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A Hybrid DEA Approach for the Upgrade of an Existing Bike-Sharing System with Electric Bikes

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Abstract: An e-bike sharing system (e-BSS) solves many of the shortcomings of BSS but requires high financial investments compared to BSS. This article proposes a sustainable and targeted extension of the existing BSS with e-bikes and charging piles. The existing BSS in the selected city area is divided into sub-areas using the Voronoi diagram and reference points (landmarks). Then, the integrated approach of the Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA) is used to assess the adequacy of the existing bike-sharing stations for updating with e-bikes and charging piles. The joint approach allows decision-makers to look at the whole process and highlight the link between the criteria assessment and user preferences in the context of the chosen reference point. This can encourage future users to use e-BSSs. Based on a thorough literature review, the defined system of criteria takes into account all dimensions of sustainability: the requirements of most stakeholders and the structural features and needs of e-BSS. Finally, the super-efficiency DEA is used to classify the suitable candidates for bike-sharing so that only the most suitable stations are updated. The test of the proposed algorithm in Ljubljana city centre confirms several suitable options for updating the BSS, depending on the reference point.

Keywords: e-bikes; e-BSS; sustainability; cyclist typology; AHP; DEA; super-efficiency model

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1. Introduction

Bike-sharing systems (BSS) have been an established form of mobility in cities for many years. They are used as an alternative to public passenger transport (bus, tram) or first-mile or/and a last-mile walking in multi-modal trips and private cars [1,2].

BSS has so far received great interest. More than 2900 BSS are operating in cities worldwide [3] to provide benefits to various stakeholders (city authorities, bike users, and government). BSS, for example, reduces the use of private cars and consequently air pollution, noise, and congestion. It also eliminates the costs of purchasing and maintaining a bike for a bike user, the risk of a bike or bike parts being stolen, as well as the worry of parking a bike [4].

Thus far, BSS has proven to be a favourable form of mobility for the younger population (pupils, students), employees in the urban area, and even tourists. BSS mainly solves mobility problems over short distances between suburbs and cities and within small and medium-sized cities (app. 2.9 km) [5]. However, BSS rarely enables trips over longer distances (between cities and within large cities). Additionally, the BSS is not exploiting its full potential in hillier areas, nor does it contribute to raising cycling among the elderly population and those with health problems. BSS is also more sensitive to bad weather and worse air quality [6].

BSS, therefore, has substantial untapped potential that could be exploited by introducing e-bikes. However, there are still some critical disadvantages of e-bikes that hinder the design of larger electric bike-sharing systems (e-BSS). Thus far, we have only witnessed small pilot projects around the world. The only major projects are BiciMAD in Madrid (Spain), which has 2000 e-bikes at 165 stations, and the e-bike-sharing system GIRA in Lisbon (Portugal), which has 600 conventional bikes and 700 e-bikes at 164 stations [2,7].

The first disadvantage is the high investment costs in e-bikes and charging docks at the station. A second weakness is the inability to use a bike during the charging, which increases the waiting time. The third problem is the frequently used dockless stations that are not suitable for e-bikes as they need to be recharged [8]. Finally, exposure to road accidents and the condition of technical infrastructure also influence the use of BSS capabilities [9,10]. It is therefore crucial to upgrade a list of social criteria for selecting the right location of e-BSS station with criteria related to the quality of bike lane markings, road lighting, quality of paths, road surface type, number of intersection arms, availability of suitable visibility aids, etc.

The above-mentioned issues related to e-BSS planning remain unanswered. The solutions cannot be found in previous studies or pilot projects. Compared to BSS, there are only a few studies on e-BSS design [1,2,5,8,11].

Villacreses et al. [12] are the only ones to propose a model for the most optimal location to install e-bike charging stations by using a multi-criteria decision-making method (MCDM). They proposed an integrated Analytical Hierarchy Process and the Technique for Order of Preference by Similarity to Ideal Solution (AHP-TOPSIS) approach.

In summary, the studies mentioned above aim to design a new e-BSS for e-bikes only, or a new e-BSS for mixed types of bikes (traditional bikes and e-bikes). However, no research exists to create e-BSS on extant BSS or to extend such BSS with e-bikes. Campbell et al. [6] are the only researchers to mention this solution.

