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Examining and optimizing the BCycle bike-sharing system – A pilot study in Colorado, US

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HIGHLIGHTS

- A case study based on the national BCycle bike-sharing program was presented.
- The bike usage patterns were compared among different membership groups.
- The spatio-temporal trends of empty and full bike stations were examined.
- The current system configuration was optimized under three hypothetical scenarios.
- This study has important implications to other cities in the BCycle program.

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ABSTRACT

Many cities around the world have integrated bike-sharing programs into their public transit systems to promise sustainable, affordable transportation and reduce environmental pollution in urban areas. Investigating the usage patterns of shared bikes is of key importance to understand cyclist's behaviors and subsequently optimize bike-sharing programs. Based on the historical trip records of bike users and station empty/full status data, this paper evaluated and optimized the bike-sharing program *BCycle* in the city of Boulder, Colorado, the United States, using a combination of different methods including the Potential Path Area (PPA) and the Capacitated Maximal Covering Location Problem (CMCLP). Results showed significantly different usage patterns between membership groups, revealed diverse imbalance patterns of bike supply and demand across stations in the city and provided three system upgrading strategies about maximizing the service coverage. This case study is committed to future energy conservation and sustainable energy systems nationwide and ultimately worldwide, by holding immerse potential to adapt the resulting optimization strategies to the cities with a similar urban context across the United States, as well as more emerging bike-sharing programs in other countries, such as China.

1. Introduction

Bikes have a great market value with features of being flexible, convenient, energy-saving, and environment-friendly [1,2]. A bike-sharing system is a service that makes bikes available for shared use on a short-term basis. A typical system consists of a set of bike stations distributed in a certain area (e.g., the whole or central area of a city) and a set of bikes available to the users. Users can borrow a bike from a station and return it at another one belonging to the same system. Since the earliest bike-share system in 1960s in Amsterdam (the Netherlands), many similar systems have been emerging in worldwide cities [3]. As of November 2017, public bike-sharing systems were available in about 1500 cities, including 18 million bikes around the world [1,2,4]. A variety of benefits have contributed to the increasing popularity of the bike-sharing systems. As an active transportation mode, it can help in reducing energy consumption and mitigating environmental pollution [5,6]. For instance, Zhang and Mi [7] found that in 2016 a bike-sharing system in Shanghai has saved 8358 tonnes of petrol and

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decreased CO_2 and NO_X emissions by 25,240 and 64 tonnes, respectively. A well optimized bike-sharing system can increase the attractiveness and popularity of bicycling and shape a healthy lifestyle among visitors and also local residents [8,9,6,10,11,7]. It has important implications for not only energy conservation, but also physical activity promotion and human health and well-being (e.g., enjoying the city and the nature).

The existing literature on bike-sharing has focused on either the bike usage patterns or the optimization of the bike-sharing system (see details in Section 2). Several knowledge gaps have existed in the current literature. First, only examining the bike usage patterns could not help much with the energy conservation (e.g., cannot be easily followed by cost-effective solutions or actions), and only optimizing a bike-sharing system without examining the recent usage patterns may reduce the efficiency of the solutions. The isolation of these two aspects can reduce the practicality of the findings. Second, the majority of existing studies has been conducted in megacities, such as Seattle and New York in the US [12,13], Toronto in Canada [14], London in the UK [15,16], Tokyo in Japan [17], and Shanghai in China [3]. Less attention has been paid to medium- or small-size cities in which bike-sharing systems may work in a different pattern [18]. Third, most studies have utilized the trip records generated by users' travel cards, without any study analyzing the station empty/full status data. The utilization of a new data source would provide additional information about bike usage patterns.

This study describes a case study in Boulder, a small US city. With strong data support from the Boulder *BCycle* bike-sharing system, this study, to our knowledge, for the first time provides a complete research-to-action framework, from investigating the bike usage patterns between different user groups, examining the spatio-temporal trends of empty and full bike stations, identifying the overused and underused bike stations, to optimizing the current configuration of the BCycle system in three hypothetical scenarios (i.e., adding a new station, deleting an existing station, and redistributing the existing docks at the existing bike stations). The findings of this study will not only contribute to improving the performance of the Boulder BCycle system, but also have important policy implications in bike-sharing system operation and transport planning, which are strongly tied to future energy conservation and sustainable energy systems. In addition, this is the first study of usage patterns and optimization of the national BCycle network, which is expected to be a landmark study and be replicated in many other US cities with the BCycle system equipped, as well as in more cities of other countries.

2. Literature review

2.1. Usage pattern examination

The bike usage data have greatly enriched the examination and understanding of usage patterns. Froehlich et al. [19] analyzed the spatio-temporal dynamics of the shared bicycling system, called Bicing, in Barcelona (Spain) using a thirteen-week bike usage dataset. By analyzing shared bike data in London, Padgham [15] found that the spatial usage pattern is largely stable, despite the variability in trip distance, direction, and frequency. O'Brien et al. [20] analyzed and compared the characteristics of 38 bike-sharing systems located in cities from different countries, such as occupancy rates and demographics of user groups. Based on a case study in Minnesota (the United States), Wang et al. [10,11] found that bike station activities are associated with proximity to city's central area, neighborhood sociodemographics, distance to other bike share stations, trial accessibility, proximity to water body as well as economic activity measures. El-Assi et al. [14] investigated the impacts of built environment and weather on bike sharing demand. They revealed a significant correlation between bike share trip activities, and land use and weather. Zhang et al. [21] adopted a multiple linear regression model to investigate the influence of built environment on bike usage. They found bike usage is positively influenced by length of bike roads, population density and mixed land uses near the station, and negatively influenced by the distance to the number of other nearby stations and city center. Saberi et al. [16] compared the spatial mobility patterns of bike usage before, during, and after a disruption in a public transportation system using more than one million bike trips.

2.2. Usage pattern optimization

When arriving at a bike station, a user that wants to take a bike may find the station is empty while another user that wants to leave a bike may find the station is completely full. For many bike-sharing systems in operation, such an imbalance of the demand and supply unavoidably exists, especially during the commuting peaking time or at the bike stations close to the bus stops or metro stations heavily used by commuters. Existing studies have tried to propose various optimization solutions to solve or mitigate the mismatch between the demand and supply of shared bikes. Some of them focus on rebalancing or repositioning the bikes from some stations to other ones so that the appropriate number of bikes and docks are available to the users. This is typically achieved by using some trucks that can move around and pick/drop bikes or some incentives to encourage users to move bikes from the full occupied stations to the less occupied ones [22]. For instance, with the target of minimizing the users' expected dissatisfaction, Raviv et al. [23] proposed several formulations for a static rebalancing problem. Ho and Szeto [24] adopted a method called 'tabu search' to solve a static repositioning problem for bike-sharing. Zhang et al. [25] presented an integer linear programming formulation to model bike-sharing static rebalancing by considering the collection of bikes that need repair. Static rebalancing typically considers the night time rebalancing, in which the number of bikes needed by each station is fixed and known before rebalancing happens. In recent years, an increasing number of studies have tried to solve the dynamic rebalancing problem that considers the situation in which the number of bikes needed by each station is dynamically changing over time [26,27]. Another line of these efforts focuses on optimizing the bike-sharing usage patterns by changing the number of bike stations (usually by adding more stations). Leigh et al. [28] developed a novel model to support the site selection of bike stations in an university context (Monash University, Australia), by integrating local regulation standards into the selection process. Wang et al. [10,11] combined spatial-temporal analysis and retail location theory to shared bikes site selection in Taipei, Taiwan. Kabak et al. [29] evaluated and optimized bike station locations with different multi-criteria decision-making methods and geographic information systems (GIS). Besides, many studies have adopted the location-allocation models, which can find optimal facility location(s) in a way that supplies the usage pattern most efficiently, to plan bike facilities and thus support the usage pattern optimization [30,31,3].

