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A GIS-MCDM Method for Ranking Potential Station Locations in the Expansion of Bike-Sharing Systems

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Abstract: Bicycle-sharing systems (BSSs) are an effective solution to reduce private car usage in most cities and are an influential factor in encouraging citizens to shift to more sustainable transport modes. In this sense, the location of BSS stations has a critical impact on the system's efficiency. This study proposed an integrated geographic information system–multi-criteria decision-making (GIS-MCDM) framework that includes the analytic hierarchy process (AHP), technique for order preference by similarity to the ideal solution (TOPSIS), and spatial data processing in GIS to determine a ranking of potential locations for BSS stations. The results of the proposed GIS-MCDM method can be used for both planning a new BSS or expanding one that is currently under operation. The framework was applied to a case study for expanding GIRA, the BSS of Lisbon, Portugal. In it, location criteria were selected in four categories, including criteria from the literature and extracted from available transaction data; in addition, we also suggested some criteria. The rebalancing operator's staff were the decision makers in this study via their responses to the AHP questionnaire. The rebalancing staff believed that the main criterion of "city infrastructure" with the two sub-criteria of "population density" and "slope" were the most important. Furthermore, the proximity to the "bike network" with the sub-criterion of "proximity to the current bike stations" had less importance. Each criterion's weight and inconsistency rate were obtained using the Expert Choice software. The geographic values of each criterion were created utilizing the ArcGIS software, and its network analyst module was employed for applying location techniques. Based on the created suitability map, the city's center was the main suitable area for establishing new stations. Forty-five new bike stations were identified in those areas and ranked using the TOPSIS technique.

Keywords: bike-sharing systems; station location; GIS; MCDM in engineering; dynamic virtual stations; rebalancing operators

MSC: 90B80; 90B50

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1. Introduction

The environmental benefits of bicycle-sharing systems (BSSs) have made this mode of transportation more popular globally [1]. Encouraging people to use BSSs intensifies a reduction in private car usage, which means that, among many other benefits, BSSs can contribute to reducing traffic intensity and pollutant emissions, in line with the sustainable transportation strategies of many cities.

Station-based (SBSSs) and dock-less (DBSSs) are the two most recent generations of BSSs. SBSSs have several fixed stations and a dedicated infrastructure that allow for the pickup and drop-off of bicycles within a delimited urban area. To rent a bike for a period, users must find and go to a nearby station with a smartphone app. At the end of the trip, it is possible to return the bike to the same or another station close to the user's destination. As a result, access to the station network restricts the utilization of SBSSs. In addition, because of the capacity limitations of each station, users may face a station with full racks when bike delivery is needed, or, on the other hand, an empty station will not meet the needs of a user who has come to rent a bike. In DBSSs, there are no fixed stations; thus, bicycles can be picked up or dropped off anywhere within the zone of operation. DBSSs are less restrictive because they do not have fixed stations.

Based on the literature, user satisfaction and the operator's profit are the two main components that must be provided in BSSs [2,3]. SBSS bikes continuously shift between stations; hence, the stations' bike inventory changes over time. Systems that cannot respond to an instantaneous demand from a user (either picking up or dropping off a bicycle) are "unbalanced". When the system is unbalanced, the user tends to be dissatisfied, and the rebalancing of the system is costly for the operator. To deal with the problem of an unbalanced system, operators have a variety of strategies for rebalancing; rebalancing based on the operator's effort by directly moving bicycles between stations (which includes static rebalancing [4] and dynamic rebalancing [5]) and rebalancing based on a scheme of incentives to users [6] are two of the main approaches. Both aim at an equilibrium point of bicycle pick-up and drop-off location availabilities. Operators typically use one or more rebalancing vehicles to move bicycles between stations in the mentioned rebalancing strategies.

There are several factors that can cause a system to be unbalanced, which can be divided into three main categories: "Users", "Environment", and "System" [7]. "Users" encompasses all user-related factors that can have an impact on network performance alone; "Environment" includes the external physical aspects that influence the system usage; and "System" incorporates the factors that are controlled or defined by the system operator and the mobility authorities, for instance, bikes, bike lanes, and stations. Regardless of which of the above factors has caused the system to become unbalanced, the operator must rebalance it. Rebalancing the system is directly related to the number and capacity of the stations and especially their location in a system.

In both SBSSs and DBSSs, planning a new system or developing one currently under operation by adding stations and changing existing station configurations are complex problems. Primarily, having an efficient system with suitable station locations (fixed stations in SBSSs [8], virtual stations in DBSSs [9], or virtual stations in a mix of both generations [10]) is a challenging task. One study [11] aimed to determine the optimal station number and distribution to enable more efficient systems. The authors considered public transport infrastructure, land use, and population density factors. In addition, some studies have paid particular attention to the impact of station capacity (number of racks in a station) [12] on the unbalancing potential. The higher the number of racks in a station, the less likely the station is to become unbalanced. However, due to limitations such as a lack of space and the higher cost of building stations with more capacity, it is not easy to create large stations in every suitable location. Apart from the number of stations in the network and their capacity, the most important challenge is finding suitable station locations, as studied in [13–15].

Nevertheless, two gaps are evident in previous studies. First, the criteria chosen for the station location generally exclude the executive and operational dimensions (i.e., system criteria that include aspects such as bike trip duration, user residence location, the existence of bike stations, and bike parking, among others). Generally, the location of a bike station (or bicycle parking) considers four main criteria categories: "bike network", "operator", "user", and "city infrastructure" [16], which we included in our study. Stations are located mainly based on theoretical criteria. However, a greater unbalancing problem will exist in stations in which the location choice considers theoretical criteria only. Conversely, unbalancing will decrease if the system's criteria are also included. Second, in most studies, the experts who prioritized the selection criteria did not consider the operators' perspective, meaning that the agent who would run the BSS was excluded from the decision-making process.

The present paper aims to fill both research gaps, i.e., identify and rank the relevant system criteria for the location of BSS stations. These criteria included all three domains of "Users", "Environment", and "System" (operational aspects). The knowledge and experience of several rebalancing operators' staff were used to identify the criteria prioritization to respond to the second gap. Eventually, the results of this study revealed the efficiency of the proposed method.