Planning a new large-scale e-BSS is somewhat risky and not the most sustainable decision due to the solution's high infrastructure investment cost and novelty. Not all BSS projects are necessarily cost-effective, or at least are not effective in the initial phase of implementation, since bikers need time to get used to the new mobility option.

To achieve a win-win effect for all stakeholders, an e-BSS has to be (1) economically sustainable (optimal investment in infrastructure and satisfactory use of the system), (2) socially efficient (not too long distances between users and charging stations, enough e-bikes when needed, enough e-bikes with full or sufficiently full batteries, potentially enough replaceable batteries, convenient e-bike features, affordable price, etc.), and (3) be environmentally friendly (minimise the environmental of building the infrastructure and managing the system (rebalancing e-bikes, etc.).

A totally new e-BSS will hardly, in the short or even medium term, meet all the sustainability aspects mentioned above.

This encourages the authors to turn their attention to "recycling" existing BSS stations. The authors suggest that e-BSS should be conceived as an extension of already existing BSSs rather than a standalone e-BSS, using an MCDM approach. Therefore, this paper upgrades the only study that applies the MCDM approach to determine the appropriate locations for new charging stations [12].

The contributions of this work are as follows:

- First, this is the first study to propose a design of an e-BSS in an existing BSS network to maintain the sustainability of the old BSS and enable further efficient implementation and use of the new one.
- Secondly, this is the second study to solve the e-bike charging station location problem using an integrated Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA) hybrid MCDM by applying a wide range of criteria.
- Moreover, this is the first time a reasonable and holistic criteria system for the siting of e-bike charging stations has been established: sustainability and crucial stakeholder requirements are considered.
- Fourth, this is the only work that merges the DEA method and the weights obtained with a two-stage AHP method to select and upgrade proper stations of the existing BSS. The weights are obtained considering the division of the area into Voronoi cells

with respect to predefined landmarks that are strongly associated with the potential users of the upgrading sharing system.

The model was employed in a case study in Ljubljana, which already has a BSS and plans to upgrade it with e-bikes. Nevertheless, the proposed model and obtained results are generalisable and can be applied in small or medium-sized cities with similar characteristics to Ljubljana.

The results benefit academics (a new hybrid model that can be upgraded) and decision makers in the e-BSS planning phase.

The rest of this paper is organised as follows. Section 2 gives an outline of the design of BSS and the criteria set. Section 3 proposes the model formulation. Section 4 presents the utilisation of the proposed model to upgrade the existing BSS in the city of Ljubljana. Section 5 is a discussion of obtained results, and Section 6 is the conclusion highlighting the obtained results and possible future research.

2. Literature Review

Upgrading existing BSSs with e-bikes and charging stations requires an extensive review of articles on BSSs and e-BSSs, as well as articles on criteria for optimal locations of charging stations for e-vehicles, as both topics are needed to define an efficient algorithm for upgrading BSSs to e-BSSs.

2.1. A Literature Review on the Design of e-BSS

There are few articles on standalone e-BSS planning [2,4,8,11,12]. Only one article was found to propose but not test the upgrade of a BSS with e-bikes [6], and one article modelled a mixed fleet BSS (traditional and e-bikes) [1]. However, the authors tested it as a standalone solution instead of an existing BSS extension.

Campbell et al. [6] explored the factors influencing shared bikes and shared e-bikes in Beijing. Based on the results, they envisioned three scenarios for e-BSS in Beijing. One of them was also e-BSS which shares a docking station with extant BSS [6]. E-bikes could serve in case of high temperatures or poor air quality. Still, they can also benefit users who carry loads or those who cannot pedal a bike. The study also revealed that e-BSS could be used with more targeted purposes than BSS in different locations (due to longer trips) and low-density areas. Due to high fixed costs and the tolerance for longer travel distances, e-BSS with a small number of large docking stations would be the most economical. However, station locations must ensure a sufficient volume of attractions in docking stations' proximity [6].