3. Overview of the bike-sharing system

3.1. Study area and data

Boulder County is located in central Colorado along the foothills. The county seat is the City of Boulder, which has a population of 97,385, according to the 2010 United States Census. The city is home to the University of Colorado at Boulder (CU), the flagship campus in the University of Colorado system (33,977 students in 2017). It is also the home to the University Corporation for Atmospheric Research (UCAR) and the National Center for Atmospheric Research (NCAR) laboratories and campuses. The downtown area of the city is located north of the main CU campus (see Fig. 1), and the main thoroughfare in this area is Pearl Street. This street transitions from motor vehicle traffic to a pedestrian and bicycle only area called the Pearl Street Mall. This mall is popular with both locals and tourists, providing restaurant and shopping services.

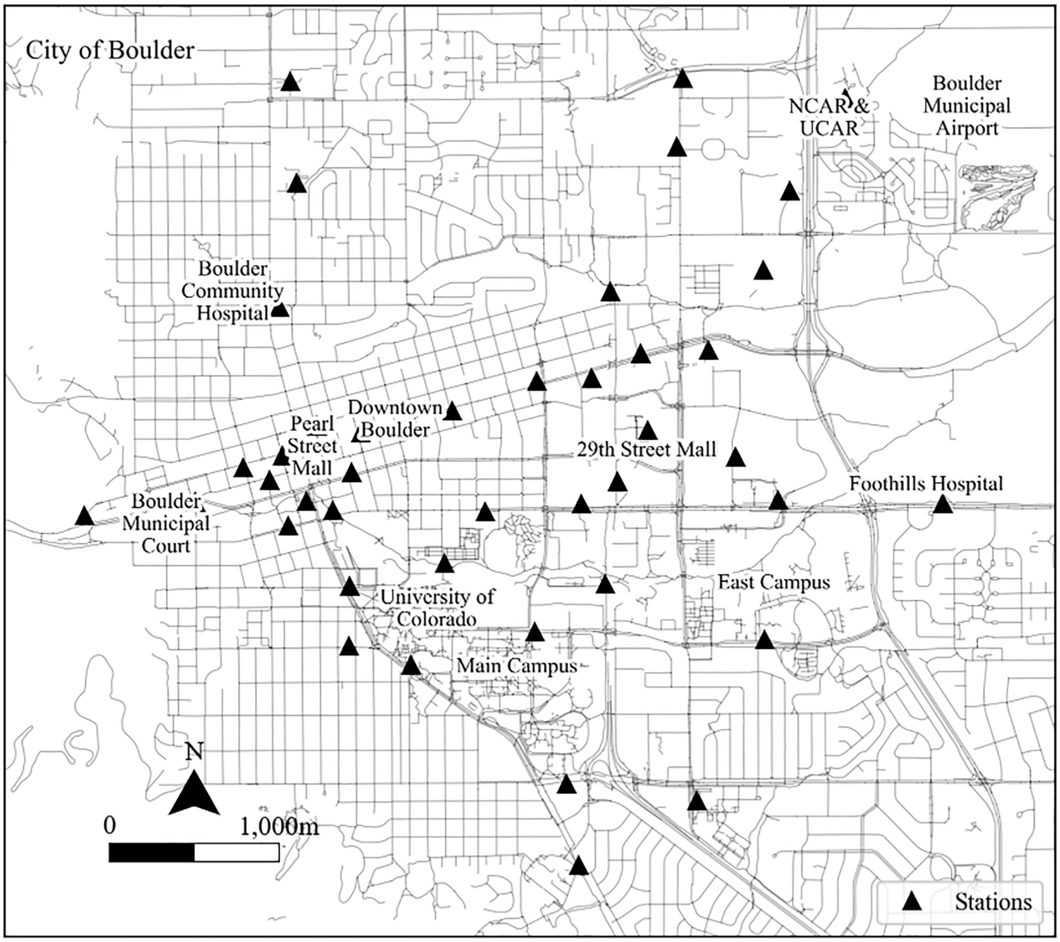

Fig. 1. Study area and BCycle stations.

Many of the dynamics in terms of population in the county and city is reflective of the City of Boulder's policy of controlled urban expansion through growth boundaries [32]. Through this policy, compact and high-density growth was promoted within the city boundary, effectively creating an open space buffer around the more densely populated urban center. Through a combination of several factors, including the growth management policies and the presence of a popular university, there is a continuing rapid increase in housing values within the city boundary (a median home value in 1990 of $122,700 to $304,700 in 2000 [33]. This increase on housing costs caused individuals and businesses to move to surrounding communities such as Niwot, Erie, Louisville, and Lafayette, where suburban development was less restrictive [33]. There is a strong Regional Transportation District (RTD) that provides public transportation connecting the City of Boulder to these communities, and the Colorado state capital of Denver.

The city has an active bike-sharing system managed by the company BCycle (https://www.bcycle.com). The BCycle system consists of stations (powered by either solar or electricity grid) and bikes. There were 39 kiosk stations and 260 bikes in active service when this research was conducted. All checking-out and checking-in transactions from May 20, 2011 to July 31, 2016 are available to us for authorized use. As listed in Table 1 and Fig. 2A, in total, there were 312,314 trip records including usage from users (264,232 trips; about 84.6%), maintenance staff (46,625 trips; 14.9%), and unrecognized sources (1,457 trips; about 0.5%). Six types of memberships are identified from the data: pay-per-trip, 24-h, 7-day, monthly, semester, and annual, while now only four types—pay-per-trip, 24-h, monthly, and annual—still remain. In addition to the trip records, station empty/full status data from January to July 2016 are accessible to us. As shown in Table 2, this dataset contains the name of the station when it becomes empty (no available bikes to rent) or full (no available docks to return the bike), the date and time when this event occurs, the type of membership that reports this event, the date and time when this event is resolved, the type of membership that resolves this event, and the event duration in minutes. This station empty/full status dataset will be used to examine the spatio-temporal distribution patterns of empty/full stations in subsequent sections.

Table 1
Bike trips by memberships.

		User Memberships						Other	
Categories	Total	Pay per trip	24-h	7-day	Monthly	Semester (150-day)	Annual	Maintenance	NA
Counts	312,314	405	100,063	5,586	5,433	9,367	143,378	46,625	1,457
%	100	0.13	32.04	1.79	1.74	2.99	45.91	14.93	0.47

Note: NA means Not Available.

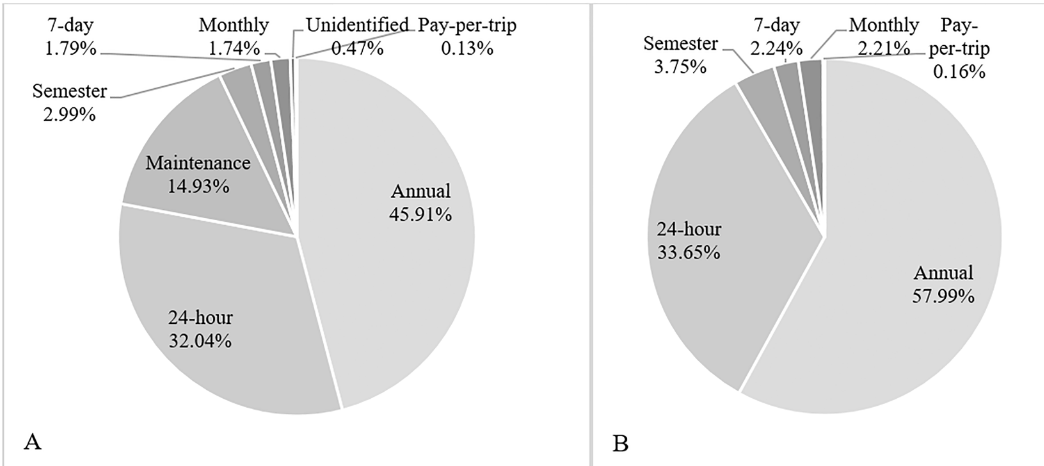

Fig. 2. Percentages of trips by memberships in: raw trip data (A) and cleaned user trip data without outliers (B).

