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Competition or Supplement? Tracing the Relationship of Public Transport and Bike-Sharing in Vienna

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Abstract

The ever-increasing popularity of bike-sharing schemes has added an additional mode to the transport regime in many cities. The data produced by lending and returning bicycles at geographically diverse stations has stimulated numerous studies. We focus on the City of Vienna bike-sharing system (CityBike Wien; CBW) and its relationship with the public transport system, asking whether bike-sharing serves as competitor, relief or supplement. We approach the question by surveying the total CityBike Wien trip data from 2015 – about 1 million records. We cleanse and route all bicycle trips and compare them with routed alternative public transport (PT) journeys in terms of travel time ratios and detour factors. After calculating and plotting the cumulative frequencies of travel times and distances of both modes of transport as well as comparing the current PT and CBW usage levels, we conclude that CityBike functions as a supplement to Vienna's public transport.

Keywords:

bike-sharing, public transport, mapping, travel time ratio, detour factor

1 Introduction

Since the new millennium, bike-sharing systems (BSS) have gained in popularity in cities around the world, sparking a lot of research, ranging from the impact of urban bike-sharing on cycling flows more generally (Faghih-Imani et al., 2014), via typologies of users (Vogel et al., 2014), to the impacts of weather on BSS usage (Gebhart & Noland, 2014) and of BSS on health (Woodcock et al., 2014).

Adding BSS as a new component to urban transport systems provides large-scale location-related mobility data that can be used to acquire new insights, raising the question of its interrelation with other parts of a transport system. How do existing transport regimes interact with this newcomer?

As BSS are another member of the family of sustainable modes, examining the interrelation with urban public transport (PT) is an interesting question: is a BSS a competitor, a relief or a supplement to PT? As the City of Vienna has a strong and lasting public transport tradition, we embark on the task of shedding light on this interrelation by means of a spatial analysis of BSS usage patterns, and by comparing BSS routes to alternative PT routes.

Due to the inherent spatial nature of recorded BSS usage data, the spatial perspective of BSS has already received a considerable amount of scientific attention. Beecham and Wood (2014a) analyse a large BSS-based dataset for geographical variation of behavioural differences between female and male users. There the distinction between trips through parks and off major roads vs. commuting trips is clearly recognizable. As shown in previous work, even the mapping of detailed group characterizations, such as after-work or lunchtime users, is possible (Beecham & Wood, 2014b). Spatial analysis of BSS-user data, for example, shows that dwelling/work locations of non-BSS-subscribers are considerably more dispersed than those of subscribers (Fishman et al., 2014). The geographic visualization of BSS flows allows the identification of changes in travel behaviour over space and time (Wood, Slingsby, & Dykes, 2011), which then aids in rebalancing the bike distribution – an issue often studied in such systems (Caggiani & Ottomanelli, 2012; Dell'Amico et al., 2014).

The second focus of studies of BSS is their relationship with PT, where different approaches have been applied already. Fishman and colleagues find in their literature review that the majority of BSS users are switching from other sustainable modes rather than from the car (Fishman, Washington, & Haworth, 2013). For Australian cities, it has been shown that where PT is the least accessible, BSS stations show the most intense flows of cyclists between stations (Fishman et al., 2014). Fuller et al. (2012) show that events which greatly constrain public transport, e.g. personnel strikes, may result in short-term travel behaviour alteration, leading to an increase in BSS usage. Fishman, Washington and Haworth (2015) report that for five different cities (2 USA, 2 AUS, 1 GBR), the proportion of users substituting BSS use for public transport trips ranges from 20 % to 57 %. Jäppinen et al. (2013) perform data mining using application programming interfaces (API) in order to model journey times of BSS complementing public transport. Their findings suggest the desirability of a large-scale BSS to serve as a complement to the PT system. These findings do not contradict each other directly, as the purpose of a BSS is strongly dependent on size of city and number of stations, as well as on the density of the city and of the BSS stations. Martin and Shaheen's (2014) study of modal split changes triggered by the introduction of BSS reported in questionnaires from North American cities shows a differentiated picture: in areas with lower population density, BSS serves as a first-/last-leg facilitator, while in higher density areas, bike-sharing offers a direct and faster alternative to short PT trips.