This paper is organized into five sections. After this introduction, Section 2 presents a brief overview of the MCDM techniques and related works. In addition, the contribution of this study to the topic will be interpreted. Section 3 describes the GIS-MCDM method used for BSS station location selection. Section 4 describes and analyzes the results of our case study. Finally, Section 5 presents the main conclusions of the study.

2. Related Work

2.1. Prior Research

The focus of this study was on BSS station location selection. Many methods have been used for facility location selection problems, some of which are related to transportation station locations, such as electric vehicle charging stations (EVCSs) [17], bus stations [18], and metro stations [19], among others. Based on the literature, many different location modeling techniques have been used to optimize the location problem, which we can categorize into three groups [16]: "Mathematical algorithms", "MCDM", and "GIS". The combination of GIS and MCDM has received more attention in recent years to locate bike stations and has more precise and practical results [16].

Rybarczyk and Wu [20] proposed an MCDM and GIS-based method to explore the spatial patterns of bicycle facilities in the city of Milwaukee, United States. In this study, the authors selected and ranked the factors influencing bike demand. Their hybrid GIS and MCDM analysis confirmed the effectiveness of the method. Later, Palomares et al. [21] proposed a method based on GIS by testing two location-allocation models (minimizing impedance and maximizing coverage) to locate the bike-sharing stations of the *MyBici* BSS in Madrid while determining the stations' capacity based on demand data. In 2013, Ghandehari et al. [22] used AHP to find the best BSS station locations in Isfahan, Iran. The authors used a paired-comparison questionnaire to determine the criteria and sub-criteria weights by interviewing municipality officers—this was one of the few studies that interviewed a non-academic group with BSS operational experience. Still, there is no evidence that any of the reviewed methods resorted to network performance criteria or necessarily interviewed BSS operators, who are key players.

Other researchers have used the GIS-MCDM method in their BSS station location studies [13–15]. Kabak et al. [13] located future station sites by comparing them to existing stations and testing the AHP and MOORA approaches. Karşıyaka, a district in the Izmir province in Turkey, was used as their case study. Twelve different criteria were considered to evaluate the current stations and select alternatives. An AHP individual pairwise comparison questionnaire for determining the criteria weights was carried out by interviewing experts (unknown number), four citizens using city bicycles, and the research team members. Guler et al. [14] used AHP, fuzzy AHP, and the best worst method (BWM) to calculate the criteria weights. Next, TOPSIS was applied to rank the alternative bike station locations. The authors were the only group responding to the pairwise comparisons to determine the criteria weights. Another study by Guler et al. [15] simultaneously tried to identify the suitable places for BSS stations and bikeways in six districts of Istanbul, Turkey. BWM and TOPSIS were used to determine the weights of eight selected criteria and the ranking of the alternatives, respectively. An experienced cyclist was the only expert to respond to the pairwise comparisons. Although this study considered only a few criteria in the location modeling, they concluded that the method provided remarkable results that could be helpful for transportation planners and policymakers.

2.2. Contributions of This Study

Previous studies have considered fewer criteria categories for selecting potential bike station locations. This study considered four categories: "bike network", "operator", "user", and "city infrastructure". As far as the literature shows, this is the first time that a study has used operational criteria. Furthermore, in most of the earlier studies, the target group responding to the MCDM questionnaire were academics [13,14]. There was no representation of the operator, who runs the network daily and is aware of its challenges. Here, we included the opinions and rebalancing experience of the operator's staff. Finally, previous studies have resorted to MCDM analysis for weighting and ranking processes. In contrast, this study proposed AHP and TOPSIS techniques to obtain criteria weights and rank the potential bike station locations, respectively.

3. Materials and Methods

3.1. Study Area

The study area included all 24 administrative districts (*freguesias*) of Lisbon, the capital of Portugal. The districts are very different regarding access to public transport stations, such as subways, BSSs, or bus and taxi hubs. Close to 5% of Portugal's population—about half a million people—reside in Lisbon, which is over 100 km^2. The European Commission designated Lisbon as the European Green Capital in 2020. From 2017 to 2020, the city invested in its cycling network and its public station-based BSS, resulting in a very significant uptake of cycling activity [23]. Lisbon is focused on reaching a 60% reduction in emissions by 2030 and going net-zero emissions by 2050, a mission assumed by other cities worldwide [24]. The city is characterized by irregular orography, making it hard to cycle in some parts. Although it is perceived as a hilly city, 54% of the streets are almost flat (<3% inclination), while 75% are below a 5% grade, which is good enough for cycling [25]. Lisbon's public BSS, GIRA, was considered when selecting the study area. Lisbon's mobility manager, EMEL, implemented GIRA in 2017 and is the current operator. Today, Lisbon has 113 GIRA stations, more than 1000 bicycles, and around 2200 docks [26]. Figure 1 shows the study area map, including its 24 zones corresponding to the *freguesias*.

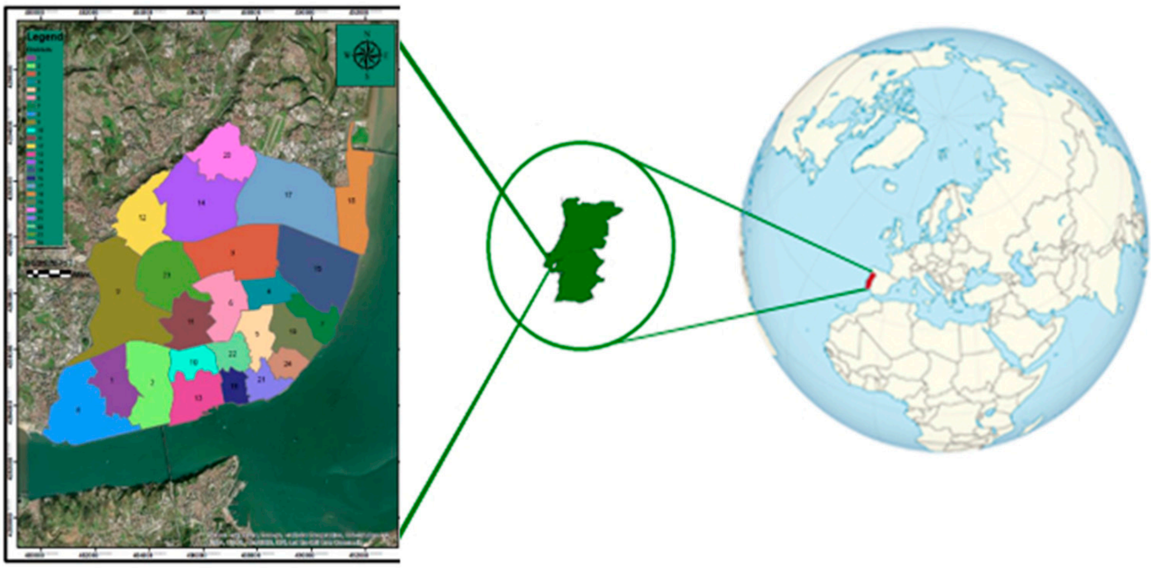

Figure 1. Map of the study area in Lisbon, Portugal.