3.2. Data preprocessing

There were some trips that lasted a very short (or long) period of time, and they were removed from the current analysis for better accuracy. For example, of the 264,232 user trips, 11,399 (4.0%) trips were completed no more than one minute. This particular duration threshold is usually employed to identify and filter bike-sharing usage outliers [18]. Most (93%) of these one-minute-or-less trips started and ended at the same stations. Many factors may contribute to the occurrence of these short trips such as when a user finds the bike in a poor condition and hence returns to switch for a better one, or that the bike is immediately locked before a user could pull it out from the dock. Likewise, we found some significantly long trips. For instance, there were 480 trips with a duration of more than 24 h and the lengthiest trip took 126 days to finish. We chose to exclude trips that lasted more than one hour (22,930 trips, about 8.7% of all trips) in this study since we found that: (1) all direct trips between stations in the city could be finished within one hour according to our analysis using Google Maps API (https://developers.google.com/maps/documentation/) and (2) according to the trip data, most of user trips (about 92% of all trips) were completed within one hour. These long trips may occur because that the dock system fails to lock the bike upon return and the users were not aware until they received the bill, or that the bike was missing or stolen after it was checked out. After ruling out the above outlier records, there remain 229,903 valid user trips—133,325 (57.99% of the remaining trips) trips made by annual members, 77,363 (33.65%) trips from 24-h members, 8616 (3.75%) associated with semester members, 5146 (2.24%) trips from 7-day members, 5090 (2.21%) trips made by monthly members and 363 (0.16%) trips from pay-per-trip members. See Fig. 2B for more detail.

4. Examining usage patterns between membership groups

This section compares bike usage patterns between the annual and 24-h membership groups. The two types of memberships were selected due to their dominant shares (i.e., 91.64%) of the total remaining user trips. Bike-sharing users of different memberships may perform distinctive usage behavior and patterns, in terms of, such as the trip duration and frequency, trip purpose, and activity space. Understanding the differences in their usage patterns is a prerequisite for the usage pattern optimization and may help build a more efficient and equal bike-sharing system.

4.1. Comparing actual trip duration with estimated trip duration by Google Maps

The actual travel times between stations were obtained by aggregating user trips by both checkout and return stations. These station-to-station actual travel times were then compared to the cycling times estimated by Google Maps API. For both 24-h and annual user groups, the actual average travel time was much longer (significant at the 0.001 level) than the estimated average time. For example, the actual average travel time for 24-h membership users was 21.89 min, while the estimated time was 10.34 min; and the actual mean time for annual membership users was 14.89 min, whereas the estimated time was 10.64 min. The pattern that Boulder BCycle users on average traveled much longer time than required indicates that both user groups usually cycle in a low speed or make one or more stops on their trips. This might be attributable to some of the bike safety laws in the city that cyclists must yield to pedestrians and enter crosswalks at an 8 mile-per-hour speed or less [34]. However, the 24-h membership users tend to cycle much slower or stop longer during their trips compared to the annual members. This may indicate that the 24-h pass trips were likely social/recreational trips that were not made in a hurry (more details are reported and discussed in next section). This pattern is also suggested by examining the scatter plots shown in Fig. 3A and B, which reveals a much stronger correlation relationship between actual and estimated travel times for the annual members (correlation = 0.84) than the 24-h members (correlation = 0.59).

4.2. Estimating trip purpose

The fact that 24-h membership users tended to make more or longer stops during their trips than annual users may suggest that the former users are likely tourists who visit the city and make recreational trips [10,11]. In comparison, the strong correlation between annual users'

Table 2
A snapshot of the station empty/full data.

Station	Event	Start date	Start time	Start membership type	End date	End time	End membership type	Event duration (min)
11th & Pearl	Full	2016-04-01	18:41:00	Annual	2016-04-01	21:40:00	Annual	179
11th & Pearl	Full	2016-04-02	07:22:00	24-h	2016-04-02	11:47:00	Maintenance	265
11th & Pearl	Empty	2016-04-09	10:51:00	Annual	2016-04-09	11:08:00	Maintenance	17

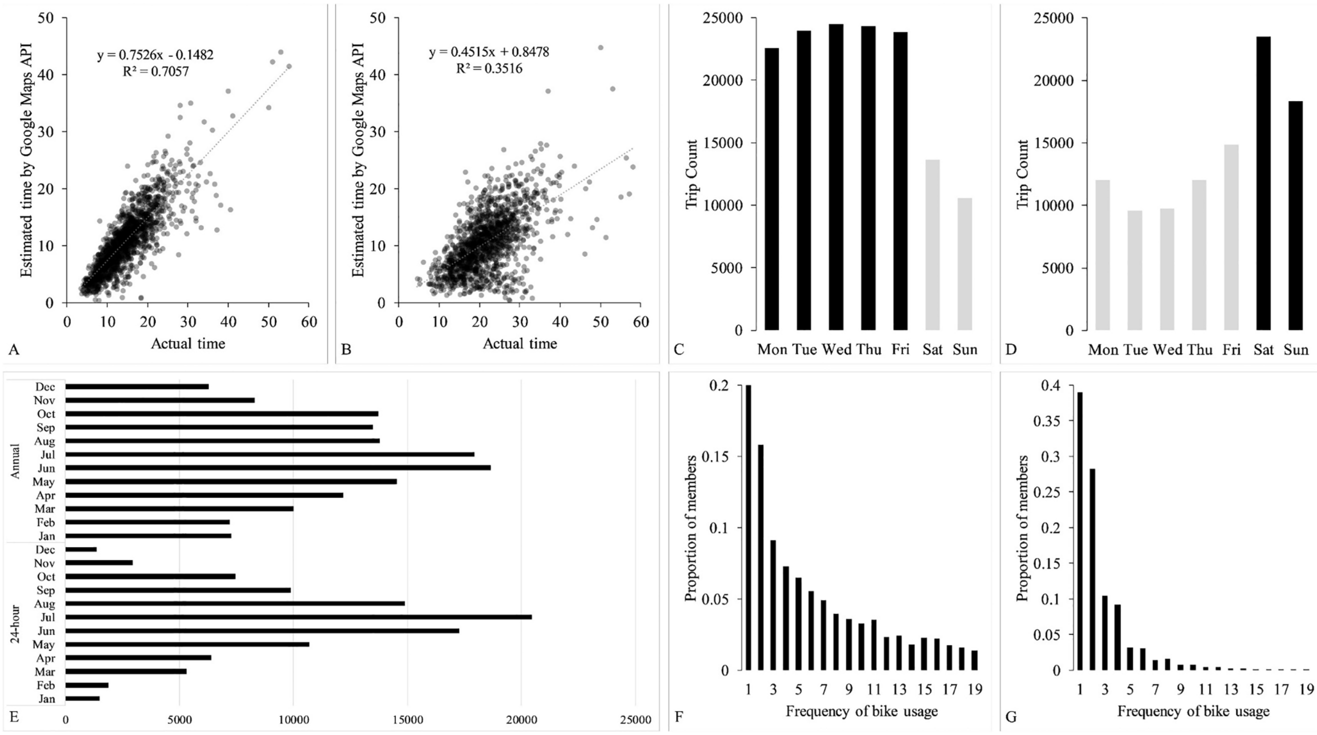

Fig. 3. Actual and estimated mean trip duration (min): annual (A) and 24-h (B) members; trip counts by the day of the week: annual (C) and 24-h (D) members; trip counts by month (E); trip frequency: annual users within a year (F) and 24-h members within a day (G).

actual and estimated travel times may suggest that these users are likely daily commuters (including some college students) who make regular trips and stop less often. This suspicion is also supported by looking at the trip frequency distribution by the day of the week between the two user groups. A majority of annual users' trips took place on weekdays (Fig. 3D), whereas significantly more weekend trips were observed for the 24-h members (Fig. 3C). Hence, the average trip duration was longer for 24-h pass riders than annual riders. We additionally examined the difference of monthly trip frequency distribution between the two user groups in Fig. 3E. A clear seasonal trend of more trips in summer than winter months was found in both groups. The summer months (June–August) saw an increase in bike checkouts with a dip on either side of the summer months. Among the popular summer months, June-July had the greatest checkouts across the years. This seasonal trend made sense as people tend to ride less in the winter months. But compared to the annual members, the 24-h members made significantly fewer trips in cold season, such as from November to February. This pattern may also suggest the above finding that the 24-h members are more likely tourists whose trip-making decisions are more affected by the weather condition, while annual users are more likely commuters who tend to make more consistent trips in a year.

