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ARTICLE

A new method for determining optimal locations of bike stations to maximize coverage in a bike share system network

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Abstract: A new method that combines maximal covering location problem and bike station importance is utilized to find optimal locations of bike stations and maximize bike share system (BSS) demand coverage within a specific distance. This method uses multi-criteria that focus on centrality measures and bike station's importance. Results of applying the new method to a real-life BSS network demonstrated that BSS efficiency improved after removing the least important bike stations up to a critical point after which efficiency started to deteriorate as the network became disconnected. The new method can be used to improve management of BSS networks.

Key words: BSS, location problem, centrality measures, TOPSIS, bike station importance.

Résumé : Une nouvelle méthode qui intègre le problème d'emplacement donnant une zone desservie maximale et l'importance des stations de vélos est utilisée pour trouver les emplacements optimaux des stations de vélos et maximiser la demande du système de vélopartage (SVP « bike share system, BSS ») dans la zone desservie, et ce, à une distance spécifique. Cette méthode utilise des critères multiples axés sur les mesures de centralité et l'importance des stations de vélos. Les résultats de l'application de la nouvelle méthode à un réseau de SVP réel ont démontré que l'efficacité des SVP s'est améliorée après le retrait des stations de vélos les moins importantes jusqu'à un point critique, après quoi l'efficacité a commencé à se détériorer à mesure que le réseau devenait morcelé. La nouvelle méthode peut être utilisée pour améliorer la gestion des réseaux de SVP. [Traduit par la Rédaction]

Mots-clés : système de vélopartage (SVP, « bike share system, BSS »), problème d'emplacement, mesures de centralité, « technique for order preference by similarity to ideal object, TOPSIS », importance des stations de vélos.

Introduction

The continuous increase in urban population in recent years presented new mobility challenges. Recently, the bike share system (BSS) has been identified as a sustainable transportation mode that can meet such challenges. BSS is a friendly non-motorized mode of transportation system which is ideal for short to medium distances, and point–to-point trips. BSS can be used for monomodal trips, or for multi-modal trips. BSS is available to members who are 18 years of age and older, and the membership can be purchased online or in any bike share kiosk. Members have access to bikes at any time during membership period, and they can use bikes from any bike station and return them any time to any bike station within the network coverage area provided by the bike share company.

A key success of BSS is the location of bike stations and their relationship to trip demand. Determining the best locations to install bike stations while accomplishing demand coverage is called "Location Problem". Public-Private Partnerships (PPP) are mostly responsible for implementing the BSS program. Public investment in public transportation is always subject to budget constraints; therefore optimization of the BSS locations is necessary to maximize the benefits through better design and implementation of BSS. The positive ideal solution (PIS) and the negative ideal solution (NIS) have been used to maximize the demand coverage of BSS. The bike stations with the largest value of PIS are called the most important bike stations while the bike stations with the largest value of NIS are called the least important bike stations. Decision makers need to evaluate the performance of the BSS network so they can improve the network efficiency by identifying new bike stations locations, and (or) relocating the least important bike stations based on the bike station importance.

The concept of Maximal Covering Location Problem (MCLP) was first introduced by Church and ReVelle (1974); then it became popular. The objective of MCLP is to locate sites for a given number of bike stations. This number is normally constrained by budget while maximizing bike demand coverage within a maximum specific distance (also known as service distance). MCLP mathematical formula is discussed in this paper under methodology. Analytical Hierarchy Process (AHP) was developed by Saaty (1980) who defined AHP as a structured technique that can analyze, organize, and check for consistency of the decision maker's pairwise preferences (comparisons). AHP supports the Multi Criteria Decision Method (MCDM) by quantifying the required weights for each criterion; higher weights indicate bike stations are more important. MCDM is a decision-making method that deals with decision problem under the presence of a multi-criteria decision. MCDM first determines weights then ranks alternatives. Technique for Order Preference by Similarity to Ideal Object (TOPSIS) is one of the MCDM techniques which will be used in this paper and applied to a case study. Its basic concept is to select the best

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alternative that should have the shortest geometric distance from the PIS, and the farthest geometric distance from the NIS. TOPSIS was originally developed by Hwang and Yoon (1981). All three techniques (MCLP, AHP, and TOPSIS) are explained in detail under methodology.

In this paper, three criteria have been used to measure the centrality of a BSS network: (1) Betweenness Centrality (BC), which measures the number of the shortest paths which pass through the subject bike station (node) and connect with other bike stations in the network. The bike station with a higher BC has more control over the network because many bikes may pass through it; (2) Closeness Centrality (CC), which measures the geodesic distances to other bike stations. The most important bike station is the closer one to other bike stations in the network; and (3) Degree Centrality (DC), which measures the number of neighbors a bike station has, the higher DC reflects the importance of a bike station in the network. One of the key issues for the BSS program to succeed is to have proper locations of BSS stations because poorly located BSS stations compromise BSS success.

The main goal of this paper is to develop a new methodology that combines both MCLP and bike station importance. The specific objectives needed to achieve this goal are to: (1) apply this new methodology to optimize locations of bike stations using bike station importance while accomplishing maximum BSS demand coverage within a specified service distance, (2) demonstrate application of the new methodology to a real-life BSS network, and (3) compare results of applying this new methodology to existing methods for identifying bike stations locations in a real-life BSS network. The service distance is a pre-defined threshold (also known as a coverage radius around bike station) and directly affects the solution of the station locations.

Literature review

The strategic placement of BSS stations sites is the role of agencies in charge of the BSS network. Previous methods used to locate bike stations include: MCDM, MCLP, mathematical models, and Geographical Information Systems (GIS). A hybrid approach which combines both MCLP and MCDM models while utilizing the AHP technique is adopted in this paper.

Literature covering previous methodologies can be divided into three types of models: MCDM, GIS, and hybrid MCDM-GIS based models. These are discussed next.

MCDM-Based models

Croci and Rossi (2014) examined the effect of different attractors on the proximity and visibility of bike share stations. They found that proximity of some activities such as metro train stations, universities, museums, and movie theaters to BSS stations significantly increase bike usage.

Liu et al. (2015) evaluated node importance in actual complex networks. They used K-Shell decomposition and TOPSIS (which includes centrality measures such as BC and CC). They found that their method outperformed other methods and was able to provide scientific support for the administration department.

Frade and Ribeiro (2015) proposed an optimization method to maximize the demand of bike share with available budget and level of service constraints. Their model determined the optimal location of bike stations and the capacity and size of bike stations.

Wen et al. (2018) proposed a methodology to rank node importance in complex networks. They used Least Square Support Vector Machine (LS-SVM). Four indicators were used with the application of AHP to evaluate node importance. They found that their proposed methodology was consistent with reality and accurately reflected node importance.

Jahanshahi et al. (2018) evaluated BSS stations in Mashhad city, Iran, and proposed an approach for locating potential future stations. They used MCDM and fuzzy membership maps. They categorized station locations using the Jenks natural breaks classification method. Also, they found that stations located on the coverage borders were very unsatisfactory because the wide spread coverage of BSS has been prioritized over efficiency and proper distribution of BSS stations.

Rahim Taleqani et al. (2020) proposed a framework to maximize the demand coverage using CC to identify candidate bike station locations, and to make sure that all other nodes in the transportation network are close enough to the bike-sharing locations within a restricted diameter. They combined traditional bike stations (docked) with locations that can serve as free-floating bike-sharing stations (dockless). Their study used cost-benefit analysis to demonstrate potential advantages of their proposed model.