3.2. Methods

This study focused on the location selection of BSS stations using a GIS-MCDM method. The proposed method uses the geospatial capabilities of GIS and the flexibility of MCDM to combine location criteria and expert opinions on their importance. As such, the method aims to help decision makers and operators obtain a rank of station locations in the context of BSS expansion. The method is separated into three steps:

- The criteria selection is detailed in Section 4.1;
- The MCDM method is described in Section 4.2;
- The GIS data processing is detailed in Section 4.3.

The first step of the proposed method is the identification of the various criteria that might influence the station location process. To support this, frequently used criteria can be determined based on literature reviews [8,11,13–15]. Still, case-specific criteria may also be considered, e.g., valuable and influential location factors can be identified from existing transaction data. We also suggested complementary criteria (which had not been considered in the literature) to be considered in the model, as described in Section 4.1.

In the next two steps, a geographic information system (GIS) and multi-criteria decision-making (MCDM) method were utilized to distinguish the spatial characteristics and evaluate the geographic values of the selected criteria. The analytic hierarchy process (AHP) [27] and the technique for order preference by similarity to the ideal solution (TOPSIS) [28] were combined with the GIS to designate the priorities and rank bike stations by assessing the selected criteria. AHP and TOPSIS are frequently preferred in most other fields that utilize station selection or rank proposed alternatives [29–31]. This research provides an AHP-TOPSIS model that takes both qualitative and quantitative elements into account. In this regard, AHP can be beneficial in bringing together different decision makers with multiple competing criteria to reach a decision. The TOPSIS approach was used to determine the alternative ratings.

The performance of the proposed GIS-MCDM method was comprehensively assessed with the case study of the GIRA public BSS in Lisbon, Portugal.

In the second step, criteria and sub-criteria are weighted to output a schema to rank the potential station sites. One of the possibilities to consider the relative importance of criteria in the problem definition is through questionnaires in which pairwise comparisons of criteria are scrutinized. In the application, a questionnaire is distributed among the three operators' staff, and the results of the pairwise questionnaire are entered in Expert Choice. Expert Choice, used for multi-criteria decision making, is based on AHP, which combines the calculation of priorities, the inconsistencies of experts' judgments, and sensitivity analysis [32]. It is a free and open-source software that can be downloaded from https://www.expertchoice.com/ (accessed on 15 April 2022) [33].

In the third step, spatial layers of information are collected from several data sources to input the location criteria. A set of GIS spatial tools are used to prepare the layers. All data are transformed and standardized to have a set of comparable units. The identified alternative bike station locations are ranked using the TOPSIS method with normalized criteria values. Finally, the best locations are identified as new locations for bike stations.

4. Results and Discussion

4.1. Criteria Selection

We selected criteria from four categories: "bike network", "operator", "user", and "city infrastructure", which were previously collected from a comprehensive literature review [16]. We complemented the set of criteria after analyzing the characteristics of a currently operating BSS. We found that relevant criteria were not included in previous studies. Table 1 specifies the criteria used in this study.

Six criteria were chosen for the "bike network" category. The first three of those criteria were directly related to the "Cycling infrastructure (C1-1)", including "Proximity to the current bike stations (C1-1-1)", "Proximity to the current bikeways (C1-1-2)", and "Proximity to the current bike parking spots (C1-1-3)". The integration of current bike stations, bike parking, and bike routes can play a significant role in successful system expansion and increasing cycling trips [14]. The uninterrupted connection between stations and parking spots increases the attractiveness of cycling and reduces exposure to accident risks (C1-1). Therefore, if new stations' locations are close to cycling infrastructures (C1-1), their suitability will be higher. Since Lisbon was the selected case study, three more sub-criteria were chosen related to the GIRA bike-sharing network and under the main criteria of "Bike network": "Proximity to the current bike stations with high transactions (C1-2)", "Proximity to the zones with high user membership density (C1-3)", and "Proximity to top ten bike stations with high duration trips (C1-4)". These criteria show how important current stations and the area close to these zones are to establishing new stations or vice versa. The mentioned criteria had not been considered in previous studies and were selected based on the performance of GIRA. Another criterion showed the difference between the sum of the total check-in and check-out and the operator's attempt to balance the station during a year.

Table 1. The final list of criteria selection.

Main Criteria	Sub-Criteria		# Criteria
(C1) Bike network	(C1-1) Cycling infrastructure	(C1-1-1) Proximity to the current bike stations	#1
		(C1-1-2) Proximity to the current bikeways	#2
		(C1-1-3) Proximity to the current bike parking spots	#3
	(C1-2) Proximity to the current bike stations with high transactions		#4
	(C1-3) Proximity to the zones with high user membership density		#5
	(C1-4) Proximity to top ten bike stations with high duration trips		#6
(C2) Operator	(C2-1) Proximity to the bike stations with unbalanced OD		#7
(C3) User	(C3-1) Proximity to the users' residence		#8
(C4) City infrastructure	(C4-1) Proximity to the points of interest (POI)		#9
	(C4-2) Proximity to the zones with higher population density		#10
	(C4-3) Proximity to the public transport	(C4-3-1) Proximity to the metro and train stations	#11
		(C4-3-2) Proximity to the taxi hubs	#12
	(C4-4) Proximity to the electric vehicle charging stations		#13
	(C4-5) Proximity to areas with a low slope		#14

The second category was the "operator". The operator is responsible for managing, maintaining, and repairing the network's elements in a BSS. Successful management from the operator will keep a BSS balanced, minimizing the occurrence of full and empty stations. Criterion number 7 refers to the stations with unbalanced origin-destination (O-D) transactions.