We consolidate both perspectives – the BSS–PT relationship, and the spatial aspects of BSS analysis. In a journey-time and route-based comparison of BSS and alternative PT journeys, we investigate whether BSS serves as a competition, a relief or a supplement to PT. The research is based on a rich dataset from 2015 containing data from CityBike Wien (CBW). In addition, we utilize the routing engines of BikeCityGuide Apps and of the Wiener Linien public transport operator.

The paper is structured as follows. Section 2 describes the data cleansing procedures for BSS station departures and arrivals. We also describe the API-based methods used for the routing of bike trips between BSS stations and the routing of alternative trips on the PT network. Section 3 presents the results, and section 4 discusses these. In section 5, we draw conclusions based on the results and discussion.

2 Materials and methods

Hypothesis

Our initial hypothesis was that on a system level the travel time ratio between PT and CityBike for origin/destination (OD) pairs is proportional to the number of trips. The travel time ratio approach is backed by Fishman et al.'s (2013) finding that BSS need to have travel times that are competitive with other modes in order to attract users. To test this hypothesis, we investigated the interdependency between PT and bike trips based on a one-year dataset of CityBike logout/login data for 121 CityBike stations. The shorter the trip by CityBike is in comparison to PT, the more CityBike trips are expected for this relation. Without knowledge of the users' actual intentions, we had to draw our own conclusions as to whether CityBike is in competition with, or a supplement to, PT based on the proportion of bike trips per OD pair.

To test the hypothesis, the existing raw data on CityBike trips had to be prepared and travel times for all OD relations had to be estimated. Due to the lack of known origin and destination points (e.g. home and office) of the access and egress trips to and from the CityBike stations, these stations need to serve as starting and end points for trips on the PT system. We are fully aware that this simplification shifts the travel time ratio in favour of bikes; we relativize this bias by highlighting the distributions of both the journey times and the journey lengths. Travel times and distances were computed for all OD connections for both modes separately – bikes and PT. These served as input data for further analysis of the behaviour of BSS users (see section 3). The process of data collection is summarized in Figure 1, and described in detail in sections 'PT data preparation' and 'Data refinement' below.

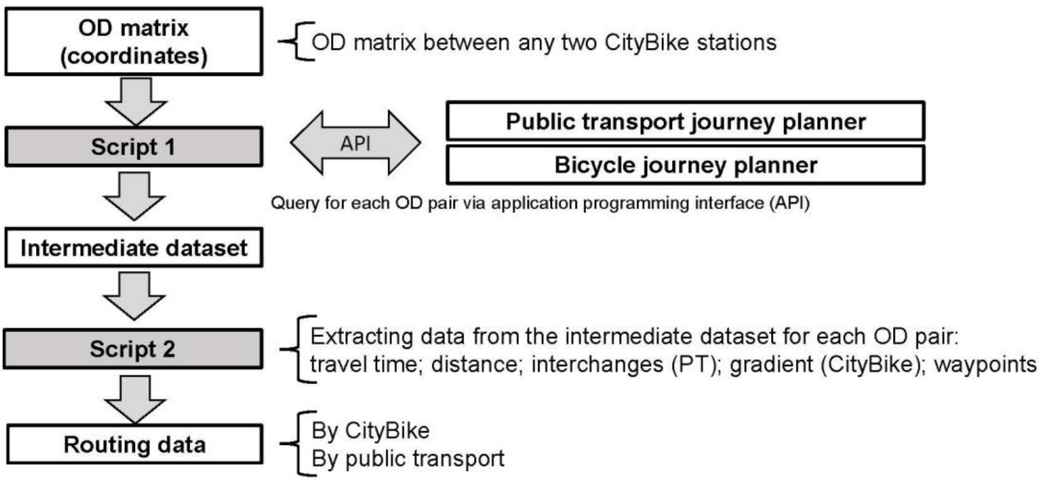

Figure 1: Data collection and refining process

CityBike data preparation

CityBike Wien (CBW) was established in Vienna in 2003, since when the system has continued to grow steadily. A station-bound system, CBW comprises 1,500 bikes organized between 121 stations with 3,097 boxes. CityBike requires users to register with a bank account or credit card. Most stations are located in the densely populated urban areas within the second ring road. Additional stations are located outside the second ring road, along major thoroughfares to the hilly west and in the flat second and twentieth districts to the north and east of the city centre.