GIS-based models

Lin and Yang (2011) and Dell'Olio et al. (2011) used GIS-based models with service level constraints to determine the number and location of bike stations. Palomares et al. (2012) calculated spatial distribution for BSS demand using a GIS-based method. They found that an increase in the number of BSS stations leads to an increase in both the accessibility to bike stations and the population coverage.

Wuerzer et al. (2012) used a GIS-based model to optimize the locations of bike stations in a BSS network in Idaho, United States. They found that 14 bike stations and 140 bikes were the optimal allocations for the study area.

To locate BSS stations, Broach et al. (2012) utilized GPS to identify hot spot stations which they considered to be important in selecting BSS locations.

Wang et al. (2016) used a GIS-based analysis and applied spatial-temporal analysis and retail location theory to public bike site selection in Taipei. They found that the spatial and temporal analysis improves the system and can be used to effectively determine bike stations location.

Hybrid MCDM-GIS based models

Rybarczyk and Wu (2010) found that GIS was a better alternative for optimizing bicycle facilities than conventional bicycle planning methods.

Milakis and Athanasopoulos (2014) proposed a methodology for cycle network planning using participative multi-criteria-GIS process. They incorporated cyclists' views to choose the cycle network segments. They applied the study in Greece where cycling demand is relatively high, and the facilities are few. Their results were found to be helpful for cities making an attempt to introduce cycling infrastructures.

Another study by Guerreiro et al. (2018) developed a methodology to design and compare bike network based on origin-destination O-D data, GIS resources, and multi-criteria analysis methods. They found that the existing bike network was ineffective for bicycle riders and further methods for planning bike networks were still needed.

The above literature review reveals that none of the above mentioned studies used bike station importance to maximize BSS demand coverage. This paper fills this major gap by combining the Maximal Covering Location Problem (MCLP) and bike station importance. In this paper, we define network nodes as bike stations and network graph links as bike paths. It has been reported by Ren and Linyuan (2014) that nodes (which are bike stations) that play more important role in functionality and structure of the BSS network are considered more important than other nodes (or bike stations) which do not display the same behavior. As such, it is critical to identify important bike stations in BSS network so that the network performance can be properly evaluated. The new methodology developed and presented in this paper combines MCLP and bike station importance to achieve maximum bike demand coverage while optimizing bike stations locations. This novel methodology is applied to a large-scale case study of a BSS network in Washington, D.C. This BSS network is called Capital Bike Share System or CBSS. Furthermore, this paper utilizes node importance, an important tool that is used for the first time to locate key nodes (bike stations) in BSS network as will be demonstrated in the case study. The output of this new methodology includes important bike stations in the BSS network. These important stations will be input to the MCLP model. The outcome of this process provides initial locations of bike stations so that agencies in charge can better manage the BSS network by adding new bike stations, or relocating, or removing existing ones based on their importance.

Methodology

The basic concept of the developed methodology in this paper is to use the most important bike stations as demonstrated in model output of bike station importance and add more bike stations to them to achieve complete coverage of BSS network. A case study of CBSS that covers the jurisdiction of Washington, D.C. is used to demonstrate the methodology. CBSS is composed of 99 bike stations. The first 50 most important bike stations which are 50% of the bike station network are used as an initial bike share network, then in the next step, the top 10 bike stations are added and the coverage is checked. These steps are repeated until 100% coverage of the BSS network is reached. The optimization was conducted by maximizing the demand coverage of bike stations and simultaneously applying a constraint of the distance between stations to be within the specified service distance. More details are provided later on in this paper.

Maximal Covering Location Problem (MCLP)

The MCLP main objective is to locate a fixed number of bike stations facilities while maximizing demand coverage within a maximum service distance. The following is the MCLP model (Church and ReVelle 1974):

$$\text{(1)} \qquad \text{MCLP model} = \max \sum_{i=1}^{N} \sum_{j=1}^{N} w_i s_{ij} x_{i_j}$$

where w_i is the bike demand at bike station i. The model in eq. 1 is subject to two constraints: (1) s_{ij} is a binary indicator which represents coverage by service distance of open bike station facilities. s_{ij} equals 1 if the distance between bike station i and bike station j is within the service distance; 0 otherwise. (2) x_{ij} is a binary indicator representing the coverage by open bike stations facilities; $x_{ij} = 1$, if point i is covered by bike station facility located at point j; 0 otherwise. N is the total number of demand points.

Evaluation of bike station importance

Evaluation of bike station importance by using only one criterion in a BSS network is a one-sided story. A bike station is considered a node while the bike share network is considered a network graph. To evaluate importance of a bike station and its location impact in the bike share network, this paper proposes a multi-ranking attribute method based on TOPSIS with the support of AHP to determine the weights of the criteria. The following three criteria were used for evaluating bike station importance: BC which is a simple and intuitive criterion, but reflects only the local characteristics of the bike station, CC which acts on a part of the network bike stations and reflects the global characteristics, but is not suitable for large-scale networks, and DC which reflects the local capacity of the bike stations, and is also not suitable for large-scale networks. Three steps are needed to evaluate bike station importance: (1) defining the criteria for bike station importance, (2) applying Analytical Hierarchy Process (AHP), and (3) calculating TOPSIS. These steps are explained below.

Table 1. Comparative matrix (CM) criteria.

CM_{ij}	BC	DC	CC	b_i
BC	3	1	1	5
DC	5	3	1	9
CC	5	5	3	13

Defining the criteria for bike station importance

The following three criteria have been used in the literature; the reader is referred to the cited references under each criterion for the detailed corresponding equation. The following three criteria will be examined in this paper:

- Closeness centrality (CC). As stated under introduction, CC of a bike station measures the geodesic distances to other bike stations. See Borgatti and Everett (2006) for the equations used to define CC. Larger values of CC indicate that the bike stations are important because they are being close to the network center.
- Degree centrality (DC). As stated under introduction, DC demonstrates the ability of a bike station to directly connect with other bike stations. See Newman (2009) for the equation used to define DC. Similar to CC, larger values of DC indicate bike station importance.
- Betweenness centrality (BC). As stated under introduction, BC measures how many paths between bike stations in the network pass through the subject bike station. See Bader et al. (2007) for the equation used to define BC.

Conducting the analytic hierarchy process (AHP)

This process is composed of the following five steps:

1. Constructing the bike stations' attribute matrix

The mathematical formulation of the attribute matrix of bike stations, M, is as follows (Yoon and Hwang 1995):

$$\text{(2)} \qquad M = \begin{bmatrix} x_1(\beta_1) & x_1(\beta_2) & x_1(\beta_3) \\ x_2(\beta_1) & x_2(\beta_2) & x_2(\beta_3) \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ x_n(\beta_1) & x_n(\beta_2) & x_n(\beta_3) \end{bmatrix}$$

where $x = [x_1, x_2, x_3 \ldots x_n]$ and refers to bike stations x_1 through x_n; the centrality criteria are defined as: $\beta = \beta_1, \beta_2, \beta_3 = (BC, CC, DC)$; $x_i(\beta_j)$ is the centrality criterion β_j for bike station x_i; $i = 1, 2, 3, \ldots, n$; $j = 1, 2, 3$; and n is the number of bike stations.