The third category referred to the "user". The "Proximity to the users' residence (C3-1)" is important because it shows the origin of most trips in the morning and destinations in the afternoon. Residence locations were identified at the block level (street segment and side) using the Portuguese postal code geocoding.

The last key criterion was "City infrastructure (C4)". The "Proximity to the Points of Interest (POI) (C4-1)" is an essential criterion as citizens frequently visit POI daily, and there is a potential for using the BSS. Thus, their suitability is higher if the proposed new station locations are close to POI. Shopping malls, parks, hospitals, museums, schools, universities, health centers, post offices, and churches are examples of POI that were considered in this study. Population density (C4-2) is a good cycling demand potential proxy indicator [34]. Hence, proximity to higher population density zones raises the appropriateness of a new station's location. Proximity to public transport (C4-3) is essential to promote intramodality with public transport and fulfill the "first-and-last miles" functionality of the BSS [35]. This research included metro, railways, and taxi hubs. If the new bike locations are close to the public transportation station, their suitability is high. Proximity to electric vehicle charging stations (C4-4) was one of the criteria that had not been considered in any study thus far. By viewing this criterion, the interaction between other transport modes will increase. In addition, because electric car drivers must wait for a long time to charge their car's battery, they can hire a bike from the nearest station to do their work. Finally, proximity to a lower gradient area (C4-5) was the last significant criterion affecting the location suitability of

SBSSs. The suitability of the proposed location is higher if it has a lower gradient that facilitates its access, namely when walking.

4.2. MCDM Technique

Based on the literature, one of the highly utilized MCDM techniques to calculate the weights of a set of criteria is the analytic hierarchy process (AHP), first introduced by Saaty [27]. AHP considers subjective factors of a group of individuals in relation to a set of linked criteria and analyzes the findings. The AHP technique includes the following steps:

1. Creating hierarchical model trees of assessment elements;
2. Building a pairwise comparisons questionnaire using a scale of 1–9;
3. Determining the weights of criteria;
4. Analyzing the consistency.

In the first step of the AHP approach, the three layered tree includes the goal, the criteria, and the station alternatives. In this study, bike-sharing station location selection was the goal layer. The criteria layer consisted of the fourteen criteria listed in Table 1. The proposed bike stations were calculated in the TOPSIS approach as the alternative layer. In matrix A, the element a_{ij} is the relative value of the ith criterion with respect to the jth criterion, built by experts, according to a pairwise questionnaire with a scale (1–9), as given in Table 2. Then, a_{ji} can be calculated as $1/a_{ij}$.

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} \tag{1}$$

Table 2. Pairwise comparison scale (1–9).

Scale of Importance	Interpretation
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong or demonstrated importance
9	Extreme importance
2, 4, 6, 8	Compromise between the abovementioned values

In the third step, the comparative importance of each criterion was assigned by three rebalancing staff working in the GIRA BSS in Lisbon. An individual explanation of the evaluation criteria was performed for rebalancing staff (as the respondents to the questionnaire) to clarify the logic of each criterion with particular emphasis on the metrics of the weighing scale. For example, C1-1-1, proximity to current bike stations, was compared with C1-1-2, proximity to current bikeways, by asking the question: “Which is considered more important for bike stations location, and how much more important is it?” The determined scale was imported to the Expert Choice software, and the software calculated the weights of each criterion.

The last step was to look for data inconsistencies in the weight results. The goal was to obtain enough information to find out whether the rebalancing staff (decision makers) were consistent in their choices or not. For example, if the rebalancing staff affirmed that the bike network criteria (C1) were more important than the user criteria (C3) and that the user criteria were more important than the operator criteria (C2), it would be inconsistent to affirm that the operator criteria were more important than the bike network criteria (if C1 > C2 and C2 > C3, it would be inconsistent to say that C1 < C3). The AHP matrix is called consistent if $a_{ik} \cdot a_{kj} = a_{ij}$, where a_{ij} is the ijth element of the AHP matrix [27]. In research with more criteria, conveying subjective opinions usually leads to matrices with inconsistency. A measure of inconsistency in a matrix can be performed through the consistency ratio (CR)

to ensure their values are less than 0.1. By using the maximum eigenvalue (λ_{max}), the consistency index (CI) can be determined through Equations (3) and (4). In Equations (2)–(4), the random index (RI) is the average random consistency random index (Table 3), n is the evaluated criteria, A is the pairwise comparison matrix of the criteria, and W is the weight's vector.

$$CR = \frac{CI}{RI} \tag{2}$$

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{3}$$

$$AW = \lambda_{max} W \tag{4}$$

Table 3. Average random consistency index.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The consistency ratio (CR) was calculated using the Expert Choice software. The matrix is suitable when the CR is less than 10%; if not, the analyst must re-estimate the pairwise comparison matrix. In this study, the CR was acceptable and less than 0.1. The final suitable criteria weights can be found in Table 4.

Table 4. The weighting of layers using AHP with the Expert Choice software.

Layer	# Criteria	Weight
(C1-1-1) Proximity to current bike stations	#1	0.026
(C1-1-2) Proximity to current bikeways	#2	0.084
(C1-1-3) Proximity to present bike parking spots	#3	0.029
(C1-2) Proximity to existing bike stations with high transactions	#4	0.098
(C1-3) Proximity to zones with high user membership density	#5	0.095
(C1-4) Proximity to top ten bike stations with high duration trips	#6	0.091
(C2-1) Proximity to bike stations with unbalanced OD	#7	0.098
(C3-1) Proximity to users' residence	#8	0.070
(C4-1) Proximity to points of interest (POI)	#9	0.038
(C4-2) Proximity to zones with higher population density	#10	0.111
(C4-3-1) Proximity to metro and train stations	#11	0.074
(C4-3-2) Proximity to taxi hubs	#12	0.044
(C4-4) Proximity to electric vehicle charging stations	#13	0.037
(C4-5) Proximity to areas with low slope	#14	0.105
	Sum:	1.000

According to Table 4, the rebalancing staff believed that the main criterion of city infrastructure (C4) with the two sub-criteria of proximity to zones with higher population density and proximity to areas with a lower slope were more important than the other main criteria. From the results, the proximity to the bike network (C1) had less importance and the proximity to current bike stations was the less critical sub-criteria.