CityBike Wien publishes XML-formatted data, including the WGS84 coordinates of each of the 121 CityBike stations. We coded a small PHP script for building up a matrix of all combinations between any two CityBike stations (121 x 120 = 14,520 OD pairs), where origins and destinations are shown as WGS84 coordinates. Because the exact bike route may depend on travel direction (e.g. because of one-way streets, or streets restricted to buses/trams), the two directions between the same pair of CityBike stations were dealt with separately. For all combinations of CityBike points, distances and travel times by CityBike and PT were calculated using input data from publicly accessible online databases.

For trips made by bike, travel time, route, ascent and descent were extracted for each of the OD pairs based on the journey planner offered by Bike Citizens[1]. Bike Citizens delivers reliable data quality and also features WGS84 location-based data for routing queries.

Since bicycle routing and travel time are virtually independent from other parameters (e.g. day of the week, time of day), the necessary data could be obtained at the actual time of query.

PT data preparation

Unlike routing, travel time by public transport does differ according to the time of day and day of the week. Therefore, trips were classified into four groups based on the PT timetable, with peak and off-peak (= night) periods for weekdays and weekends. The four times of day, shown in Table 1, were used as departure times in the query for PT travel times.

Table 1: Classification of time periods.

Type of day	Date of request	Peak period	Request time	Night period	Request time
Weekday	Wed., Sept. 14th 2016	5 am – 9 pm	8 am	1 am – 5 am	2 am
Weekend/ holiday	Sun., Sept. 18th 2016	9 am – 9 pm	3 pm	1 am – 5 am	2 am

For PT trip routing, the publicly available journey planner from Wiener Linien, Vienna's municipal public transport operator, was used. The journey planner also contains the

[1] www.bikecitizens.net, BikeCityGuide Apps GmbH

timetable and station data of other operators. Using WGS84 coordinates, we calculated distances and durations of PT trips between CityBike stations, including access, egress and interchanges.

From the OD pairs with four time classifications, a short script (script 1 in Figure 1) generated queries for the journey planner. Utilizing a second script (script 2 in Figure 1), travel times were calculated for each of the OD pairs and the four departure timings from the returned data. For the queries, several detailed parameters, such as walking speed, interchange time and maximum number of interchanges, were left at default, as CityBike users are assumed to have the same preferences as average public transport users.

Data refinement

In both cases, the queries were sent a few seconds apart in order to avoid overloading the server of each journey planner. The raw data was temporarily stored as intermediate data, and once the data for all the OD pairs became available, travel time, distance and all of the waypoints for each of the OD pairs were listed for both transport modes. For cycling, information about ascent and descent was added; for PT, information about interchanges, the bus/other routes used, and the actual time of the journey were added.

The PT data needed some further adjustment before utilization. The starting CityBike stations for a small number of trips did not provide routing to the geographically closest PT stops, a problem which was addressed by manually assigning the closest PT stop to the CityBike stations affected. Furthermore, the routing procedure skipped some trip sections on foot, which had to be added manually afterwards to provide reasonable trip durations. Finally, sometimes the PT routing during the night time (when only the underground and some bus lines operate) provided journeys including the last or first service of the regular daytime timetable, including tram and bus schedules, thus producing implausible journey times. These journeys had to be eliminated from the data set in order to obtain realistic journey times at night.

In parallel with extracting travel times and additional properties for all OD pairs for cycling and PT trips, we prepared the actual CityBike trip data. The raw dataset comprises all trips made using CityBike bikes which started after 1 January 2015 00:00 and ended before 31 December 2015 24:00. Departure and arrival times and stations, anonymized user ID and sex are included for each trip. In general, raw data from BSS require data cleansing to meet analysis requirements (Vogel, Greiser, & Mattfeld, 2011). Negative rental periods (resulting from incorrect return procedures) and trips with no return station (bikes reported stolen) were filtered from the dataset, as were trips from and to temporary stations used for particular events and tests. As giving one's sex is not a compulsory part of user registration, CityBike Wien attributed a user's sex by comparing the person's given first name(s) with an online name/sex database[2]. As we needed only direct trips for our further calculations, we also removed round trips (identical departure and arrival stations) and indirect trips (going from A to B via somewhere else): having no knowledge about the actual routes taken by the riders, we defined direct trips as trips with an average speed of at least 7 km/h. The average

[2] http://www.albertmartin.de/vornamen/datei-abgleich

speed was calculated as quotient of rental duration and routed trip distance. The threshold of 7 km/h was derived from a trip duration distribution which deviates from the Gaussian distribution curve between 1 and 7 km/h (see Figure 2, right). The approximate Gaussian distribution of trip speeds was derived from Schnötzlinger (2017, forthcoming), who analysed the speed distribution for all Bike Citizens GPS tracks for 2015 in Vienna (Figure 2, left). The lower mean of the CityBike speed distribution (11 km/h vs. 15 km/h from Schnötzlinger's analysis) may be the result of the heavier build of the CityBike bikes in comparison to regular bikes. Two thirds of trips could thus be identified as direct trips (see Table 2).