Martinez et al. [1] presented an algorithm to locate stations for a mixed fleet BSS. They used a Mixed Integer Linear Program (MILP). The authors also designed and tested several systems and demand scenarios (lifespan of infrastructure and bikes, e-bike use, annual card for traditional bike use, individual trip fee, and other e-bike use). The results proved that the scenario "individual trip fee" is the most profitable in terms of financial performance (daily revenue, total costs, net income, and annual balance) and does not need any additional financial support. Scenarios "annual card for a traditional bike with an additional fee for e-bike riding" and "e-bikes-oriented system" would require some financial contribution to survive. However, "full demand coverage" would require considerable external financial support. Scenarios "individual trip fee" requires 276 stations. In the case of "annual card for a traditional bike with an additional fee for e-bike riding" scenarios, 272 stations are required. The "e-bikes-oriented system" requires only 228 stations which were placed in areas of high demand density and where the altimetry variation in the surrounding areas may pay off using an e-bike.

Four papers were found to propose a model for the optimal design of e-BSS. The authors even tested their validity on a real case example of BSSs, but only as a standalone solution and not a mixed BSS and e-BSS option.

Soriguera et al. [4] and Soriguera and Jiménez [13] are two of four papers that present a model for the optimal design of public BSS that also considers e-bikes. A model was also tested on a real case example in Barcelona with respect to traditional bikes. The results show that e-bikes require greater infrastructure and operative costs. In their case, users' behaviour was not affected by the use of e-bikes. The authors concluded that battery recharging is not a restriction and that station-based BSS is well designed for the implementation of e-bikes. However, they claim that if e-bikes do not result in additional benefits (greater or more balanced demand, for example), there is no reason to implement them.

Chen et al. [8] proposed and tested an optimal deployment of e-BSS stations. The authors formulated a problem as a bi-level programming model. They present an e-BSS network where the trip costs are measured as the sum of the delay costs at the station and the travel time on the route. In addition, "two important measures were proposed to reduce the overlong delay cost caused by the charging activities needed at stations (quick-charging technology and the reservation policy" [8]. The authors tested a model on the existing BSS along the bus rapid transit line in Tianhe, Guangzhou, in China, concluding that sharing stations are bottlenecks of the e-BSS and that the waiting time caused by the battery's recharging is unacceptably long. Authors claim that quick-charging technology and the reservation policy could reduce waiting time.

Villacreses et al. [12] are the only ones to propose the most feasible locations for e-BSS by using multi-criteria decision making and testing the model in the city of Quito. The city has many slopes, and e-bikes are necessary. The authors integrated the AHP method to calculate the weights. TOPSIS was used to calculate the results, and the Geographic Information System (GIS) was used to prioritise locations for e-BSS charging stations. The application of the model in Quito highlighted the need to connect more distant parts of the city to e-BSS and not only places in the centre of the city.

Macioszek and Cieśla [14] propose a discussion on the development of a public BSS that takes into account external environmental analysis methods in order to improve energy-efficient methods. In addition, Ploos van Amstel et al. [15] suggest revising the design tool for psychological ownership. This includes the inclusion of "giving feedback" in the list of facilitators and the recognition of a reciprocal relationship between the service provider and the service user in closing-the-loop activities. The risks of cyclists on the road and their safety are also external aspects that can influence the use of BSSs [9,10].

In summary, few studies on optimally designing standalone e-BSS exist, which may also be a reason for such a low number of large-scale e-BSS implementations. A review of the literature proves that this area is undernourished. However, it is encouraging that most authors apply invented models for e-BSS in a real case study, which proves their viability. There are many similarities with BSS, but the only difference, the battery, significantly affects finances, travel dynamics, etc.

2.2. A Criteria System for e-Bike Charging Stations Evaluation

The evaluation criteria for the e-BSS charging station were identified by considering the existing scientific literature, feasibility study reports, and perspectives of key stakeholders, namely bike users, policy makers (municipalities' staff), experts (implementers of BSSs and suppliers of bikes and/or batteries), and academics conducting research in the field.