- **TOPSIS Approach**

The technique for order preference by similarity to the ideal solution (TOPSIS) is an MCDM method used for selecting the ideal choice by decision makers. A simple approach is followed in this method: the best alternative (Si*) must have a minimum distance to a positive (Si^{+}) solution. Simultaneously, it must have a maximum distance to a negative (Si^{-}) solution. The TOPSIS method was used to rank the alternative bike stations' locations after they were selected. The TOPSIS method was used to obtain more reliable suggestions. TOPSIS equations are not shown in this paper because of the word limitations, and [28] is recommended for a detailed explanation.

4.3. GIS Analysis

After weighing the fourteen criteria for bike station locations, the ArcGIS 10.7.1 software from ESRI was employed to process the related spatial data. Additionally, it was used to map the resulting values and analyze the results. To obtain a final combination map, first, each criterion's map must be created separately. Then, to guarantee measurement integrity, we normalized the results obtained for each criterion according to three levels of evaluation—minimum (level 0), intermediate (level 0–1), and optimum (level 1)—and used these levels to build up raster layers covering the area of Lisbon. Hence, each criterion map layer portrayed normalized values. Then, we combined all map layers of each criterion into one final index using a raster weighted sum, considering the weights calculated in Section 4.2.

Figure 2 shows the raster suitability map for the bike station location, where each cell depicts the final weighted combination of all selection criteria. The darker the cell is, the more suitable it is to locate a BSS station. Based on the suitability map, the central area of the map, which represents the districts of Alvalade, Avenidas Novas, and Areeiro, showed three main suitable areas for establishing the new bike stations. These corresponded to the Central Business District of Lisbon, also known as the Central Axis. In the northeast of the city, Parque das Nações, was also ranked high. This is a new neighborhood and centrality of Lisbon with mixed uses (residence, commerce, services, and public transport interfaces), built upon former brownfields in the 1990s. Conversely, the city's southwest area, close to Belém, Ajuda, and Alcântara, had the lowest rates, indicating that these sites were not as suitable for constructing BSS stations, according to the opinion of rebalancing staff. However, from a demand perspective, these areas have important tourist attractions. In other cities, it was demonstrated that demand from tourists can be an important part of the overall BSS demand [36].

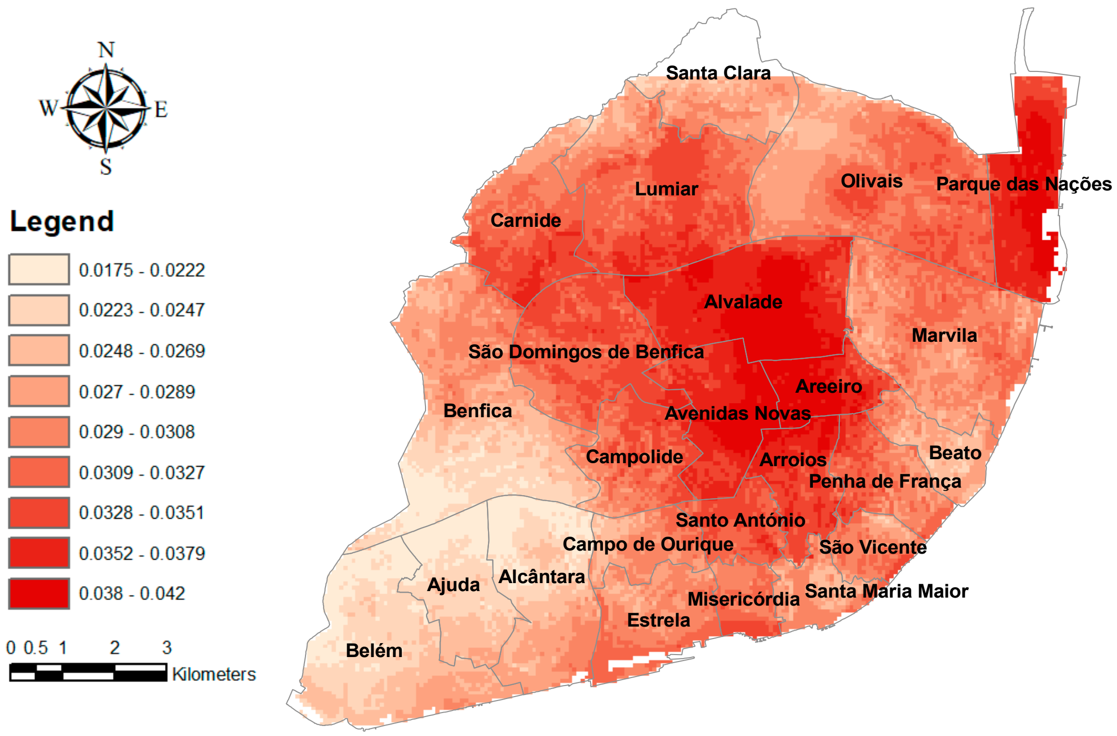

Figure 2. Normalized suitability map for alternative BSS station locations.

Applying the MCDM-GIS method to the case study of Lisbon mapped the suitability zones for BSS station location. However, the areas were too vague, and we could not find any classification method to identify more specific alternative station locations (spots) [13]. Figure 2 illustrates the more suitable reddish areas with values ranging from 0.0379 to

0.0420 (bottom class in the legend's scale). Interestingly, the places that scored greater than 0.0289 (median value of the scale) encompassed the current BSS stations, matching the selection procedure of EMEL's planners. Therefore, due to the high construction cost of bike stations and initial budget constraints, we raised the bar for the area's suitability for new bike stations and defined a lower limit of 0.0353 on the suitability scale. In addition, a minimum distance of 250 m was considered between the proposed stations and current stations [13,15], as the weights of criteria numbers 1 and 3 highlighted the importance of this factor. Figure 3 illustrates the areas suitable for installing new BSS stations. In the figure, areas with light colors are highly unsuitable, and areas with blue and pink colors have higher suitability. In Figure 3, the current bike stations are symbolized by red stars, and new proposed stations are identified by black circles next to the bikeways network. The new proposed stations are much closer to the bikeways by considering the suitable classification compared to the previous stations. In addition, in the location selection of the new proposed stations, the importance of criteria with high weight (see Table 4), such as population density and slope, had had a higher impact. Figure 3 shows the suitability differences between the location of the current stations and proposed stations. Based on Figure 3, stations 27, 55, and 11 are not in the appropriate locations, while the proposed stations 8, 32, 29, 30, and 33 are located in extremely suitable locations. In downtown, stations 46, 61, and 82 are located in less suitable locations in comparison to the new proposed stations in the same area, which are stations 28, 3, and 4.