4.3. Measuring trip frequency

According to the trip data, the number of trips grew drastically for both pass types. For instance, the total number of trips increased by 231% and 236% for the 24-h and annual pass types, respectively, between 2012 and 2015. Several reasons may have contributed to the growing trip-making over years, such as an increasing ridership, rising number of trips made by members, and increases in the number of stations and bikes. An examination of the ridership indicates a 140% growth for 24-h pass riders and 87% increment for annual members in the same period of time. The slower growth rate of ridership relative to trip-making for both pass types may indicate that both types of riders, on average, used bike-sharing more than once during their membership. This speculation led us to inspect how often each type of riders used the service. As shown in Fig. 3F, the majority of 24-h members (about 87%) used bikes four times or less within 24 h, while the same proportion of annual members used bikes 12 times or less within a year (Fig. 3G). Note that about 52% of annual members used the bike-sharing four times or less within a year. The findings reveal that the annual pass riders significantly underused the service. The BCycle company and active transportation advocates should be aware of this pattern and propose some incentives for this group to raise the usage frequency.

4.4. Detecting popular station connections

Connections between the check-out station and return station were created based on the trip data. The total number of bi-directional trips (origin and destination stations were interchangeable) was calculated for each connection. The top connected stations for annual members were stations 23 and 34; 40 and 41; 25 and 5; and 7 and 11. Fig. 4A displays these connections using the Bezier curves method [35], which uses color opacity to reflect the number of trips—the larger the number of trips, the more obvious the curve. The size of the circle for the station reflects the number of check-outs, or trip starts, for that station for the annual membership. Station 23 is the station closest to the Boulder Municipal Court and Boulder County Justice Center. This station is most active from Monday to Friday with an average 1252 check-outs, versus an average of 410 check-outs on Saturday and Sunday. Station 34 is located next to a bus stop serving the 'Dash' and 'Skip' routes. 'Skip' connects the northern city limits with the southern portion. 'Dash' connects the city with surrounding communities such as Louisville and Lafayette. This connection suggests that it is a popular connection between commuters using public transportation, possibly reaching the county court buildings.

Another popular connection is between Stations 41 and 40. These stations are close to the UCAR and NCAR foothills campus. It is possible that BCycle is being used to connect the buildings of these research campuses. Station 25 is adjacent with the Boulder Community Hospital, and connects most frequently with station 5, north of the Pearl Street

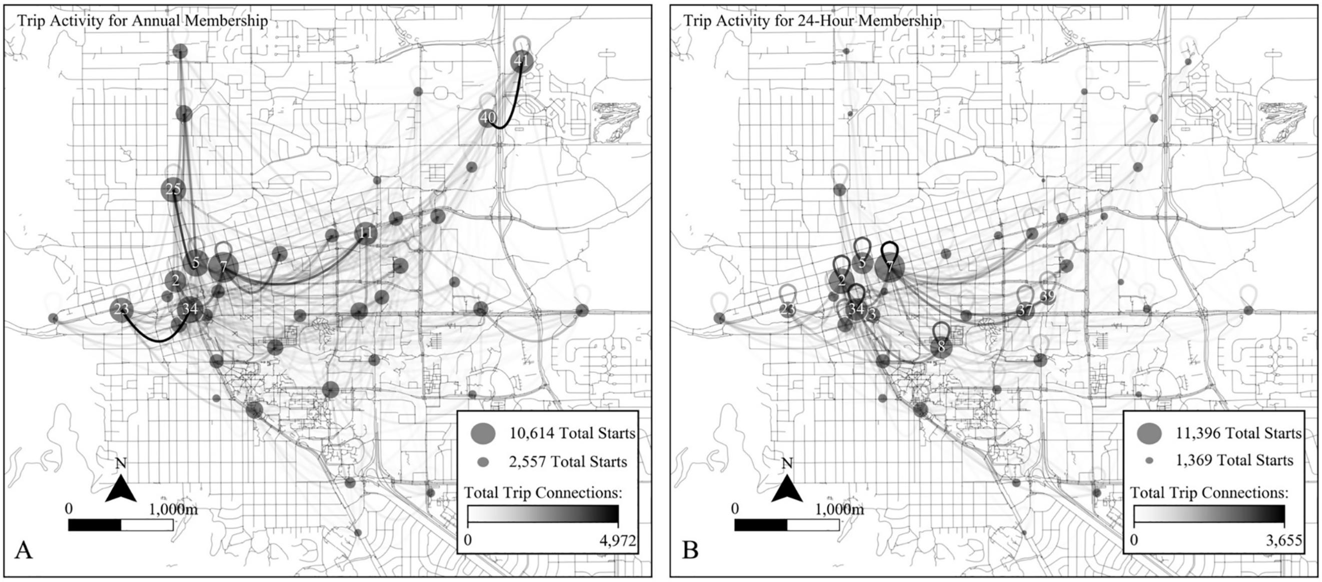

Fig. 4. Connections between stations for the annual members (A) and 24-h members (B).

Mall. It may be that station 25 uses BCycle as a way to access restaurants and services along the mall from the hospital. Station 7 is located at the eastern portion of the Pearl Street Mall, and connects most frequently with station 11, next to the 29th Street Mall and close to housing areas. Station 11 is adjacent with bus stops along the 'Hop' route that connects the downtown with the main CU campus.

Fig. 4B presents the connections for the 24-h membership. The main distinction with this membership is that the check-out and return stations are often the same. In some ways this suggests that users are somehow unfamiliar with the system. The most popular of these stations are 7, 5, 2, and 34. All of them are close to the Pearl Street Mall. Station 8 is also active and is located on the north side of the main CU campus.

4.5. Identifying activity space

Time geography, first proposed by Hägerstrand [36], is a powerful framework to investigate human activities under various constraints in a space-time context. It adopts a three-dimensional orthogonal coordinate system with two spatial axes representing geographic space, and time added as the third orthogonal axis [37]. Space-time prism is a concept from time geography that expresses the behavioral uncertainty of an individual in time and space [38,39]. Fig. 5 shows a typical space-time prism with a fixed origin i and destination j, and a time window $(t_j - t_i)$. The two-dimensional footprint of the prism is known as a Potential Path Area (PPA). It defines the set of locations an individual can reach for an activity purpose with a trip starting from the origin i and ending at the destination j within the given time window $(t_j - t_i)$ [40]. It is an ellipse in two-dimensional space with foci i and j and a major axis of length $(t_j - t_i - a_{ij})v_{ij}$, where a_{ij} denotes the activity time (which may be 0), and v_{ij} is the maximum travel velocity. It is formulated as [38]:

$$g_{ij} = \{\mathbf{x} | \|\mathbf{x} - \boldsymbol{i}\| + \|j - \mathbf{x}\| \leq (t_j - t_i - a_{ij})v_{ij}\}. \quad (1)$$