2. Constructing the comparative matrix criteria

The comparative matrix of criteria (CM) is a tool that can be used to rank a set of decision-making criteria. This matrix needs to be constructed so that the criteria can be ranked based on relative importance. The authors of this paper used logical assumptions to construct the CM matrix which is displayed in Table 1.

$$\text{(3)} \qquad \text{CM} = \text{cm}_{ij} = \begin{cases} 5, \text{ if indicator } i \text{ is more important than indicator } j, \\ 3, \text{ if indicator } i \text{ and indicator } j \text{ are equally important}, \\ 1, \text{ if indicator } i \text{ is less important than indicator } j, \end{cases}$$

The following offers an explanation for the authors' reasoning of the relative weights in the CM. Since CC indicates how centralized the bike station is in the network, it is considered of high importance to BSS as in a monomodal transport. Hence, it makes sense to consider CC as the most important criterion. Whereas BC is indicative of global connectivity in the network, which is normally less important in in a monomodal BSS network. Therefore, compared to CC, BC is considered to be the least important criterion. This leaves DC, which is a local characteristic of the bike station; DC will be considered more important than BC but less important than CC. In Table 1, b_i is the row sum of criteria cm_{ij} in the Comparative matrix. Please note that the above choices of 5, 3, and 1 in the CM matrix is arbitrary and these numbers can be replaced by 7, 5, and 1, for example. However, what is critical here is the relative importance between the different criteria and with the explained logic this makes sense. The CM matrix and its assumptions will be checked for consistency under the fifth step of AHP explained later on.

3. Determining the judgment matrix

The judgment matrix determines the weight of each criterion (BC, CC, and DC) based on its level of importance; its formulation is as follows (Yoon and Hwang 1995):

$$C_{ij} = 9^{\left(b_i - b_j\right)/(\max(b_i) - \min(b_i))} \tag{4}$$

where

$$b_i = \sum_{j=1}^{3} \mathrm{cm}_{ij} \tag{5}$$

b_i or b_j is the row sum of criteria cm_{ij} in the comparative matrix CM (shown in Table 1).

Weight vector.—Weight vector is a process of equations that decomposes a square matrix to its eigenvector. In this paper, the weighted judgment (3 × 3) matrix (with 3 criteria) will be decomposed to a weight vector of (3 × 1) matrix. The following defines the weight vector equation (Yoon and Hwang 1995):

$$\overline{W_i} = W_i \Big/ \sum_{i=1}^{3} W_i \tag{6}$$

where

$\overline{W_i}$ is the weight vector for criterion i
$W_i = \sqrt[4]{M_i}$, and
W_i is the weight of criterion i,
M_i is the product of the judgment matrix of criterion i, e.g., $M_1 = C_{11} * C_{12} * C_{13}$, and the same applies to the other three criteria, and
C_{ij} is the judgment matrix.

Based on the above, the final judgment matrix (C), and the weights vectors are included as follow:

$$C = C_{ij} = \begin{array}{c} \\ \mathrm{BC} \\ \mathrm{DC} \\ \mathrm{CC} \end{array} \begin{array}{cccccc} \mathrm{BC} & \mathrm{DC} & \mathrm{CC} & M_i & W_i & \overline{W_i} \\ \end{array}$$

$$\begin{bmatrix} 1 & \frac{1}{3} & \frac{1}{9} & \frac{1}{27} & 0.4387 & 0.1180 \\ 3 & 1 & \frac{1}{3} & 1 & 1 & 0.2689 \\ 9 & 3 & 1 & 27 & 2.2795 & 0.6131 \end{bmatrix}$$

The weight vector of (3 × 1) matrix $\overline{W_i}$ is as follow:

$$\overline{W_i} = \begin{bmatrix} 0.1180 \\ 0.2689 \\ 0.6131 \end{bmatrix} \tag{7}$$

We can see from the final weighted judgment matrix above that the weight of CC is 61.31% of the total weight, while the weights of DC and BC are 26.89% and 11.80% respectively. The total sum of the calculated weights' percentages is 100%. These weight percentages reflect the importance of the criteria according to the assumptions made by the authors in the comparative matrix.

4. Calculating the normalized matrix

Due to the different weights of the three centrality criteria (BC, CC, and DC), the attribute matrix M shown in eq. 2 needs to be normalized. The normalization process produces another matrix, T, with its elements being the product of weights found in the previous step 3 and the a_{ij} factors, where a_{ij} is defined as follows (Yoon and Hwang 1995):

$$a_{ij} = \frac{x_i\left(\beta_j\right)}{\sqrt{\sum_{i=1}^{N} x_i\left(\beta_j\right)^2}} \tag{8}$$

Please note that β_j and $x_i(\beta_j)$ were defined earlier under eq. 2 and N is the number of bike stations. The normalized matrix, T, which has elements t_{ij} is calculated according to eq. 9 below (Yoon and Hwang 1995):

$$T = t_{ij} = \overline{W_i} a_{ij} = \begin{bmatrix} \overline{W_1} a_{11} & \overline{W_2} a_{12} & \overline{W_3} a_{13} \\ \overline{W_1} a_{12} & \overline{W_2} a_{22} & \overline{W_3} a_{23} \\ . & . & . \\ . & . & . \\ . & . & . \\ \overline{W_1} a_{1n} & \overline{W_2} a_{2n} & \overline{W_3} a_{n3} \end{bmatrix} \tag{9}$$

where: $\overline{W_i}$ are the calculated weight vectors from the previous step 3 using eq. 7, and a_{ij} is defined in eq. 8 above.

A detailed table which shows an example of how to use the previous equations for bike stations will be provided later on under the case study.

5. Checking the comparative matrix consistency

This is the fifth and last step of applying the AHP. In this step, it is important to make sure that the comparative matrix is consistent. This is another test to validate the assumptions made by the authors under the section titled "constructing the comparative matrix criteria". According to Saaty (1980), this consistency is measured by the consistency index (CI). CI measures the consistency of judgements across all pairwise comparisons.

In AHP, the consistency ratio (CR), is produced by dividing CI by the random index, RI, where RI is calculated by taking the average of CI values from a relatively large sample of random simulations. The judgment matrix is considered to be consistent if the corresponding CR is less than 10% (Saaty 1980). When calculating CI in this paper using the equation provided in Saaty (1980), it was found to be 0, which means that the CR is also 0. This indicates that the assumptions made by the authors have resulted in the best decision-making for the importance criteria.

Calculating TOPSIS.—This is the final step of the methodology. TOPSIS was first introduced by Hwang and Yoon (1981) then was extended by Zeleny and Cochrane (1982). There are three steps to implement TOPSIS which are well explained by Zeleny and Cochrane (1982): calculating PIS and NIS, calculating Euclidean distance to the positive and to the negative ideal soultions (S^+), and (S^-) respectively, and determining the closeness degree (C). The closeness degree (C) measures the degree of closeness of the alteranatives to the ideal solution (Hwang and Yoon 1981).

A Case study applying the methodology to a real-life BSS network

Capital Bike Share System (CBSS)

The case study chosen for this paper is a real-life BSS network located in Washington, D.C. metropolitan area and is called Capital Bike Share System or CBSS. CBSS was launched in 2010, has more than 4,300 bikes available at 500 bike stations, and covers

Table 2. An example of detailed calculations for TOPSIS.