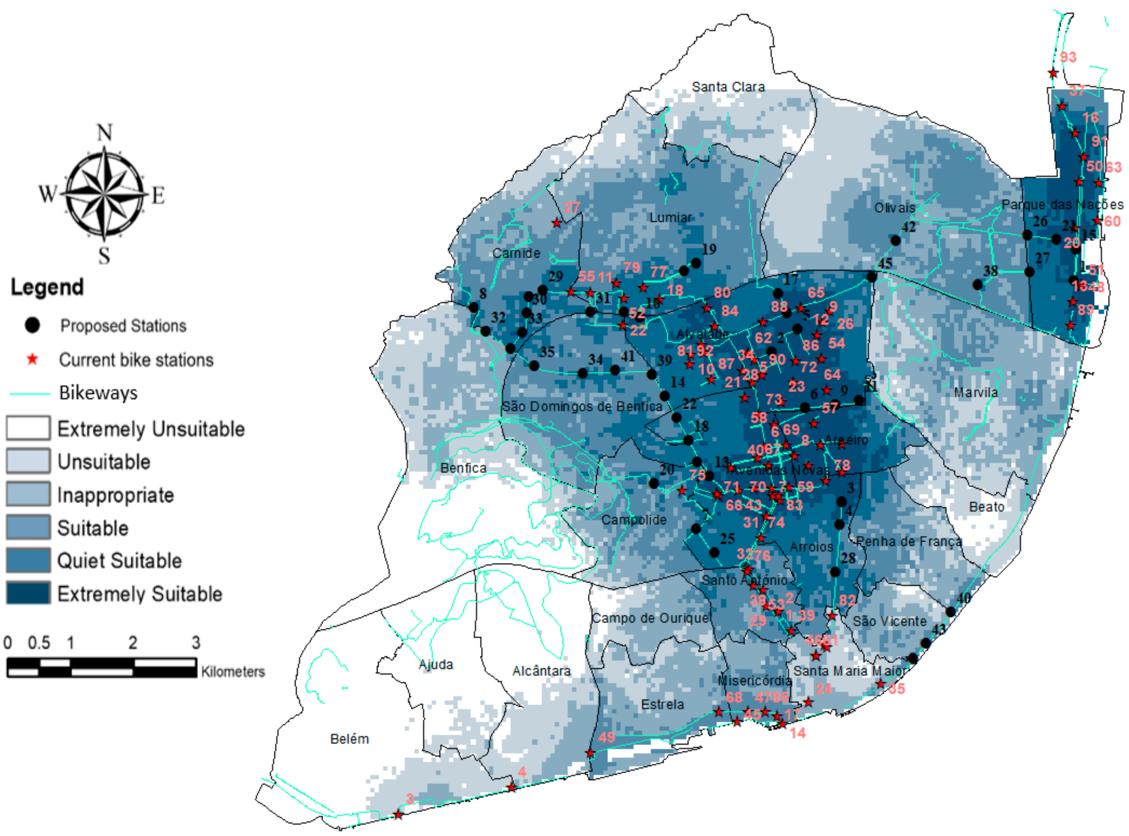

Figure 3. Suitability map for new stations in Lisbon.

According to this approach, forty-five new bike stations were identified. The construction feasibility of new bike stations was evaluated by conducting field visits to determine the absence of obstacles to their construction. Figure 4 shows the locations of the forty-five alternative new BSS stations' locations. As constructing fixed stations requires substantial initial investment and, usually, financial resources are limited, ranking and prioritizing proposed stations is crucial for planners as a decision support tool. To this end, the TOPSIS approach was applied to rank the proposed stations.

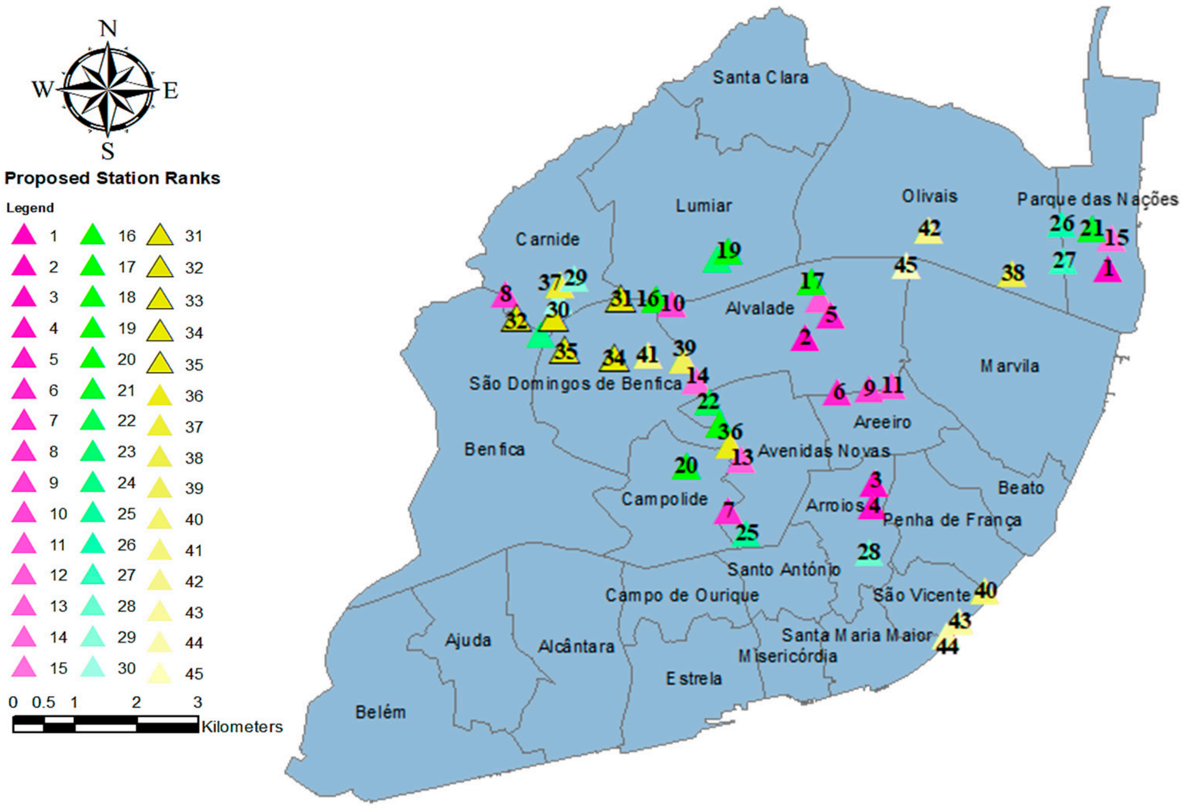

Figure 4. The ranking of the proposed stations.