To calculate the PPA, we used an assumed constant velocity of 2.3 m per second, or 8 km per hour. This is on the low side of the range of velocities that have been observed in other studies [41,42]. This slower pace was meant to reflect the urban environment (e.g. traffic signals), terrain, and style of bicycle (e.g. not a performance bicycle). Trip time was provided by the average trip duration for annual membership, and median trip duration for 24-h membership. Using the average for the 24-h membership was not practical since very long trips could skew the

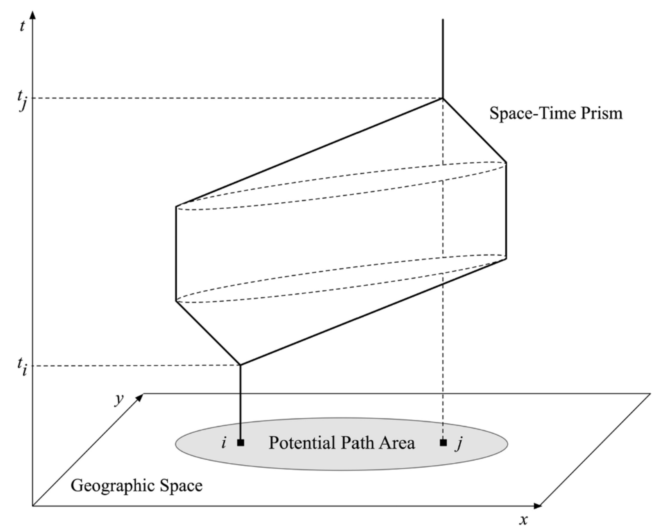

Fig. 5. An illustration of space-time prism and potential path area [38].

average.

Fig. 6A presents the PPA for the most frequent connections for annual membership. The average trip duration for each connection was used as the potential travel time (i.e., 14.89 min). The ellipses showed the potential area of activity for riders traveling between stations, or in some cases the range of activity possible with the same beginning and ending station. Because of the conservative velocity selected, the ellipses were relatively small. In particular, the thin narrow ellipse between station 23 and 24 suggests little room to deviate from a direct network path between them. One explanation for this is that the bicycles were used to quickly transfer between bus stops, and multimodal commuting. However, the connections between station 7 to 7 indicates a larger activity area, although the main focus of this part of Boulder is the Pearl Street Mall. An annual membership user may be using station 7 for quick access to the mall and other commercial activity.

In contrast, Fig. 6B presents the PPA for the most frequent connections for 24-h membership. Most trips began and ended at the same station, and the median trip duration for each connection was 45 min. This value was used for the potential travel time. Trips beginning and

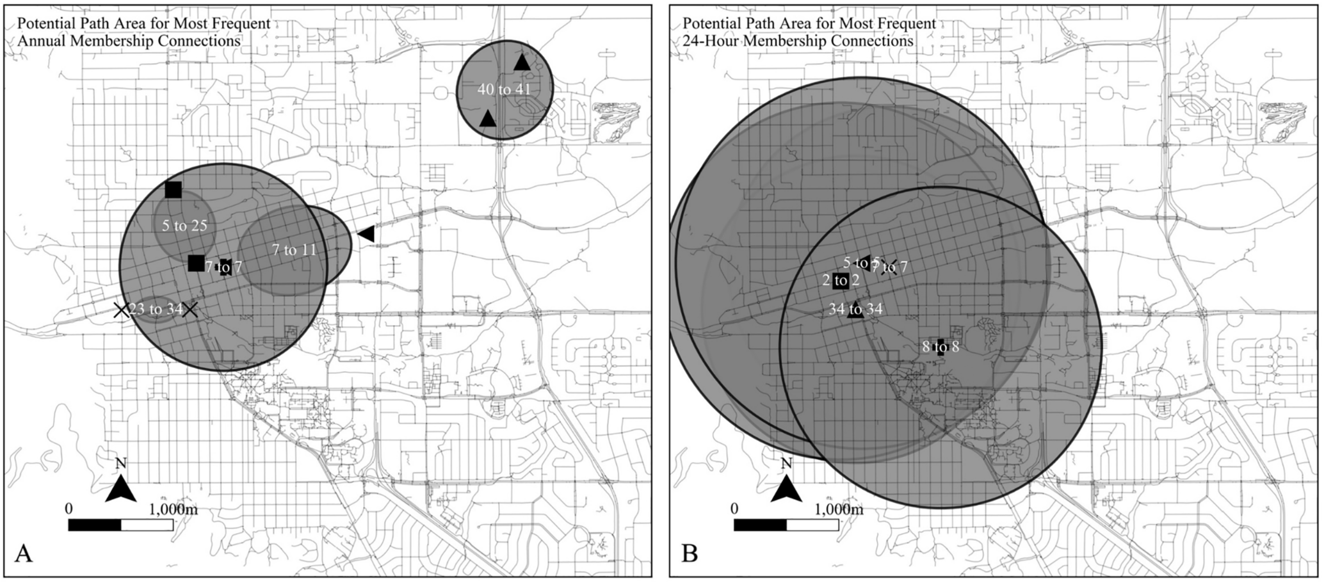

Fig. 6. PPA for the most frequent connections for annual membership (A) and 24-h membership (B).

ending at station 8 cover the main campus and east campus. It is possible that students use this station for trips between the two campuses. It is also possible that students begin at this station and attend class while keeping the bicycle checked out (minimum undergraduate class length is 50 min). Trips to and from stations 5 and 7 would fit with a potential tourist user pattern. They are close to a tourist destination (Pearl Street Mall) and would have time to access other tourist spots near there (e.g. the Boulder Dushanbe Teahouse). From station 34, a visitor using the bus system to access Boulder could easily reach the main campus within the timeframe or visit the Pearl Street Mall.

5. Spatio-temporal distribution patterns of empty/full stations

From time to time, BCycle users may find a station empty (no available bikes to rent) or full (no available docks to return the bike). When a customer tries to return a bike for the first time at a full-dock station, the customer is allowed to report the full-dock status on the kiosk machine and obtain an additional 15 min for finding another available dock nearby to return the bike. Based on the empty/full station dataset between January and July 2016 listed in Table 2, this section examines the spatio-temporal distribution patterns of empty/full stations. This analysis is to answer which stations (and at what times) are more likely to be overused or underused. The findings could benefit the system planning and improve the service efficiency and quality.

Fig. 7A shows the spatial distribution patterns of empty stations, where a larger circle indicates a greater occurrence of empty events at a station (the two bounding count thresholds in the legend represent the maximum value and the median, respectively). It appears that stations 7 (next to the Pearl Street Mall) and 34 (downtown, next to a bus stop serving the ‘Dash’ and ‘Skip’ routes) are the two stations where we are more likely to observe empty docks. This may indicate that the demand at both stations is high, while the current number of bikes at both stations was not enough to meet such high demand. Fig. 7B illustrates the spatial distribution pattern of stations with full docks. Stations 34, 3, and 5 were more likely to be full and users had to return their bikes at other nearby stations. Station 34 is highlighted in both Fig. 7A and B, indicating a significant shortage of bikes (and docks) at this station. It is found that station 34 had only 9 docks, which is the minimum number of docks at any stations in Boulder. When station 34 becomes full, users are more likely to return bikes to its nearest station—station 3 that is less than 200 m away—and this spillover effect could explain why station 3 usually becomes full. The addition of more docks at these stations could better balance the supply and demand and mitigate the impacts of full/empty service at these stations.