	R-output			Equation 8			Equation 9			TOPSIS		
Bike station ID	BC	DC	CC	BC	DC	CC	BC	DC	CC	S+	S−	Topsis = *C*
14	0.0239	0.2121	0.0080	0.1117	0.9930	0.0372	0.0132	0.2671	0.0228	13.9913	14.9912	0.48275
15	0.0483	3.0000	0.0078	0.0161	0.9999	0.0026	0.0019	0.2689	0.0016	14.0030	15.0029	0.48276
16	0.0012	1.3939	0.0052	0.0009	1.0000	0.0037	0.0001	0.2689	0.0023	14.0047	15.0046	0.48277
17	0.0233	0.7273	0.0060	0.0320	0.9995	0.0083	0.0038	0.2688	0.0051	14.0010	15.0009	0.48276
18	0.0084	0.7879	0.0063	0.0107	0.9999	0.0080	0.0013	0.2689	0.0049	14.0035	15.0034	0.48276
19	0.0482	0.7677	0.0060	0.0626	0.9980	0.0078	0.0074	0.2684	0.0048	13.9974	14.9973	0.48276
20	0.0200	0.4040	0.0054	0.0494	0.9987	0.0135	0.0058	0.2686	0.0082	13.9989	14.9988	0.48276
23	0.1001	2.1414	0.0088	0.0467	0.9989	0.0041	0.0055	0.2687	0.0025	13.9993	14.9992	0.48276
24	0.1292	2.7273	0.0086	0.0473	0.9989	0.0031	0.0056	0.2686	0.0019	13.9993	14.9992	0.48276
25	0.0221	1.1212	0.0097	0.0197	0.9998	0.0087	0.0023	0.2689	0.0053	14.0025	15.0024	0.48276
26	0.0750	0.0909	0.0070	0.6355	0.7699	0.0592	0.0750	0.2071	0.0363	13.9283	14.9282	0.48267
27	0.0404	0.2828	0.0077	0.1413	0.9896	0.0268	0.0167	0.2662	0.0164	13.9879	14.9878	0.48275
31	0.0965	1.9596	0.0080	0.0492	0.9988	0.0041	0.0058	0.2686	0.0025	13.9990	14.9989	0.48276
33	0.0000	0.8182	0.0052	0.0000	1.0000	0.0063	0.0000	0.2689	0.0039	14.0048	15.0047	0.48277
41	0.0186	0.0505	0.0068	0.3421	0.9312	0.1256	0.0404	0.2505	0.0770	13.9629	14.9629	0.48271
43	0.0158	0.3939	0.0074	0.0400	0.9990	0.0189	0.0047	0.2687	0.0116	13.9999	14.9999	0.48276
46	0.0124	1.5354	0.0074	0.0081	1.0000	0.0048	0.0010	0.2689	0.0030	14.0039	15.0038	0.48276
47	0.0399	1.3838	0.0072	0.0288	0.9996	0.0052	0.0034	0.2688	0.0032	14.0014	15.0013	0.48276

six jurisdictions: Washington, DC; Arlington, VA; Alexandria, VA; Montgomery County, MD; Prince George's County, MD; and Fairfax County, VA. CBSS is available for use 24 hours a day, 365 days a year. The annual members of CBSS system have a key, and a code to unlock a bike. CBSS system collects data automatically from the start to the end of each bike trip. The dataset includes: bike number, trip start details such as day, time, and bike station ID, user type (annual, casual 24-hours, or 3-day member), and for annual trips they include the member's home zip code. The case study dataset is a historical data that was downloaded from the website of CBSS. The size of the dataset is around one million trips that took place in the fourth quarter of 2018. The CBSS network that only covers the jurisdiction of Washington, D.C. contains 99 bike stations and was used in this paper. The data needed for this research includes the distance between bike stations which was calculated using the latitude and longitude of bike stations, and the bike stations demand, which was provided in the dataset.

Spatial distance matrix measuring distances between bike stations

The study area in this research contains 99 (N = 99) bike share stations. Spatial distance matrix was found by calculating the Eucildian distance which was based on bike stations latitudes and longitudes that were provided in the dataset. The minimum and maximum distances between CBSS stations were between 0.05 and 2.5 miles, with an average distance of 0.27 mile. Bike flows were determined using origin-destination matrix. The highest and lowest daily bike flows from/to CBSS stations were 54 and 2 bikes respectively.

Evaluating bike stations importance

The novel method developed in this paper was used to evaluate the CBSS stations using their lattiude and longitude coordinates and integrating that into the MCDM technique. Then, AHP was applied to determine the weight coefficients of the evaluation criteria. In this paper, bike station importance is mainly based on topology (which means the three centrality measures: BC, CC, and DC) and also bike flows. The bike station importance in a BSS network refers to bike stations that have high location impact on the network structure and its closeness centrality measure. And in this particular case study, the more important the bike station is, the more location impact it has on the CBSS network.

Evaluating the bike station importance based on the defined criteria

BC, CC, and DC evaluation criteria are used for ranking bike stations, and are compared one by one as a single criterion with the multi-criteria TOPSIS method adopted in this paper, see Table 2. This table demonstrates how to apply the equations under the methodology developed in this paper to a subset or sample of the 99 bike stations in the case study with their IDs shown in the first column of this table. In the second column, the R software output contains computations of the three centrality measures (BC, CC, and DC) for the listed bike stations. The centrality measures have different scales (because of their different characteristics). To use similar scale, eq. 8 is applied to produce the a_{ij} factors for these three measures and results are shown in the third column of this table. The three centrality measures have different weights based on their importance (see assumptions based on authors' perspective), therefore the matrix needs to be normalized using the calculated weights in eq. 7 and the calculated a_{ij} factors in eq. 8 to produce the normalized T matrix using eq. 9; the final results are shown in the fourth column. To calculate TOPSIS in the final column, where TOPSIS is equal to the closeness degree (C), we need to calculate the Euclidean distances (S^+) to the PIS and (S^-) to the NIS using the equations reported by Zeleny and Cochrane (1982). Calculating TOPSIS is based on the concept of choosing the alternative that has the shortest distance to PIS and the farthest distance to NIS.

After ranking the centralities (BC, CC, and DC) and TOPSIS (C) for all stations as demonstrated in Table 2, the comparison between bike stations rankings was carried out using each bike station ID and the results are shown in Table 3. It can be seen from Table 3 that the bike stations with ID numbers: 234, 113, and 16 were ranked as the top three most important bike stations by both TOPSIS and degree centrality measure (DC). Please note that due to different characteristics of the centrality measures, bike stations do not have to have the same ranking across the centrality measures. For example, as shown in the highlighted fourth grey row before the end of this table, bike station 26 was ranked as the top bike station under the BC measure, but was ranked fifth under the CC measure. Similarly, the DC measure and TOPSIS have shared some similar bike stations rankings such as bike station 61 which was ranked 13th under TOPSIS and DC measure but was ranked 78th under BC and CC measures. Also, bike station 69 was ranked 94th under TOPSIS and DC measure. Moreover, bike station 41 (the last row in Table 3 highlighted in grey) was ranked as the most important bike station under CC measure but the least important bike station under TOPSIS and DC measure.

Table 3. Comparison between TOPSIS bike stations rankings and rankings based on the three centrality measures (DC, BC, and CC).