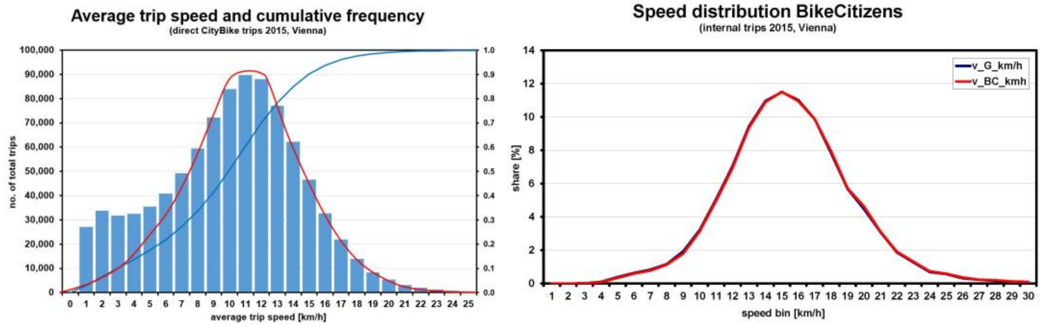

Figure 2 : Left: speed distribution of CityBike Wien, 2015 data, with cumulated frequency (blue) and a superimposed approximate Gaussian distribution (red) denoting the cut-off value; Right: actual distribution of average trip speeds from the 2015 BikeCityGuide Apps GPS-tracking dataset for Vienna.

Table 2: Data-cleansing process

Description of data	Number of trips
Raw dataset 2015	**1,005,856**
- Rental duration ≤ 0 seconds	- 19,950
- Bikes reported stolen	- 470
- Round trips (identical departure and arrival stations)	- 77,464
- Temporary stations (event and test stations)	- 230
- Indirect trips	- 237,782
Refined dataset	**669,960**
- Weekday peak (5 am to 9 pm)	406,597
- Weekday night (1 am to 5 am)	24,186
- Weekend or holiday peak (9 am to 9 pm)	111,661
- Weekend or holiday night (1 am to 5 am)	18,430

As the analysis is based on the comparison of the duration of direct bike trips and the duration of PT trips, we divided the refined dataset into four time periods – weekday peak and night, and weekend/holiday peak and night (see 'PT data preparation' above).

3 Results

The comparison of the number of trips with the travel time ratio of CityBike to PT for all 14,520 possible OD connections results in a triangle-shaped distribution. Figure 3 (left) shows the relative scatter plot density for weekday peak trips (n being the number of OD connections used in this time period, = 13,565); Figure 4 (left) shows the relative scatter plot density for weekday night trips (n = 6,542). The weighted average travel time ratios are 0.575 (weekday peak) and 0.496 (weekday night). For other days and periods and for standard deviations, see Table 3. The most frequent relations occur between ratios of 0.5 and 1.0, with a convergence around 0.5 as the number of trips per OD pair increases. This indicates that when trips by bicycle take longer than by PT, PT is preferred over CBW. PT trips are potentially substituted when they take longer than bike trips (due to longer routes or having to switch modes of transport).