To carry out the TOPSIS calculations, normalized cell values of each criterion were obtained. Then, the TOPSIS approach and equations were used to rank the forty-five alternatives listed in Table 5. Figure 4 shows the calculated rankings of bike station alternatives for the GIRA BSS. In addition, the proposed bike station locations could be assessed according to their ranks. While the first top three rankings were A15, A04, and A40, the top three lower rankings were A08, A45, and A44.

Many factors have an impact on the status of a station being balanced or unbalanced. Factors such as station location, the capacity of the station (rack numbers), initial bike inventory, differences in the actual and predicted demand for bicycles in stations, and others are included in Table 1. In this study, the factor of station location as one of the critical and most important was evaluated to have a lower unbalancing status in the expansion of a network. As mentioned before, previously proposed station location approaches generally exclude the demand and operational dimensions of BSS. Criteria number seven, "Proximity to the bike stations with unbalanced OD", was included to contribute to solving the unbalancing problems of stations. An unbalanced station can be a full (close to full) station or an empty (close to empty) station. When the stations are full, adding capacity obviously solves a part of the problem; our proposed method correctly identified those unbalanced stations. Figure 5 shows the top unbalanced stations for the one-year operation of Lisbon's BSS among all current stations and newly proposed and ranked stations. According to the study's assumption that "unbalancing will decrease if the system's criteria are also included in station location" and Figure 5, it seems that the hypothesis we adopted is correct.

Table 5. Ranking of the alternative BSS station locations.

Name	Si^+	Si^-	*CI*	Rank
A15	0.088882958	0.140040658	0.611735304	1
A04	0.091233584	0.135940295	0.598397561	2
A40	0.096605647	0.14394044	0.598390278	3
A41	0.109656855	0.128021589	0.538633572	4
A03	0.131059307	0.133650033	0.50489353	5
A07	0.12560168	0.124561019	0.497920031	6
A38	0.12669852	0.122971407	0.492535921	7
A25	0.130357085	0.122987796	0.485456014	8
A06	0.124052981	0.11478928	0.480607075	9
A18	0.134845643	0.119024555	0.468840202	10
A05	0.126527572	0.10821999	0.46100581	11
A02	0.144632137	0.109240907	0.430297386	12
A36	0.128454319	0.094168643	0.422996094	13
A32	0.146582481	0.10209533	0.410552631	14
A14	0.140414162	0.092141112	0.396211666	15
A19	0.133052769	0.084490795	0.388385632	16
A01	0.157939848	0.100213325	0.388193273	17
A34	0.140539908	0.086731511	0.381620845	18
A16	0.139251163	0.081144315	0.368175951	19
A37	0.143721413	0.083153979	0.366518284	20
A13	0.151684641	0.086628276	0.363506422	21
A33	0.149902944	0.084849844	0.361443391	22
A17	0.138844637	0.07729919	0.357628487	23
A27	0.147309495	0.080128726	0.35230985	24
A39	0.151795452	0.082127917	0.35108898	25
A12	0.152617435	0.081748797	0.348807916	26
A11	0.153948217	0.07998719	0.341919981	27
A42	0.146373457	0.072104987	0.330032499	28
A21	0.151286565	0.066995825	0.30692272	29
A23	0.153283053	0.057215906	0.271810874	30
A20	0.152817038	0.056022965	0.268257824	31
A26	0.169204518	0.059491254	0.260132724	32
A24	0.159746155	0.055040461	0.256256474	33
A29	0.15048036	0.051577062	0.255259428	34
A28	0.163754441	0.055762386	0.254023289	35
A35	0.152205992	0.051237498	0.251851254	36
A22	0.165782542	0.053489415	0.243940976	37
A10	0.164065828	0.052597037	0.242759815	38
A31	0.154227641	0.047843031	0.236763853	39
A43	0.159672107	0.049148287	0.23536153	40
A30	0.163431281	0.046659063	0.222090469	41
A09	0.168982944	0.042669948	0.201603427	42
A44	0.165982278	0.039410741	0.191879651	43
A45	0.171071673	0.037698146	0.180572776	44
A08	0.178627648	0.025676569	0.125678116	45

Apparently, the proposed method located new stations close to more unbalanced stations. Considering the classified suitability areas in Figure 3 and the location of unbalanced stations in Figure 5, it is apparent that most of the unbalanced stations are in areas that have highly suitable weights. The weight given by the rebalancing staff to the criteria indicates that the areas suitable for the construction of new stations are often areas close to the top unbalanced stations. In addition, this means that current unbalanced stations do not need to be relocated to expand the BSS (as they are in highly suitable areas), and it would be better to build new stations in their vicinity. In other words, rebalancing operators with their executive experience showed areas for the construction of new stations where the network would be more productive and, as a result, users would be more satisfied.