	Bike station ranking by TOPSIS and each single criterion centrality measure			
Bike station ID	TOPSIS	DC	BC	CC
234	1	1	89	97
113	2	2	87	98
16	3	3	88	89
15	4	15	77	94
418	5	8	80	91
102	6	28	66	99
46	7	5	85	77
33	8	4	90	70
59	9	26	67	96
145	10	23	71	93
84	11	25	70	95
370	12	16	75	88
61	**13**	**13**	**78**	**78**
272	14	20	74	86
302	15	17	76	80
96	16	21	73	75
351	17	29	65	82
409	18	27	69	72
18	19	11	83	64
115	20	38	57	90
47	21	31	63	76
109	22	6	86	59
149	23	37	59	81
24	24	46	48	92
23	25	45	51	83
25	26	24	72	62
31	27	50	46	84
204	28	7	91	46
249	29	18	79	57
248	30	12	84	52
153	31	9	92	45
171	32	14	81	50
230	33	55	40	79
51	34	40	54	69
386	35	10	93	43
242	36	47	49	74
92	37	59	37	85
17	38	34	61	63
387	39	51	44	71
53	40	41	53	61
229	41	67	31	87
274	42	39	56	60
137	43	58	38	68
199	44	32	64	48
103	45	19	82	40
159	46	63	35	73
19	47	61	36	66
114	48	49	50	54
108	49	48	52	49
214	50	64	34	65
82	51	57	39	55
301	52	22	94	28
207	53	66	32	58
397	54	36	62	37
20	55	52	45	42
367	56	65	33	56
394	57	30	68	33
125	58	56	41	39
399	59	76	24	67
43	60	43	55	32
443	61	72	27	41
186	62	78	20	47
391	63	54	47	27
54	64	82	17	53
319	65	85	14	51
135	66	71	28	36
76	67	33	95	15
91	68	87	13	44
251	69	35	96	12
79	70	79	21	35
107	71	77	23	34
185	72	70	29	26
413	73	44	60	14
104	74	73	26	25
310	75	81	19	29
148	76	60	43	17
349	77	88	12	38
390	78	69	30	18
188	79	74	25	22
147	80	42	97	7
336	81	53	58	10
27	82	86	15	21
193	83	84	16	20
83	84	91	9	31
348	85	89	11	24
200	86	62	42	8
106	87	92	8	30
14	88	80	22	11
187	89	90	10	13
74	90	93	7	16
206	91	83	18	6
141	92	95	5	19
357	93	98	2	23
69	**94**	**94**	6	9
393	95	68	98	3
26	96	99	**1**	**5**
86	97	75	99	2
117	98	96	3	4
41	**99**	97	4	**1**

This table demonstrates that there have been some similarities between bike station rankings by TOPSIS and DC measure, and between BC and CC measures. This finding cannot be generalized because it was a result of application to one case study, and it is unclear if the same results will hold for other BSS networks. Nonetheless, TOPSIS uses multi-criteria and is more inclusive and robust than any single criterion measure such as DC, BC, or CC. The next section explains why TOPSIS is still superior to any of the three single criterion centrality measures including DC which showed similar results to TOPSIS in Table 3.

Evaluating bike station importance based on multi-attribute ranking TOPSIS method

The global efficiency of a network graph E(G) measures the efficiency of a network in terms of exchanging information between the network nodes and measuring performance of the weighted network graph (Latora and Marchiori 2001). In this paper, E(G) is used to evaluate the efficiency of the CBSS network before and after a set of bike stations are being systematically removed. Please note that the E(G) equation provided in the above mentioned reference will be used to calculate E(G) for the CBSS case study. Figure 1 shows a comparison between TOPSIS and centrality

Fig. 1. Comparison between TOPSIS and the three centrality measures criteria for CBSS network. [Colour online.]

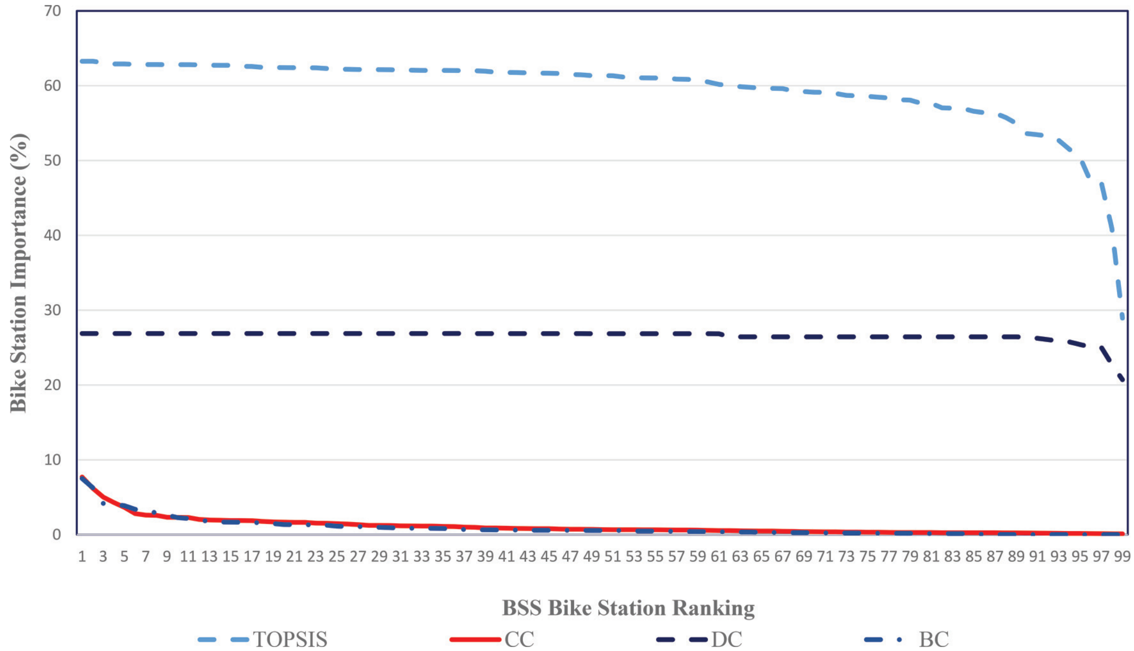
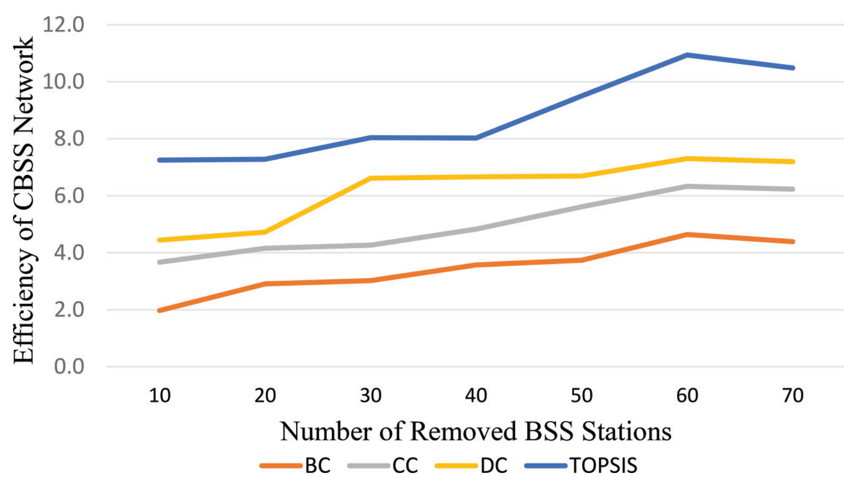