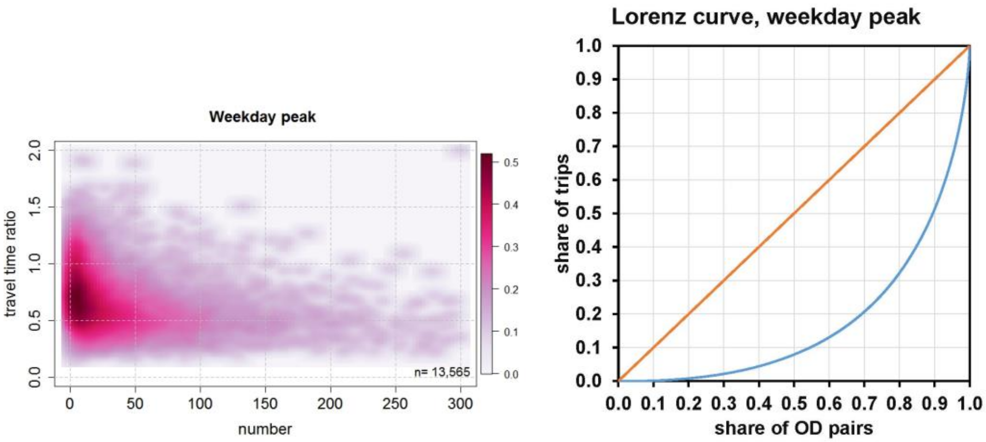

Figure 3: Left: weekday peak distribution of travel time ratio bike to PT over number of trips for OD pairs (for visibility reasons, the x-axis is cut off at 300 trips; the maximum number of trips for one OD connection is 1,369); Right: the corresponding Lorenz curve for OD pairs and trips

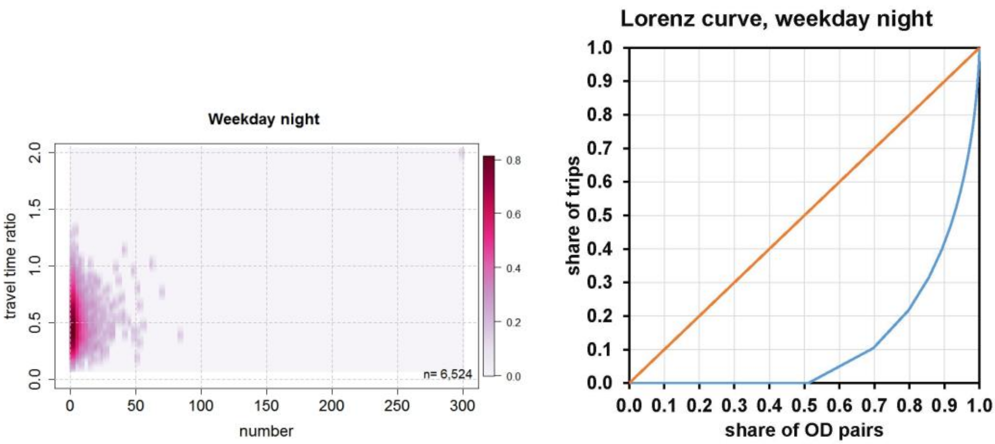

Figure 4: Left: weekday night distribution of travel time ratio bike to PT over number of trips for OD pairs; Right: the corresponding Lorenz curve for OD pairs and trips[i]

Table 3: Weighted means and standard deviations of travel time ratios according to different days and periods of the day

Day and period	Weighted mean	Standard deviation
Weekday peak	0.575	0.212
Weekday night	0.496	0.171
Weekend peak	0.600	0.223
Weekend night	0.494	0.203

To illustrate the proportionality of the number of frequent and rare trips, a Lorenz curve was calculated for the weekday sub-sets (Figures 3 and 4, right) and the total sample. Originally used for representing the inequality of wealth distribution, a Lorenz curve shows the difference between the actual distribution (blue) and a perfectly equal distribution (orange). Delbosc and Currie (2011) used it in the transport sector to assess public transport equity. The Lorenz curve indicates that 10 % of the total sample's trips take place on 50 % of OD connections. On 402 potential connections, no direct CityBike trips at all were detected in the 2015 dataset. 45 % of trips take place on 10 % of connections. The total sample's Gini coefficient[3], used for describing the Lorenz curve mathematically, is 0.628. The Gini coefficients for the sub-samples are 0.652 (weekday peak) and 0.761 (weekday night).

Locating the effects

To shed light on the question of whether the Viennese BSS is a competition or a supplement for the PT system, we assigned the direct trips to the PT and bike networks (Figure 5). The left-hand map shows the PT routes which are potentially disburdened by switching to the bike routes shown in the right-hand map. The brightness and thickness of lines is proportional to the number of assigned trips.

Our analysis reveals three features in particular:

- Trips to and from locations associated with students (university student residences) (no. 1 in Figure 5)
- Feeder trips to and from the local and regional transport hub 'Landstraße – Wien Mitte' (no. 2 in Figure 5)
- Trips along the new pedestrian and shared-space zone 'Mariahilfer Straße' (no. 3 in Figure 5).

Our analysis also strengthens the perception that PT trips are focused on a few axes while bike trips are more distributed over the network as a whole. With the results of the travel time ratio calculation in mind, this allows the conclusion that CityBike is used for tangential trips, e.g. in the peripheral areas of the PT network, where PT connections are not well developed or are inconvenient due to the need for interchange.

