.57
Off-peak	0.062	1.89
Non-business day	0.168	4.30
Business day loop	0.144	3.77
Non-business day loop	0.236	5.80

Score **z** shows the standard deviation for each Moran's I calculation.

The results show that there is randomness in the error terms and therefore no spatial bias in the specification of the models associated with the Evening Peak and Off-Peak categories with respect to the defined neighborhood. For the other models there are signs of positive spatial autocorrelation between the regression residuals. However, the values of the Moran's I for these models are between 0.144 and 0.236, so this effect would not be strong enough to discard the modeling results just because of the spatial autocorrelation. Likewise, it is important to note that these Moran's I values serve as a reference, but do not allow strong conclusions to be drawn regarding spatial autocorrelation and its possible effects in the case study, as this would require further analysis that is out of the scope of this work.

5.2. Optimal allocation of BSS stations in Santiago

After estimating the bike-sharing trip demand models, an optimal location model was applied to Santiago using the coefficients related to each selected variable in the models. Then, the following scenarios were analyzed.

5.2.1. Base scenario

During the observed month, a total of 167,069 trips were generated within all the 6 selected trip categories in the system. Adapting the observed locations of the 168 stations to the proposed optimization model structure, this value raises to 169,304 trips, mainly because the total area of influence in the modeled situation is slightly larger than that of the observed situation. The modelled spatial distribution of the stations is shown to the left of Fig. 8.

Adjusting the location model to optimally allocate 168 stations yields the result present to the right of Fig. 8. This allocation has a theoretical generation of 277,070 monthly trips, which represents a 63.65% increase in trips compared to the modeled base scenario and a 65.84% improvement in relation to the observed base scenario. The result renders a greater concentration of stations in the central and central-eastern sectors of the city, mainly in the municipalities of Santiago and Providencia. Additionally, a set of 8 stations are allocated in the southern sector of the city, isolated from the rest of the stations. These are chosen by the model mainly due to their high values of total bicycle path length and average street length, in addition to the presence of other built environment attributes that are considered in the model. Nevertheless, the location of the rest of the stations does demonstrate an expected dense pattern. In fact, the average Euclidean distance between every pair of stations in the system is 7.3 km for the observed system, a value that decreases to 5.9 km in the optimal setting and to 4.6 km if the cluster in the south is not considered in the calculation. This result shows a more

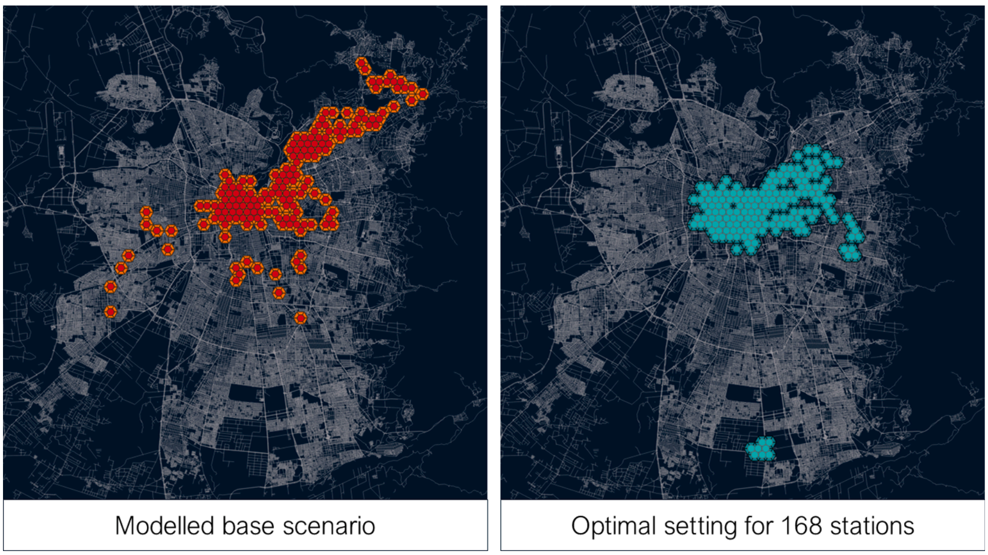

Fig. 8. Spatial distribution of 168 stations for the base and optimal settings.

compact system, something that coincides with the recommendation of the literature of promoting higher station density in the design of BSS (ITDP, 2013; Rixey, 2013; Wang & Lindsey, 2019).

An important point to mention in this part is that both the observed scenario and the optimized scenario present a location of stations concentrated in higher income communes. For the observed case, this is related to strategic decisions that capture a greater demand thanks to the potentially higher willingness to pay by the inhabitants of those municipalities. On the other hand, in the case of the optimized scenario, this responds to the variables selected in the generation models and their spatial distribution in the area considered in the optimization. Despite this, it is interesting that a set of stations appears in a low-income location, away from the main set of stations and the one that probably does not have much interaction with the main set. However, the fact that the proposed modeling does not include variables related to the level of income prevents drawing clear conclusions regarding the financial viability of the optimal scenarios (ITDP, 2013; Médard de Chardon et al., 2017). It also does not consider possible bike relocation difficulties for the operator.