Fig. 8A and B illustrate the number of empty/full stations by the hour of the day in Boulder. Clearly, a significant high number of empty stations were observed at 8:00 a.m., 12:00 p.m., 3:00 p.m., and, in particular, 5:00 p.m. within a day. This temporal fluctuation pattern indicates the dynamics of the demand and supply at stations during the day but 5:00 p.m. is the time when the greatest shortage of supply is observed. Similarly, the number of full stations changes during the course of the day. Three peaks were spotted; they are 8:00 a.m., 12:00 p.m., and 5:00 p.m. In the three time periods, users are more likely to see full stations without available docks, and they have to travel to other stations to return the bikes. The time overlap between empty-station and full-station events suggests that maintenance staff may need to prioritize rebalancing operations at 8:00 a.m., 12:00 p.m., and particularly, 5:00 p.m. to minimize the delay in the service.

On the other hand, a few stations were found to be underused. A good example is station 43 on campus of CU. This station has the largest number of docks (22) in the entire system. Nonetheless, this station is less likely to be full or empty, indicating a relatively high supply than demand at this station. BCycle officials may consider reducing the number of docks at this station and moving them to other shortage stations like station 34 if demand at both stations are projected to stay stable.

Currently, about 42% of the full-station events was resolved by maintenance staff within four minutes and about 33% of the empty-station events resolved within the same length of time (see Fig. 8C). This indicates that more than half of the empty or full stations could not be used by members within four minutes of the time when the events occurred. For example, five-percent of these stations were not ready to use only until one hour after the stations were reported empty or full. When performing rebalancing, the maintenance staff could utilize the above spatio-temporal distribution patterns of empty or full stations and adjust their schedule for a more effective and efficient rebalancing effort.

6. Optimizing the bike-sharing system

The empty/full station analysis (Fig. 7A and B) reveals that some stations, such as 7 and 34, were largely overused relative to others, and some stations, like station 43, are greatly underused. This suggests a

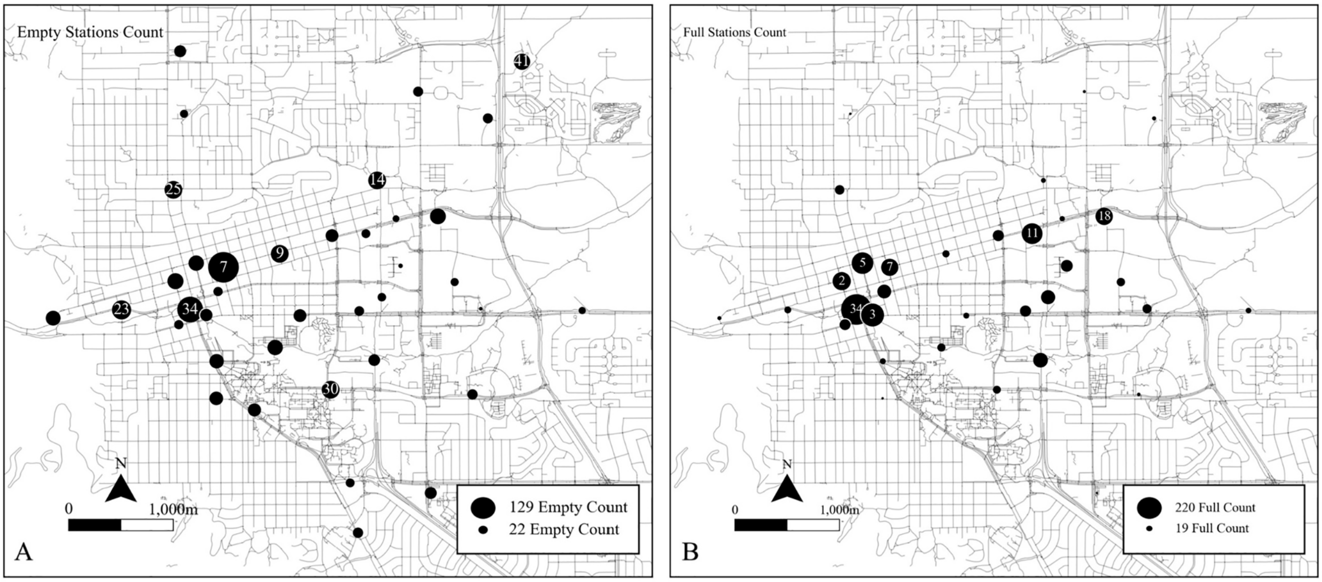

Fig. 7. Spatial distribution patterns of empty stations (A) and full stations (B).

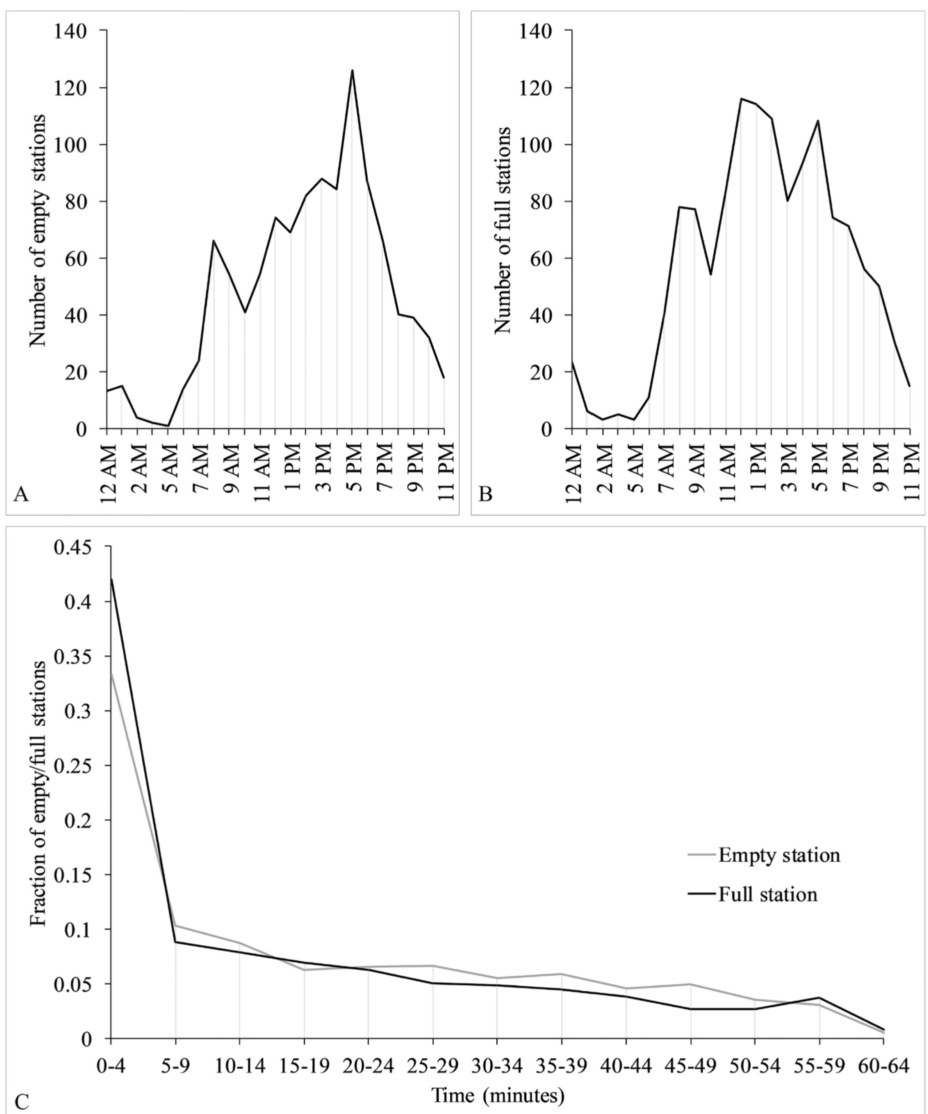

Fig. 8. The number of empty (A) and full (B) stations by the hour of the day, and the usual length of time for an empty or full station to be serviceable (C).