[3] The Gini coefficient is the ratio of the area between the line of equality and the Lorenz curve divided by the total area under the line of equality. The larger the value, the more uneven the distribution.

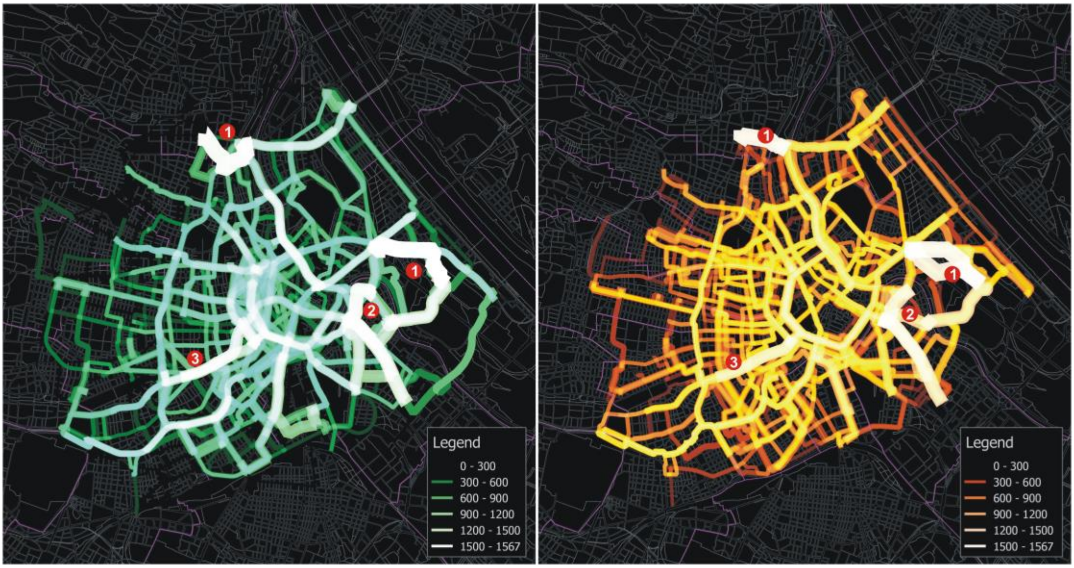

Figure 5: Potential decrease of trips on PT network (left) and corresponding increase of bike trips (right); 1: areas with university student residences; 2: area around regional transport hub 'Landstraße – Wien Mitte'; 3: pedestrian / shared-space 'Mariahilfer Straße'

Detour factors

By comparing the direct (beeline) distance of OD pairs to the routed distance, we found the detour factor of the 2015 CityBike trips to be 1.29, while for the corresponding PT trips it was 1.40. This means that CityBike trips, and thus bike routes in the inner districts of Vienna, are about 30 % longer than the beeline (Figure 6, left) while PT trips add up to 40 % to the beeline distance (Figure 6, right). Not only are the corresponding PT trips 11 % longer, on average, than CityBike trips, the lower R^2 indicates also that individual trips scatter more widely around the regression line (Figure 6, right).

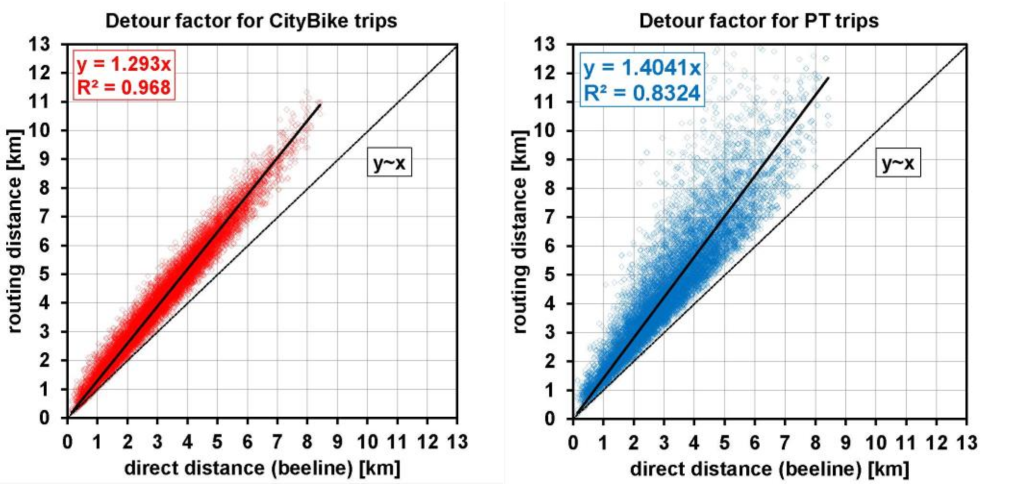

Figure 6: Detour factor based on OD pairs for CityBike trips (left) and the corresponding PT trips (right).