5.2.2. BSS optimal expansion

Fig. 9 shows how the optimal locations of the stations of the BSS varies when the budget restriction is relaxed, in terms of the number of stations that can be installed in the city. As more stations can be placed, the influence area of the system becomes larger, and the number of monthly generated trips increases.

Fig. 9. BSS optimal location and expansion.

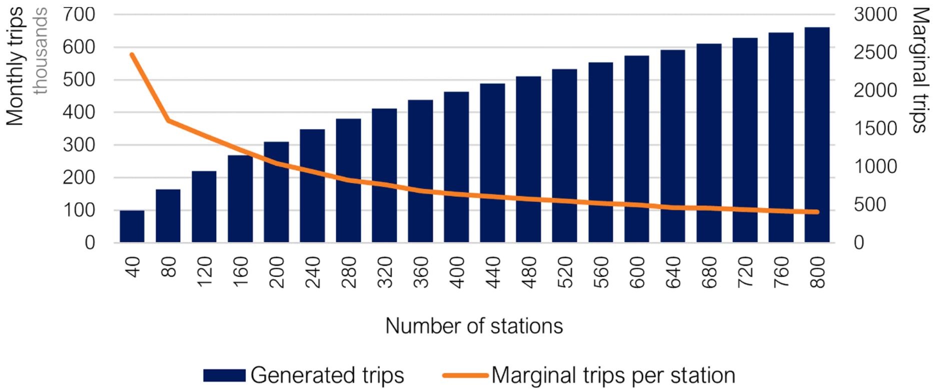

Fig. 10. Total and marginal increase in BSS monthly trips as the system grows.

As the number of allocated stations increases, the growth in the number of generated trips is lower than in the previous scenario, since the model tends to allocate stations in the best places first. The effect associated with accessibility does not outweigh the effect by locating stations in relatively less convenient places, and therefore the marginal increase in trips in the system decreases with the number of stations, as can be seen in Fig. 10.

Figs. 9 and 10 show results for a system that can operate in the whole city. In contrast, Fig. 11 shows the difference in the total demand generation in the optimal setting both for the unrestricted area and for the operational area that is observed in the data, that is, within the 14 municipalities where it operated in 2016. Around the 800 stations, the system is hypothetically at its maximum demand generation for the observed operating zone. As expected, the les restricted scenarios show better results systematically.

5.2.3. *Bicycle infrastructure expansion scenario*

In this section a scenario with a hypothetical extended network of bike lanes in Santiago is presented. The base bicycle path data used for this study considers a network of 224 km of bicycle routes, while the projected network used in this scenario also includes the bicycle route projects that have been registered by different sources such as CONASET and some municipalities, among other institutions (GORE RM, 2012), for a total registry of 741 km of bike lanes distributed throughout Santiago.

The results of the optimization of 168 BSS stations in this scenario is presented in Fig. 12. Here, the demand increases from 277,070 monthly trips in the basal optimum to 424,641 monthly trips with the projected bikeway network. In addition, the variable total length of bicycle lanes goes from explaining 40.44% of trips (in the base optimal model) to explaining 74.11% of trips, ceteris paribus. Although this effect may be over-represented due to the linearity of this variable, the results indicate a greater dispersion of stations than in the basal optimum, due to the higher presence of pike paths in different areas of Santiago. This could improve connectivity across the city in response to the greater provision of cycling infrastructure in areas where this built environment attribute could be improved.

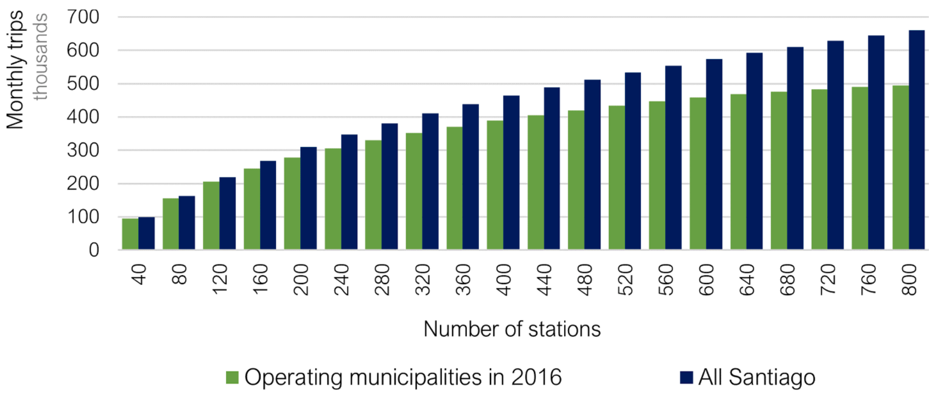

Fig. 11. BSS optimal demand regarding the number of stations and the available operating area.