Fig. 2. Comparing global efficiency of CBSS network under TOPSIS and the three centrality measures (BC, CC, and DC), and optimal removal of least important bike stations (60 bike stations). [Colour online.]



measures (BC, CC, and DC). In this figure, bike station importance was based on the normalized *T* matrix calculated for TOPSIS, BC, CC, and DC and converted to a percentage. The DC curve is almost flat but exhibits a slight variation between the standardized values of bike station importance. This indicates that most CBSS stations have the same or similar degree of centraliy (DC), therefore we cannot depend only on DC to differentiate between bike station importance. Similarly, BC and CC centrality measures exhibit slight variations (within less than 10%) in bike station importance. On the other hand, TOPSIS has the highest standardized value of bike station importance capturing the most important bike station in the network at the origin of the graph showing 63% importance. A sudden drop is clearly demonstrated by both DC and TOPSIS at the end of the curve. This confirms the previous observation from Table 3 that both DC and TOPSIS measures share similar rankings of the 10 least important bike stations, and BC and CC measures share similar rankings of the 10 most important bike stations. However, TOPSIS shows more variations than any other single criterion centrality measure including DC measure especially towards the last part of the curve. Therefore, TOPSIS is more sensitive than single criterion measures.

To evaluate the effects on the global efficiency of the network before and after a set of bike stations have been removed, the CBSS network was improved by removing the least important bike stations. Figure 2 shows that after removing the first 50 least important bike stations, the global efficiency (E(G)) of CBSS network has improved. The efficiency of the CBSS network kept increasing until the 60 least important bike stations were removed. After that point, and if we continue removing more of the least important bike stations to reach 70 removed bike stations, the efficiency starts to drop. This is because after removing the 60 least important bike stations out of 99 bike stations (or after removing 60% of the CBSS

Table 4. Common and overlapping bike stations between service distances 0.19 mile and 0.25 mile (a total of 85 bike stations overlapped).

No. of bike stations	Bike station ID (service distance = 0.19 mile)	Bike station ID (service distance = 0.25 mile)
1	**14**	**14**
2	15	15
3	16	16
4	**17**	**17**
5	**18**	**18**
6	**19**	19
7	**20**	**20**
8	**23**	**23**
9	**24**	**24**
10	**25**	25
11	**26**	**26**
12	**27**	**27**
13	**31**	31
14	33	33
15	**41**	**41**
16	**43**	**43**
17	46	46
18	**47**	47
19	**51**	**51**
20	**53**	**53**
21	**54**	**54**
22	59	59
23	**61**	**61**
24	**69**	**69**
25	**74**	**74**
26	**76**	**76**
27	**79**	**79**
28	**82**	**82**
29	**83**	**83**
30	**84**	84
31	**86**	**86**
32	**91**	**91**
33	**92**	**92**
34	**96**	**96**
35	102	102
36	**103**	**103**
37	**104**	**104**
38	**106**	**106**
39	**107**	**107**
40	**108**	**108**
41	**109**	**109**
42	113	113
43	**114**	**114**
44	**115**	**115**
45	**117**	**117**
46	**125**	**125**
47	**135**	**135**
48	**137**	**137**
49	**141**	**141**
50	145	145
51	**147**	**147**
52	**148**	**148**
53	**149**	**149**
54	**153**	**153**
55	**159**	**159**
56	**171**	**171**
57	**185**	**185**
58	**186**	**186**
59	**187**	**187**
60	**188**	**188**
61	**193**	**193**
62	**199**	**199**
63	**200**	**200**
64	204	**204**
65	**206**	**206**
66	**207**	**207**
67	**214**	**214**
68	**229**	**229**
69	**230**	**230**
70	**234**	**234**
71	**242**	**242**
72	**248**	**248**
73	**249**	**249**
74	**251**	**251**
75	**272**	**272**
76	**274**	**274**
77	**301**	**301**
78	**302**	**302**
79	**310**	**310**
80	**319**	**319**
81	**336**	**336**
82	**348**	**348**
83	**349**	**349**
84	**351**	**351**
85	**357**	**357**
86	**367**	**367**
87	**370**	**370**
88	**386**	**386**
89	**387**	**387**
90	**390**	**390**
91	**391**	**391**
92	**393**	**393**
93	**394**	**394**
94	**397**	**397**
95	**399**	**399**
96	**409**	**409**
97	**413**	**413**
98	**418**	**418**
99	**443**	**443**
Total number of used stations =	**90**	**86**

network bike stations), the network starts to exhibit the characteristics of a disconnected graph. The largest improvement in efficiency of the CBSS network occurs when removing the least important bike stations based on the results of TOPSIS. This demonstrates that TOPSIS is more efficient than the other three criteria.

Maximal Covering location problem (MCLP)

The bike demand matrix W_{ij} for the above CBSS network in this case study was calculated by averaging the bike flow per day between bike station i and bike station j. The symmetric travel distance matrix d_{ij}, where bike flow from bike station i to bike station j was the same in both directions, was computed using the extracted latitude and longitude of bike stations. The first phase of BSS used 300 meters as spacing between bike stations similar to New York, London, and Paris per the guidelines of the Institute for Transportation and Development Policy (ITDP 2018). In this paper, three designated service distances, d_s, have been used: 300 meters (0.19 mile) which was based on the ITDP guidelines, 0.25 mile (402 meters), and 0.31 mile (500 meters). The last

Table 5. Common and Overlapping Bike Stations Between Service Distances 0.19 mile and 0.31 mile (a total of 78 bike stations overlapped).

No. of bike stations	Bike station ID (service distance = 0.19 mile)	Bike station ID (service distance = 0.31 mile)
1	**14**	**14**
2	15	**15**
3	16	**16**
4	**17**	**17**
5	**18**	**18**
6	**19**	**19**
7	**20**	20
8	**23**	**23**
9	**24**	**24**
10	**25**	**25**
11	**26**	**26**
12	**27**	**27**
13	**31**	**31**
14	33	**33**
15	**41**	**41**
16	**43**	**43**
17	46	**46**
18	**47**	**47**
19	**51**	**51**
20	**53**	**53**
21	**54**	**54**
22	59	**59**
23	**61**	**61**
24	**69**	**69**
25	**74**	**74**
26	**76**	**76**
27	**79**	**79**
28	**82**	**82**
29	**83**	**83**
30	**84**	84
31	**86**	**86**
32	**91**	**91**
33	**92**	92
34	**96**	**96**
35	102	102
36	**103**	**103**
37	**104**	**104**
38	**106**	**106**
39	**107**	**107**
40	**108**	**108**
41	**109**	109
42	113	113
43	**114**	114
44	**115**	115
45	**117**	**117**
46	**125**	**125**
47	**135**	**135**
48	**137**	**137**
49	**141**	**141**
50	145	**145**
51	**147**	**147**
52	**148**	**148**
53	**149**	**149**
54	**153**	153
55	**159**	**159**
56	**171**	171
57	**185**	185
58	**186**	**186**
59	**187**	**187**
60	**188**	**188**
61	**193**	**193**
62	**199**	199
63	**200**	**200**
64	204	204
65	**206**	**206**
66	**207**	**207**
67	**214**	**214**
68	**229**	**229**
69	**230**	**230**
70	**234**	**234**
71	**242**	**242**
72	**248**	**248**
73	**249**	**249**
74	**251**	**251**
75	**272**	**272**
76	**274**	**274**
77	**301**	**301**
78	**302**	**302**
79	**310**	**310**
80	**319**	**319**
81	**336**	**336**
82	**348**	**348**
83	**349**	**349**
84	**351**	**351**
85	**357**	**357**
86	**367**	**367**
87	**370**	**370**
88	**386**	**386**
89	**387**	**387**
90	**390**	**390**
91	**391**	**391**
92	**393**	**393**
93	**394**	**394**
94	**397**	397
95	**399**	**399**
96	**409**	**409**
97	**413**	413
98	**418**	**418**
99	**443**	**443**
Total number of bike stations needed to cover service distance =	**90**	**84**

two distances of 0.25 miles and 0.31 miles were recommended by Frade and Ribeiro (2015).