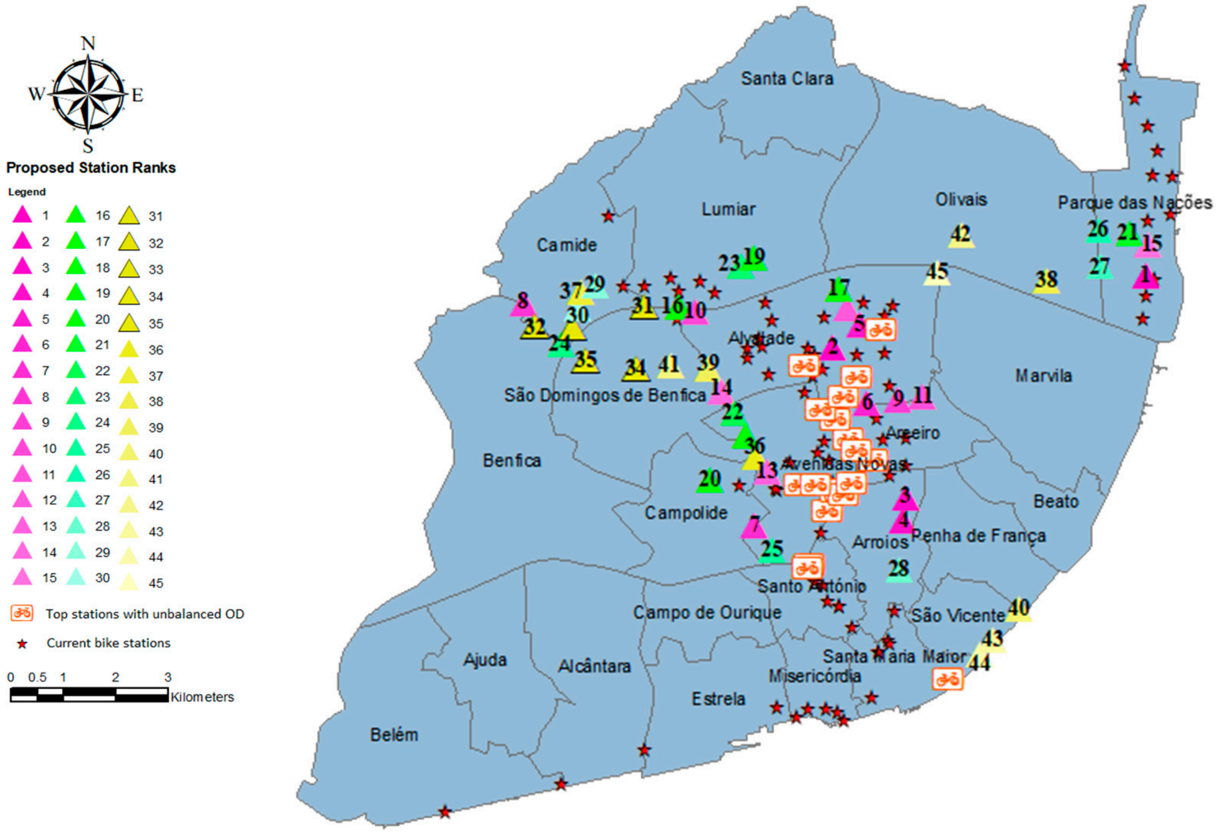

Figure 5. Location of unbalanced stations and proposed stations in Lisbon.

When the expansion of a BSS is needed, two approaches are included: first, the capacity of existing stations is expanded; second, new stations are located in areas not covered by existing stations. The first approach will solve the unbalancing problem of current full stations (i.e., without available racks for parking). The second approach will satisfy latent demand from origins and destinations that are not currently covered by the network. Still, we acknowledge that the method proposed here will not solve the unbalancing problem of empty stations. This involves other approaches, such as bike fleet management and distribution. Instead, it aims to provide planners and decision makers with a method to locate stations. We partially improved the unbalancing situation with this extension capacity and covered the area with no response to demand. In addition, it should be noted that the full and unbalanced stations vary over time and are not the same during each day. Our method can suggest where stations can be present to diminish the problem of unbalancing; however, it is not enough to say how, because many factors impacting the station's status need to be addressed: for example, increasing the capacity or increasing the redistribution by using more rebalancing vehicles. As mentioned in the introduction, dynamic virtual stations using the geofencing technique can be a solution. The term "dynamic" refers to each station's size, which can have a variable capacity, and the term "virtual" means that the station is not a fixed station as it is in SBSSs (it can be just a designated area in the street or a part of a sidewalk). By having different capacities during the operation hours, dynamic virtual stations can be located using our proposed model to diminish the rate of unbalanced status in the stations.

5. Conclusions

As BSSs are not an ownership-based mode of transport, it is expected that a BSS can integrate urban transportation systems. Nevertheless, some essential factors need to be managed carefully to maximize the positive impacts of BSSs. One of the most critical problems in shared networks is the complex decision-making procedure, including the determination of station locations in the system. Two gaps are evident in previous studies: First, the criteria chosen for the location of the stations previously were not enough to include executive and operational dimensions, such as “membership density”, “stations with unbalanced OD”, and “zones with high user membership density”. Second, in most studies, the experts who prioritized the selected criteria did not have operational experience or executive vision. Thus, the operators of BSSs did not have a representative among the expert decision makers who were determining the location of bike stations.

This study explored how to determine the locations of new bike stations by using the combined GIS-MCDM method effectively according to the experience of the operator’s rebalancing staff. The methodology of the study can be broken down into three basic steps. When the expansion of a BSS is required, it includes two approaches: first, the capacity of existing stations is expanded; and second, new stations are located in areas not covered by existing stations.

The first step was identifying 14 criteria by referring to the primary literature sources, operation challenges of a real BSS, and experts’ suggestions. The second step included weighting the criteria using the AHP method. The third stage involved preparing the layers of each criterion in the GIS environment and performing the spatial analyses of fourteen criteria to create the final integrated suitability map. The most suitable suggested bike station locations determined with the GIS-MCDM approach are shown in Figure 2. Figure 3 shows the final suitability map illustrating the suitable locations for establishing the new bike stations. Finally, Figure 4 illustrates the alternative stations with their ranking. The number of stations in the network was 93, and 45 new stations were proposed for the extension of the system. The results of the third stage showed that with mixed AHP, TOPSIS, and GIS techniques, superior station alternatives could be achieved as the model’s output. Since the weighting results from the AHP method were accepted by the ranking approach from the TOPSIS technique, it was verified that the hybrid method of AHP-TOPSIS can be used in station location selection studies. However, although the proposed method did not aim to solve the unbalancing problem, it improved the unbalancing situation with extension capacity and covered the area with no response to demand. Dynamic virtual stations using the geofencing technique may be an example to implement the results of this study.

For future bike station location studies, we suggest that other groups, such as bike users and academic experts, should be added to respond to the questionnaire simultaneously with operator experts. Using other operational criteria, such as rebalancing vehicle routing and bike duration trips based on each station, is recommended to obtain a proper station location selection. In addition to using MCDM techniques, such as AHP, VIKOR, MOORA, and TOPSIS, which are based on objective factors, we suggest that some subjective-based techniques, such as entropy, be used to avoid interference from human factors. In addition, the bike inventory and rack capacity of alternative stations can be included in such studies.

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