Travel time and trip distance distributions

Plotting cumulative frequency distributions for trip distance and travel time (Figure 7) indicates that CityBike trips (red) and sole PT rides (dashed blue, not including access/egress walks) exhibit very similar distributions. It appears that the addition of access and egress walking time (Figure 7, right) distinguishes the total PT trip from the CityBike trip. From the point of view of distance, the access and egress walks appear to shift PT from slightly below CityBike to slightly above (Figure 7, left).

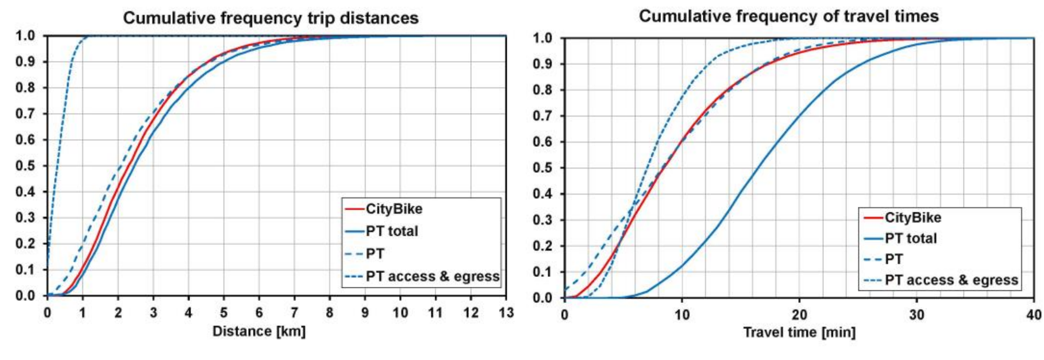

Figure 7: Cumulative frequency distributions of distance (left) and travel time (right) for CityBike trips (red) and PT trips (blue). PT trips of total length (solid line) include the sole PT ride (dashed) and the access and egress walks (dotted) to/from starting/final stops.

The most frequent OD pair (weekday peak) was identified as having 2,631 trips per year in both directions combined, which is less than 1 trip per hour on average.

4 Discussion

Interpretation

Travel time ratio distributions show an accumulation of densities around 0.5 in the form of average values and the ratio of journeys between two points with very high demand, the number of trips per OD relation reaching more than 300. All surveyed periods (weekdays vs. weekends, and peak vs. night) suggest that the use of CityBike is likely to be for relations where alternative PT trips take around twice as long.

The travel time ratio is systematically biased in favour of bikes due to the definition of CBW stations as starting and end points. However, the inclusion of access times to and egress times from CBW stations would only shift and stretch the resulting distribution of travel time ratio bike to PT over number of trips without changing the conclusions: the lower the travel time ratio bike to PT, the more CBW trips occur.

The Lorenz curves indicate that, although appearing more compact in the density scatter plot, night-time connections are less evenly distributed than daytime ones. As a single measurement (within the year 2015), the Lorenz curve and Gini coefficient combined are only conclusive on the skewness of CityBike usage. The indicator would gain value if compared in a time series or with other BSS around the world. High frequency trips appear to play an important role in the BSS but are limited to just a few connections.

Most studies, for example Rietveld et al. (1996), Weijermars et al. (2008), and Meeder (2015), define or use the detour factor as the ratio between the shortest distance along the network and the Euclidean distance. The Dutch 'Design manual for bicycle traffic' (CROW, 2016, p. 66) gives a target value of 1.2 for a well-designed main-route network and allows the detour factor to reach values of 1.3 to 1.4 for the network beyond.

Only a few references widen the concept of detour factor to actually chosen routes in comparison to shortest possible ones. See, for example, Krenn, Oja and Titze (2014), who derived a median of the specific detour factor of 7.6 % for a median trip length of 2.3 km.