In this CBSS case study, we have assumed that the decision-maker is interested in covering all existing CBSS demand within a desirable service distance. The main objective is to minimize the number of bike stations needed to achieve coverage within the desirable distance. The number of bike stations ranges from 1 up to the minimum needed to achieve full coverage. Tables 4–7 present the solutions of the MCLP-TOPSIS model when applied to the case study. These tables show common and overlapping bike stations between different combinations of the above three service distances. Tables 4–6 show common and overlapping bike stations for different combinations of two service distances at a time, while Table 7 shows common and overlapping bike stations for all three service distances. In each of these tables, all 99 bike stations were listed and bike station IDs for the bike stations needed to cover the subject service distance (0.19, 0.25, and 0.31 mile) are shown in bold font. The total number of bike stations that were needed to cover bike demand under each of these three service

Table 6. Common and overlapping bike stations between service distances 0.25 mile and 0.31 mile (a total of 74 bike stations overlapped).

Bike stations count	CBSS bike station ID (service distance = 0.25 mile)	CBSS bike station ID (service distance = 0.31 mile)
1	**14**	**14**
2	15	**15**
3	16	**16**
4	**17**	**17**
5	**18**	**18**
6	19	**19**
7	**20**	20
8	**23**	**23**
9	**24**	**24**
10	25	**25**
11	**26**	**26**
12	**27**	**27**
13	31	**31**
14	33	**33**
15	**41**	**41**
16	**43**	**43**
17	46	**46**
18	47	**47**
19	**51**	**51**
20	**53**	**53**
21	**54**	**54**
22	59	**59**
23	**61**	**61**
24	**69**	**69**
25	**74**	**74**
26	**76**	**76**
27	**79**	**79**
28	**82**	**82**
29	**83**	**83**
30	84	84
31	**86**	**86**
32	**91**	**91**
33	**92**	92
34	**96**	**96**
35	102	102
36	**103**	**103**
37	**104**	**104**
38	**106**	**106**
39	**107**	**107**
40	**108**	**108**
41	**109**	109
42	113	113
43	**114**	114
44	**115**	115
45	**117**	**117**
46	**125**	**125**
47	**135**	**135**
48	**137**	**137**
49	**141**	**141**
50	145	**145**
51	**147**	**147**
52	**148**	**148**
53	**149**	**149**
54	**153**	153
55	**159**	**159**
56	**171**	171
57	**185**	185
58	**186**	**186**
59	**187**	**187**
60	**188**	**188**

Table 6 (*concluded*).

Bike stations count	CBSS bike station ID (service distance = 0.25 mile)	CBSS bike station ID (service distance = 0.31 mile)
61	**193**	**193**
62	**199**	199
63	**200**	**200**
64	**204**	204
65	**206**	**206**
66	**207**	**207**
67	**214**	**214**
68	**229**	**229**
69	**230**	**230**
70	**234**	**234**
71	**242**	**242**
72	**248**	**248**
73	**249**	**249**
74	**251**	**251**
75	**272**	**272**
76	**274**	**274**
77	**301**	**301**
78	**302**	**302**
79	**310**	**310**
80	**319**	**319**
81	**336**	**336**
82	**348**	**348**
83	**349**	**349**
84	**351**	**351**
85	**357**	**357**
86	**367**	**367**
87	**370**	**370**
88	**386**	**386**
89	**387**	**387**
90	**390**	**390**
91	**391**	**391**
92	**393**	**393**
93	**394**	**394**
94	**397**	397
95	**399**	**399**
96	**409**	**409**
97	**413**	413
98	**418**	**418**
99	**443**	**443**
Total number of bike stations needed to cover service distance =	**86**	**84**

distance scenarios is also shown at the very bottom of theese tables in bold font. Clearly this total is different between these three distance scenarios. However, bike stations actually overlap between the solution sets of these three distance scenarios. For example, Table 4 shows that a total of 90 and 86 bike stations are needed to cover service distances 0.19 mile and 0.25 mile respectively, and 85 of these bike stations overlap between the two service distances. Whenever there is an overlap, bike station IDs are shown in bold font and the bike station ID cells are highlighted in both second and third column of this and the other subsequent tables through Table 7. Similarly, Table 5 shows 78 overlapping bike stations between service distances 0.19 mile and 0.31 mile, where we need only 84 bike stations to cover bike demand within service distance of 0.31 mile. Table 6 shows an overlap of 74 bike stations between 0.25 mile and 0.31 mile service distances. Table 7 shows the results for all three service distances (0.19, 0.25, and 0.31). The highlighted bike station IDs in this table are for the 74 bike stations that are common and overlapping between all of these three service distances.

Table 7. Common and overlapping bike stations between service distances 0.19 mile, 0.25 mile, and 0.31 mile (a total of 74 bike stations overlapped).

Bike stations count	CBSS bike station ID (service distance = 0.19 mile)	CBSS bike station ID (service distance = 0.25 mile)	CBSS bike station ID (service distance = 0.31 mile)
1	**14**	**14**	**14**
2	15	15	**15**
3	16	16	**16**
4	**17**	**17**	**17**
5	**18**	**18**	**18**
6	**19**	19	**19**
7	**20**	**20**	20
8	**23**	**23**	**23**
9	**24**	**24**	**24**
10	**25**	25	**25**
11	**26**	**26**	**26**
12	**27**	**27**	**27**
13	**31**	31	**31**
14	33	33	**33**
15	**41**	**41**	**41**
16	**43**	**43**	**43**
17	46	46	**46**
18	**47**	47	**47**
19	**51**	**51**	**51**
20	**53**	**53**	**53**
21	**54**	**54**	**54**
22	59	59	**59**
23	**61**	**61**	**61**
24	**69**	**69**	**69**
25	**74**	**74**	**74**
26	**76**	**76**	**76**
27	**79**	**79**	**79**
28	**82**	**82**	**82**
29	**83**	**83**	**83**
30	**84**	84	84
31	**86**	**86**	**86**
32	**91**	**91**	**91**
33	**92**	**92**	92
34	**96**	**96**	**96**
35	102	102	102
36	**103**	**103**	**103**
37	**104**	**104**	**104**
38	**106**	**106**	**106**
39	**107**	**107**	**107**
40	**108**	**108**	**108**
41	**109**	**109**	109
42	113	113	113
43	**114**	**114**	114
44	**115**	**115**	115
45	**117**	**117**	**117**
46	**125**	**125**	**125**
47	**135**	**135**	**135**
48	**137**	**137**	**137**
49	**141**	**141**	**141**
50	145	145	**145**
51	**147**	**147**	**147**
52	**148**	**148**	**148**
53	**149**	**149**	**149**
54	**153**	**153**	153
55	**159**	**159**	**159**
56	**171**	**171**	171
57	**185**	**185**	185
58	**186**	**186**	**186**
59	**187**	**187**	**187**
60	**188**	**188**	**188**
61	**193**	**193**	**193**

Table 7 (*concluded*).