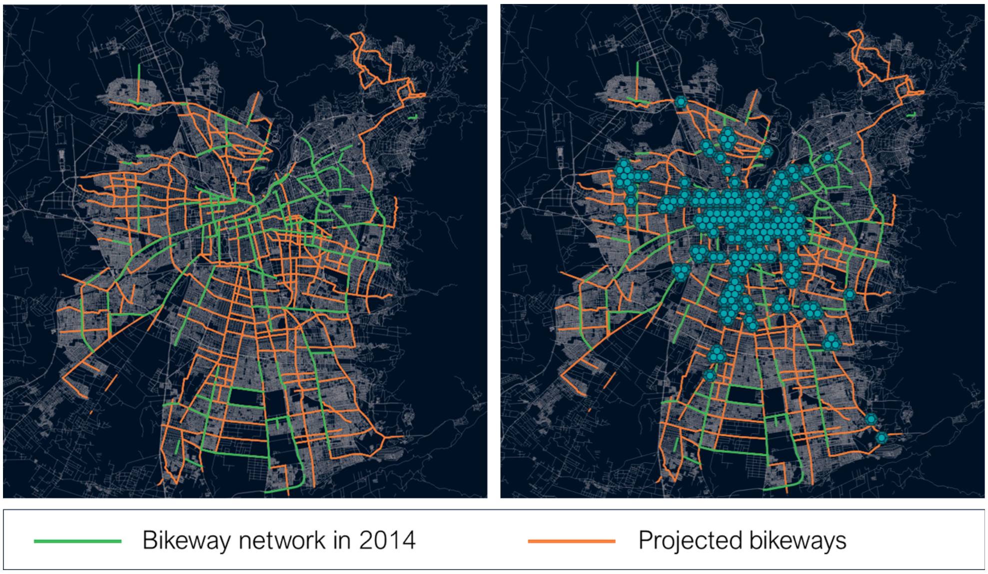

Fig. 12. Optimal distribution of stations with the projected network of bicycle paths in Santiago, for a system of 168 stations.

6. Conclusions

In this study, a methodology to sequentially model bike-sharing trip generation, in relation to the built environment and accessibility measures, and the optimal allocation of BSS stations has been proposed. While the model is calibrated and applied to a city already operating a BSS, the application of the model to cities with no BSS could provide relevant insights and a starting point for the planning process.

In relation to the case study, the demand models show that Bike Santiago BSS trips are highly represented by commuting trips and other work-related trips. Trips related to first and last mile transport in connection to the subway appear to be less frequent. The difference between mobility patterns of OD trips and loop trips is also confirmed, the latter being independent of accessibility measures and possibly related to recreational trips during weekends. In general terms, these results match with the outcomes from previous studies.

Even though the proposed demand modelling method for the BSS trip generation did not consider socioeconomic information of the users, it has shown relatively high confidence levels only using built environment attributes and accessibility measures that were proposed based on the available data. These results might be useful to be considered in the analysis of new BSS to be deployed in cities for the first time and when further transportation data is scarce.

The optimal analysis of these systems has confirmed that far and isolated stations in the system are usually less attractive for the system configuration than additional stations in more densely serviced areas. The expansion of the systems to new areas in the cities should therefore be provided with a significant number of stations so the system is substantially attractive for the user to be preferred instead of other transport modes. This is confirmed by the relevance of the accessibility measures in the model, that give a higher weight to the attributes in new stations when they are located in distances between one and three kilometers. This effect was not directly addressed in previous studies.

Results have also shown that limiting the access of these systems to a reduced subset of the city districts in a city leads to suboptimal solutions. This situation impedes BSS to achieve its highest possible impact in a city and to give a better service for the users. Therefore, local governments should foster the promotion of these systems across the whole city, so people can have better access to a greener mode of transport like this one.

Once again, the presence of bike lines and cycling infrastructure shows up to be a major incentive for cycling, specifically for bike sharing in this case. In cities like Santiago, with low rates of rain and relatively good conditions for cycling in general, there is a big opportunity for fostering more sustainable transport modes. Nevertheless, quality cycling infrastructure should be provided to increase the safety levels for cycling in the city and to incentive more users to start using this transport mode more frequently.

As for the limitations of this research, the presented methodology does not consider logistical aspects related to the operation of BSS, such as the size of the stations, the use of the available bicycles in the system, the redistribution difficulties or system costs. Also, the proposed location model gives a reference location for each station but does not go into detail about the specific location for the station within the selected area, something that is relevant for potential space limitations, for the safety of the cyclist and for the system's visibility. Other limitations come from the fact that the shortest path routes used to compute accessibilities ignore several elements that are known to influence route (and even destination) choice, such as the presence of cycling infrastructure and other built environment elements (Rossetti et al., 2019; Echiburu et al., 2021), factors related with safety and comfort or the slope. Regarding the latter, while not relevant for most of the areas of our case study, it may play a significant role in zones near the mountains, where slopes can be steeper (Oliva et al., 2018). Future studies could incorporate these aspects and include relevant data of different cases to build more robust models that can be applicable across different types of cities.

CRediT authorship contribution statement

Richard Mix: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft. **Ricardo Hurtubia:** Conceptualization, Validation, Writing – review & editing, Supervision, Resources, Funding acquisition. **Sebastián Raveau:** Conceptualization, Validation, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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