The average detour factor (routed distance / beeline) of 1.29 that we found for CityBike trips is well within the range given above. Hence CityBike's smaller detour factor (11 % points) and smaller variation support the notion that this poses a structural advantage for the CityBike over PT.

However, the detour factor represents only one of the three requirements (directness) for a bicycle-friendly network; cohesion and safety could not be measured with this method. Detour factors of 2 or higher (detour twice as long as the beeline) appear in the range of short distances (up to around 2 km beeline). This could indicate that one-way streets closed for contra-flow cycling are considered a problem in the case of riding a bike. In the PT case, with detour factors in excess of 2 km beeline, this may point to less favourable PT connections in terms of interchange or accessibility. Vienna's rivers are crossed by only a few bridges, which might add to the phenomenon in selected cases.

Travel time ratios and detour factors suggest that CityBike has the potential to be a competitor to PT. This suggestion is strongly supported by the results of a parallel questionnaire survey which revealed that 60 % of CityBike users consider their use of CityBike to be substituting a PT trip (Leth et al., 2017), backing up Fishman et al.'s (2013) findings.

In contrast, the cumulative frequency distributions contradict this notion. As CityBike and the sole PT journeys exhibit similar characteristics in terms of distances and travel times, the potential appears to lose importance in the light of the simplification addressed above, due to the lack of primal origins and final destinations for those trips.

The low absolute number of CityBike trips in comparison to PT passenger numbers also supports the counter-argument. The most frequent OD pair (during workday, peak) accounts for less than 1 trip per hour, thus being nowhere near a competitor to the Viennese PT. 939 million annual PT trips are rivalled by 1 million BSS trips.

Possible further refinements

Our methodology could be further refined by using GPS data. Detailed movement data of CityBike trips would not only help to improve the data-cleansing procedure (real speeds and identification of detours), it would also add real routes (i.e. those actually chosen), in contrast to our routing via BikeCityGuide Apps. In the meantime, GPS data collected by tracking apps such as BikeCityGuide Apps, Strava or Runtastic could help to identify these real routes. However, these apps are known to be used primarily for non-routine or sports activities, thus adding a bias to routes chosen compared to everyday trips such as commuting to work.

One major way of taking our work forward would be to consider CBW trip and station data in conjunction with adjoining urban densities (e.g. number of residents) and trip generators (e.g. transport hubs) (McNally, 2007). Regional and express train stations, large educational institutions, shopping centres and other leisure facilities are known to produce and attract trips and thus could distort the number of trips to and from adjacent CityBike stations. However, for our current study this effect only stretches the x-axis of Figure 3 and does not affect any of its conclusions.

As the strong impact of weather phenomena on commuting by bike generally (Nankervis, 1999) and on BSS usage patterns (Gebhart & Noland, 2014) has been proven, including fine-grained extreme weather data (intense rain, heavy snowfall, extreme temperatures) would improve the understanding of the CityBike's role as a supplement to public transport. For example, the modal split of cycling in Vienna falls from 5.6 % in summer to 3.1 % in winter; conversely, for PT it increases from 35.1 % in summer to 39.1 % in winter (Tomschy et al., 2016).

Further research could examine other factors influencing mode and route choice, such as the travel times and distance ratios of bikes vs. cars.

5 Conclusion

The approach presented in this paper advances previous research by contributing a quantitative and qualitative depiction of the relationship between BSS and PT. This includes the travel time ratios, route-base heat maps, detour factors and cumulative frequencies of trip distances and travel times. We conclude from our analysis that CityBike cannot yet be considered a general competitor to PT, but it can be seen as a supplement to it.

Our study did not aim to look at possible extensions of the existing system, in terms of either geographical extent or density of stations. However, the accumulation of trips on relations with low travel time ratios bike to PT suggests that PT trips that require interchanging connections are avoided by using CityBike. Thus urban regions with poor PT cross-connections might be a promising target for BSS. Furthermore, we applied the Lorenz curve for the first time in assessing a BSS. This approach showed that roughly half of the direct CityBike trips occur on only 10 % of the relations.

If in the future the BSS was to cover larger areas of the city than it does today, CityBike data could be used in a locally partitioned manner to check for the cycle-friendliness of routes (directness) in these areas. This could be important in helping to reduce the built barriers to cycling.

Some refer to BSS as a mode of public transport, with a limited number of stops but an almost limitless number of lines. Within this understanding, too, the size of Vienna's BSS today makes it a supplement to the public transport system rather than a competitor.

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