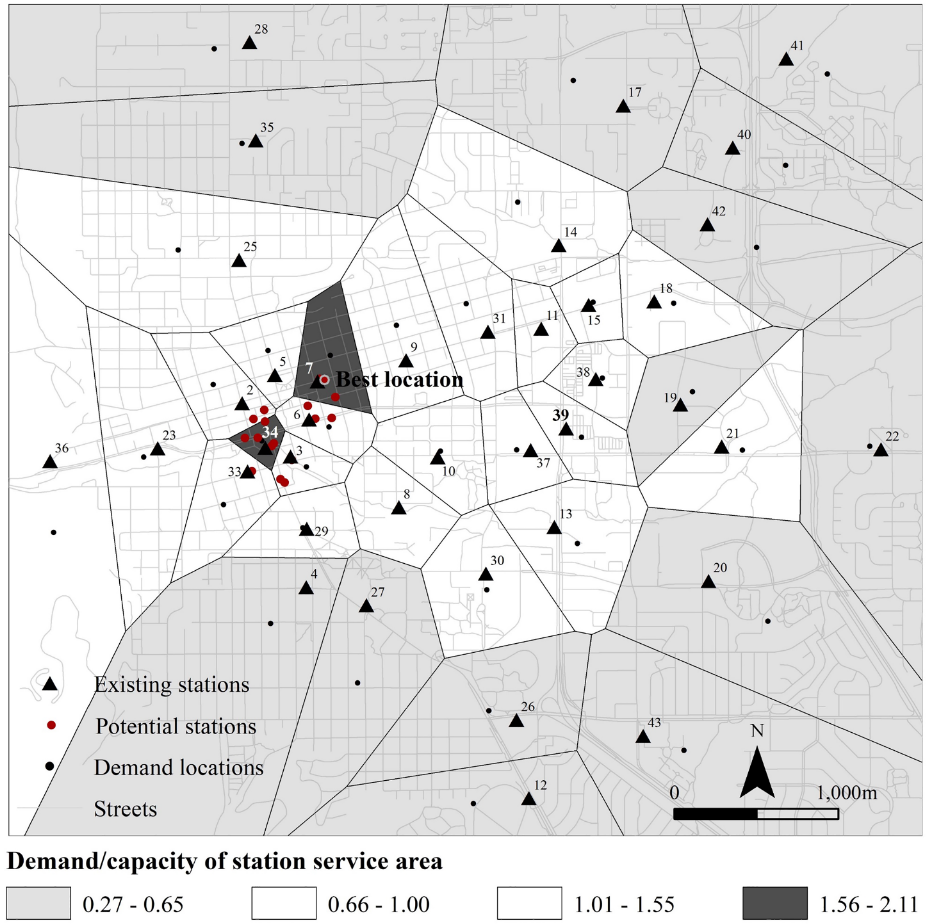

Fig. 9. Bike-sharing demand and supply.

substantial imbalance of bike-share demand and supply at or near these stations. To more fully identify the mismatch between supply and demand, we estimated demand around each station based on historical checkout and return trips that cover a much longer time period. Specifically, we retrieved the average numbers of checkout and return trips at each station from the 2015 to 2016 trip data (the two time periods rather than the entire five years were selected to reflect the most recent demand). The two numbers were then added together as a proxy for the demand at each demand location. The demand locations were approximated by the centroids of Thiessen polygons generated from the existing 39 station locations. As shown in Fig. 9, stations 7 and 34 (in the two dark Thiessen polygons) had significant shortage of bike supply than demand, which is consistent with the pattern observed from the full/empty station data. On the other hand, stations in the light gray polygons experienced substantial waste of bike resources due to relatively lower demand. This imbalance pattern calls for more optimal system configuration. Here, we propose three hypothetical scenarios: (1) without altering the existing stations (both locations and capacity), find the best place to build a new station, (2) find the best station that can be removed without changing other stations (both locations and capacity), and (3) find the best reallocation of docks across existing stations.

In essence, all three scenarios can be described as the capacitated maximal covering location problem (CMCLP) [43]. The CMCLP seeks to solve the best location decision that maximizes the service coverage provided by a specified number of bike stations. For scenario 1 where a new station is to be added, the CMCLP can be formulated as follows [43]:

$$\textit{Minimize} \quad \sum_{i \in I} a_i U_i, \tag{2}$$

subject to

$$\sum_{j \in N_i} X_{ij} + U_i = 1, \ \forall\ i \in I, \tag{3}$$

$$\sum_{i \in M_j} a_i X_{ij} \le k_j Y_j, \ \forall\ j \in J, \tag{4}$$

$$\sum_{j \in J_1} Y_j = 1, \tag{5}$$

$$Y_j = 1, \ \forall\ j \in J_0, \tag{6}$$

$$Y_j = \begin{cases} 1, & \textit{if a station is sited at location } j \\ 0, & \textit{if otherwise} \end{cases}, \tag{7}$$

where

i is a demand location,
j is a potential bike station location,
I is a set of demand locations,
J_0 is a set of existing bike station locations,
J_1 is a set of potential locations for a new bike station,
J is a collection of $J_0 \cup J_1$,
a_i is demand at location i,
k_j is the capacity of a bike station at location j,
X_{ij} is the fraction of demand at location i assigned to station j,
U_i is the percentage of demand at location i that is not covered by any station,

N_i is a set of bike station locations that can be reached from demand location i,
M_j is a set of demand locations that can reach the bike station location j.

The objective function (2) is to minimize the total demand that is not covered by any bike station. Constraint (3) ensures that the sum of the percentage of demand at each demand location assigned to a bike station location that covers it and the fraction of demand at each demand location that is not covered by any bike station equals one. Constraint (4) ensures that the total demand assigned to a bike station does not exceed the capacity (i.e., number of docks) of that station. It also makes sure that demand is only assigned to bike stations that are sited. Constraint (5) defines that the number of new bike stations to be sited is one. Constraint (6) ensures that the existing 39 stations in the bike-sharing system are unchanged (remain sited). Constraint (7) declares a binary decision variable—a potential bike station must be either sited or not.

We identified 17 bus stops that are within 250 m from stations 7 and 34—the two stations that are most likely to be full or empty—and they were used as candidate bike stations (see Fig. 9). This particular selection was made in regard to Boulder's plan to locate more stations at or near bus stops so as to encourage bus riders to use the service and also mitigate the last mile problem [44]. Locating bike-sharing programs close to public transportation stops/stations is a common planning strategy, as they "act as a seamless feeder service" [45]. The capacity at each of the 17 candidate stations was set to 13—the average number of docks across existing 39 bike stations. According to a recent study by Xu et al. [46], the maximal service distance for each bike-sharing station was set to 500 m, indicating that all demand locations that are within 500 m of a bike station can use the service at that site.

The problem formulation for scenarios 2 and 3 is quite similar to scenario 1, and hence the equations are not shown. The three problems were solved using the Gurobi Optimizer (http://www.gurobi.com/). Based on the estimated demand and capacity in each bike station service area (Thiessen polygon), we also evaluated the demand coverage for the current system configuration as a baseline scenario. Results are summarized in Table 3. Note that all the demand coverage estimates were made by assuming no changes to the existing rebalancing schedule. Results show that the current system layout can cover 89.2% of the total demand with some stations overused and others underused (see Fig. 9). Solving scenario 2 finds that 92.5% of the total demand could be covered when station 39 (Twenty Ninth Street South) were to be removed. This station has 9 docks and covers a demand of 7 (a 0.77 demand-to-capacity ratio), indicating a higher level of capacity than needed at this station. Two other stations are accessible to the users of station 39 if this station was to be removed; they are station 38 (Twenty Ninth Street North) with 14 docks and a 0.78 demand-to-capacity ratio and station 37 (The Village) with 14 docks and a 0.92 demand-to-capacity ratio. After station 39 is removed, both stations 37 and 38 would reach a more balanced supply and demand, leading to a more efficient system configuration. The demand coverage would be further increased to 95.5% when scenario 1 is to be performed. The best location for the new station is at the Pearl Street & 15th Street alighting stop of the HOP bus line (highlighted in Fig. 9). Obviously, this new station can help alleviate the service shortage at and around station 7 and hence improves the overall performance. Most interestingly, the solution of scenario 3 suggests that 30 of the existing 39 stations could cover all of the demand when the docks are reallocated. For example, stations 7 and 34 are suggested to be removed in the new layout, and their corresponding users can, instead, use stations 5 and 2, respectively. See Fig. 10 for the suggested system layout and the flow patterns. Of the three optimization scenarios, scenario 3 appeared to have the most service coverage improvement than either adding or removing a station, indicating that the current system would benefit more from solely moving docks around across existing stations. This may suggest that the demand was not well estimated or considered when making decisions about how many docks each station should have. The city should be aware of this when redesigning or making updates to the system in the future.