Bike stations count	CBSS bike station ID (service distance = 0.19 mile)	CBSS bike station ID (service distance = 0.25 mile)	CBSS bike station ID (service distance = 0.31 mile)
62	**199**	**199**	199
63	**200**	**200**	**200**
64	204	**204**	204
65	**206**	**206**	**206**
66	**207**	**207**	**207**
67	**214**	**214**	**214**
68	**229**	**229**	**229**
69	**230**	**230**	**230**
70	**234**	**234**	**234**
71	**242**	**242**	**242**
72	**248**	**248**	**248**
73	**249**	**249**	**249**
74	**251**	**251**	**251**
75	**272**	**272**	**272**
76	**274**	**274**	**274**
77	**301**	**301**	**301**
78	**302**	**302**	**302**
79	**310**	**310**	**310**
80	**319**	**319**	**319**
81	**336**	**336**	**336**
82	**348**	**348**	**348**
83	**349**	**349**	**349**
84	**351**	**351**	**351**
85	**357**	**357**	**357**
86	**367**	**367**	**367**
87	**370**	**370**	**370**
88	**386**	**386**	**386**
89	**387**	**387**	**387**
90	**390**	**390**	**390**
91	**391**	**391**	**391**
92	**393**	**393**	**393**
93	**394**	**394**	**394**
94	**397**	**397**	397
95	**399**	**399**	**399**
96	**409**	**409**	**409**
97	**413**	**413**	413
98	**418**	**418**	**418**
99	**443**	**443**	**443**
Total number of bike stations needed to cover service distance =	**90**	**86**	**84**

Next, we compare the MCLP-TOPSIS multi-criteria model with the MCLP using a single criterion measure. Table 8 demonstrates the results of this comparison. In this table, cells highlighted in grey under thte "Number of Bike Stations" columns refer to the total number of bike stations needed to achieve nearly 100% bike network demand coverge for the specified service distance in the table. While cells highlighted in grey under the "Coverage (%)" columns indicate the exact percentage of bike network demand coverage achieved for this distance. As shown in this table, using 50 intial bike stations located within 0.19 mile service distance (which were the top 50 most important bike stations from the output of bike station importance), a service distance of 0.19 mile, and a demand of 850 bikes per day for these 50 bike stations, we get a 48.1% bike network demand coverage. In the second row of the table, and after adding the next top 10 most important bike stations, thus increasing the number to 60 bike stations, a bike network demand coverage of 54.9% is achieved. The calculations continued until 99.5% (or close to 100%) bike network demand coverage is reached. This 99.5% coverage was achieved using only 90 of the 99 bike stations and was only achieved after removing the 10 least important bike stations in the CBS network. In addition, the results indicate that increasing the service distance leads to decreasing the number of bike stations due to the overlapping between bike stations in the solution sets as explained when commenting on the previous Tables 4–7.

Now, we compare between the results of using MCLP based on TOPSIS (multi-criteria decision making) or MCLP-TOPSIS as accomplished in this paper and the results of MCLP using a single criterion or MCLP-CC (here we choose Closeness Centrality (CC) as used in Rahim Taleqani et al. 2020 for this comparison). As can be seen from Table 8, while TOPSIS was able to achieve maximum bike network demand coverage using only 90 bike stations, the CC single criterion needed 98 out of the 99 bike stations to achieve this same coverage for the same service distance of 0.19 mile. Similarly, for service distance of 0.25 mile, MCLP-TOPSIS achieved close to 100% or maximum coverage using only 86 bike stations compared to 98 bike stations as needed by the CC single criterion method. And for service distance 0.31 mile, MCLP-TOPSIS used only 84 bike stations compared to 98 bike

Table 8. Comparison of bike network demand coverage between MCLP-TOPSIS and MCLP-Close Centrality methods for the CBSS case study network.

Service Distance ds (Mile)	Number of Bike Stations	Demand (Bikes/Day)	Coverage (%)
MCLP - TOPSIS			
0.19	50	850	48.1
	60	970	54.9
	70	1144	64.8
	80	1387	78.5
	90	1757	99.5
0.25	50	925	52.4
	60	1039	58.8
	70	1213	68.7
	80	1425	80.7
	86	1763	99.8
0.31	50	936	53.0
	60	1077	61.0
	70	1264	71.6
	80	1476	83.6
	84	1766	100.0
MCLP - Closeness Centrality (MCLP – CC)			
0.19	50	766	43.4
	60	938	53.1
	70	1192	67.5
	80	1390	78.7
	90	1591	90.1
	98	1761	99.7
0.25	50	779	44.1
	60	951	53.9
	70	1205	68.2
	80	1403	79.4
	90	1604	90.8
	98	1755	99.4
0.31	50	783	44.3
	60	955	54.1
	70	1209	68.5
	80	1407	79.7
	90	1608	91.0
	98	1759	99.6

stations required by the MCLP-CC method to achieve maximum coverage. It is obvious that MCLP-TOPSIS has outperformed single criterion centrality measures such as the CC method. These results are consistent with Palomares et al. (2012) who maximized the population covered within a 200 m (0.12 mile) radius around bike stations in the CBSS network.

In summary, this paper introduced an innovative approach through the integration of bike station importance into the MCLP optimization model to achieve maximum demand coverage within a desired service distance. The hybrid methodology introduced for the first time in this paper, can be used to determine if there is a need to add a new bike station, or relocate or remove the least important existing bike stations. This new methodology can also be used to optimize the number of bike stations subject to budget and resource allocations constraints.

Conclusions and recommendations

This paper makes a unique contribution by developing a new methodology for identifying and evaluating BSS networks. The developed MCLP model was used to maximize the demand coverage within a desired service distance in the BSS network. Bike station importance has been integrated into the MCLP model using three centrality measures as criteria (BC, CC, and DC) instead of a single criterion which uses only one of these centrality measures as has been reported in the literature. A Multi Criteria Decision Method (MCDM) was developed based on the Technique for Order Preference by Similarity to Ideal Object (TOPSIS) to comprehensively evaluate bike station importance. This newly developed methodology has been applied to a case study of the Capital Bike Share System (CBSS) in Washington, D.C. A historical data file containing data from the fourth quarter of 2018 for the entire 99 bike stations of the CBSS network was used to run the models that were developed as part of the new methodology and results were demonstrated thoroughly in this paper.

It was found that removing the least important CBSS bike stations and using the most important ones will maximize the CBBS network demand coverage and improve its efficiency. Furthermore, the new method developed in this paper, which uses multi-criteria, was compared to existing methods that use only a single criterion (e.g., Closeness Centrality) and the results of this comparison indicate that the new method was more efficient and has outperformed the single criterion centrality measures.

Findings of this research have a great potential. For example, the new methodology can be used to optimize bike stations locations and to determine if there is a need to add a new bike station or relocate or remove an existing one based on bike station's importance. For the expansion of this research, it is recommended to explore additional criteria in the evaluation of bike station importance such as geographic location, human activities in the vicinity of bike stations, and to examine other and additional optimization objectives such as minimizing travel time between bike stations.

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