7. Conclusions and discussion

This paper provides a systematic analysis of the usage patterns of a bike-sharing system, called as BCycle, in Boulder, Colorado, the United States. Combining various methods, we examine the bike usage patterns from various perspectives (e.g. trip length, trip purpose, trip connection, and activity space), the spatio-temporal trends of empty and full stations and optimize the current configuration of the system in different hypothetical scenarios, using historical user trip records and station empty or full status data. Major findings are summarized as follows.

Results show that the annual pass riders in Boulder are probably commuters and local professionals wanting to have access to areas of the city, while the 24-h users are probably temporary visitors to the city, focusing on the more touristy areas like Pear Street Mall. This population difference between the annual and 24-h pass riders likely results in varying station connection patterns. A majority of annual trips connect between different stations, such as UCAR and NCAR foothills campus, Boulder Community Hospital and Pearl Street Mall, and Boulder Municipal Court and surrounding communities. On the contrary, most 24-h trips start and end at the same station. The PPA analysis also suggests a similar spatial trend. The PPAs for the annual riders appear to be narrow ellipse that does not reach the start and end locations, indicating fast direct travel between the stations and multi-modal commuting, whereas the PPAs for the 24-h riders look circular and cover a much broader area of the city. Despite an increasing ridership over years, results show that the annual members significantly underuse the bike-sharing system during their membership—about half of the riders used the bikes four times or less within a year. This calls for some policy interventions such as price incentives being proposed for the annual pass holders in order to raise their usage.

At the station level, some stations are more likely to be empty or full, indicating the imbalance of bike supply and demand. These stations are clustered in the Pearl Street Mall and downtown area. In particular, station 34 that is close to a bus stop serving the 'Dash' and 'Skip' routes in downtown is more likely to be empty or full. A spillover effect is also observed—stations in close proximity to station 34 are likely to experience higher demand than usual when station 34 becomes empty or full. Policymakers should note this spatial mismatch pattern and update the system configuration accordingly to better serve the residents. Our analysis also finds that the spatial mismatch pattern

Table 3
Total demand covered by bike-sharing stations under different optimization scenarios.

Scenario	Number of Stations	Number of Docks	Total Demand Covered	Percentage of Total Demand Covered
0—Baseline	39	540	396	89.20%
2—Remove a station	38	531	411	92.50%
1—Add a station	40	553	424	95.50%
3—Reallocate docks	30	444	444	100%

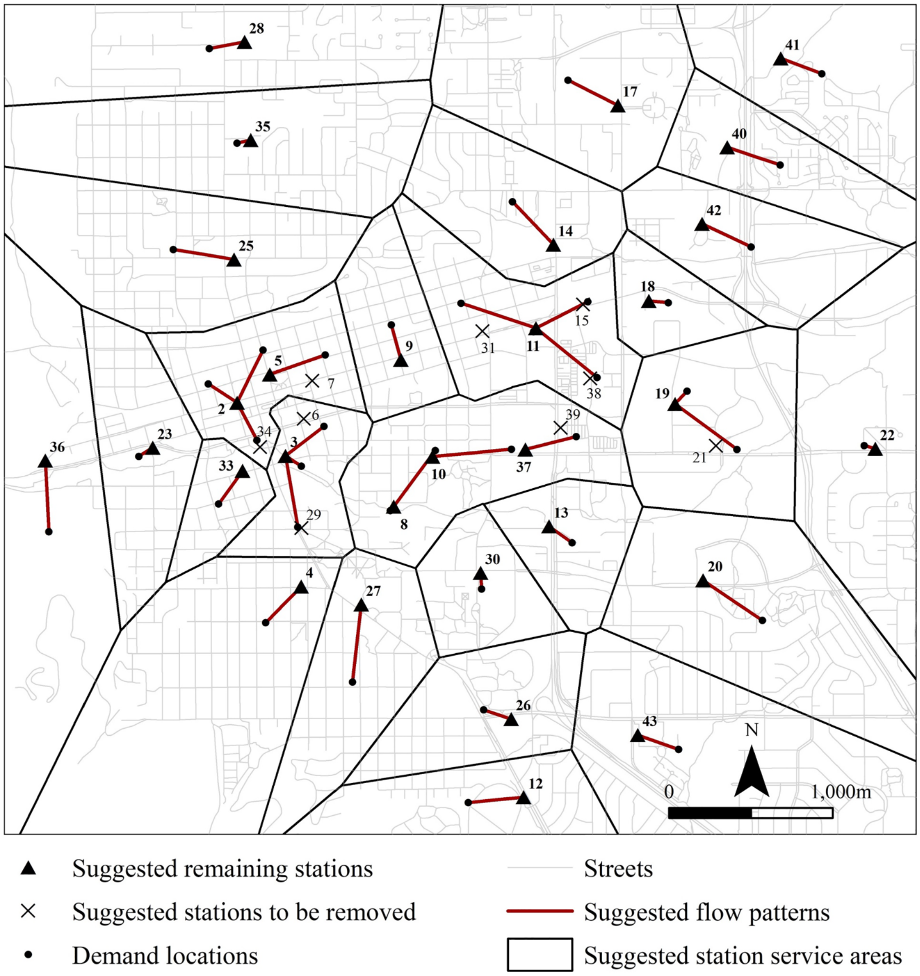

Fig. 10. Suggested bike-sharing layout under scenario 3.

fluctuates during the day. For instance, most stations are more likely to turn empty or full at certain time periods, such as 8:00 a.m., 12:00 p.m., and particularly, 5:00 p.m. This temporal trend suggests that the maintenance staff may consider prioritizing the system rebalancing operations at these times in order to minimize the service delay.

Given the overall imbalance of supply and demand, three optimization models based on the CMCLP were implemented to optimize the system configuration for maximal service coverage. These models were built upon three hypothetical scenarios with a consideration of adding a new station, removing an existing station, or redistributing existing docks across present stations. Results suggest that removing a station could improve the coverage from 89.2% in the current configuration to 92.5% and adding a station could further raise the rate towards 95.5%, while, most surprisingly, redistributing docks across existing stations could cover all the demand. When making future updates to the system, the findings could be beneficial to the system planners.

The present study has some limitations. The analysis of empty/full station patterns could benefit from a more complete data set that covers longer time period. Due to data unavailability, the optimization analysis does not consider the dynamic demand in real time but rather used past trip records to approximate demand. In addition, the optimization analysis would become more practical if the costs of adding a station, removing a station, and shifting a dock between stations are available to us. These issues would be addressed by requesting more data from the Boulder BCycle in future studies. Nevertheless, the analytical models presented in this research can be readily replicated to other data sources or regions.

This unique case study has a direct contribution to improve the performance of the BCycle system in Boulder. Also, it holds potential to provide implications to similar cities for system operation, transportation planning, delineation of functional areas, and policy making and improvement [47,48]. It can further promote future energy conservation and sustainable energy systems nationwide and ultimately worldwide, such as by adapting the resulting optimization strategies in different cities and countries.

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