The authors examined 44 scientific articles on charging stations for many types of e-vehicles (e-cars, e-scooters, e-taxis, e-bikes), not just e-bikes, for two reasons: (1) the small amount of research in the field of e-bikes (only six articles were found) and (2) the similarity of the criteria with other e-vehicles. The operation and use of car-sharing systems are similar for all e-vehicles, with certain exceptions related to the size of the vehicles and batteries. Therefore, in this case, it is sustainable to use criteria that already exist in the literature and expand the list with specific criteria for e-bikes. All the papers found were published in peer-reviewed journals.

In order to ensure a holistic approach to the subject, a preliminary list of all possible criteria was drawn up in the first stage. We took the list of criteria proposed by Karolemeas et al. [16], as they consider the three main pillars of sustainability (social, economic, and environmental) and the crucial needs of stakeholders. Figure 1 shows the main level of the final set of criteria, i.e., the nine groups most frequently used by the international authors of the 44 papers examined. A detailed structure of the criteria set is presented in Table A1.

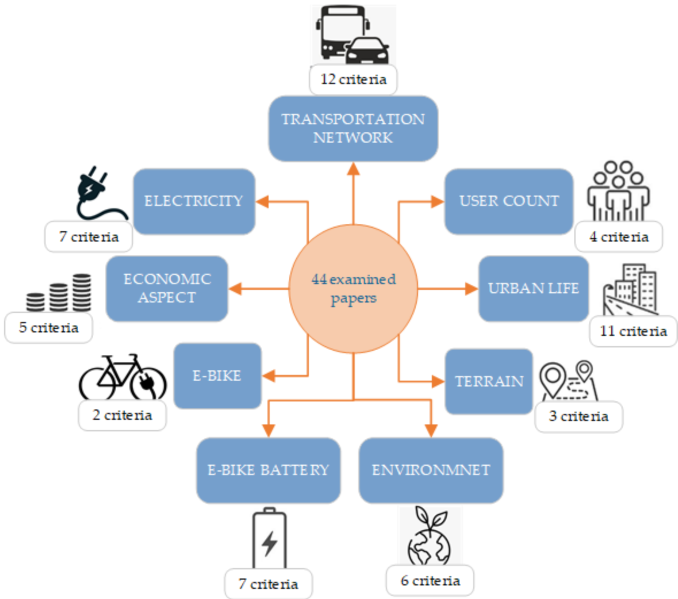

Figure 1. Criteria set at the main level.

In summary, the proposed list of criteria (Table A1) is comprehensive. It reflects the needs of key e-BSS stakeholders and supports some targets of United Nations Sustainable Development Goal 11 (support economic, social, and environmental links in urban areas and provide access to safe, affordable, accessible, and sustainable transport systems). In the third step of the proposed algorithm (Section 3.3), the set of criteria is elaborated to determine the most appropriate criteria for the MCDM model.

2.3. Research Gap

All authors point out the high financial investments in e-BSS. Some even claim that investing in e-BSS is meaningless if it does not bring additional advantages compared to BSS. However, no one except one author [6] has thought about upgrading the existing BSS with e-bikes and ensuring the sustainability of both the old BSS and an upgraded e-BSS system. This paper aims to fill this gap and propose a tool to evaluate existing BSS stations and, from the viewpoint of crucial groups of stakeholders, select those most convenient to be upgraded with e-bikes and charging piles.

Three research questions (RQ) were set:

RQ1: What criteria are relevant to undertake a sustainable upgrade of existing BSS stations?

RQ2: Does the use of the selected urban area influence the upgrade of BSSs with e-bikes and piles?

RQ3: To what extent does the upgrade with super-efficiency DEA ranking influence the upgrade and costs?

3. Materials and Methods

From the proposed literature review, it can be seen that there are many similarities between the BSS and the e-BSS. Therefore, an MCDM model is defined to select from the existing set of BSS stations those for which it is reasonable to upgrade them to e-BSS stations of the BSS network in an urban area. The main steps of the algorithm are:

- Subdivision of the urban area region into sub-areas around landmarks: places of economic, cultural, or public interest. The subdivision of the area is executed with the help of the Voronoi diagram.

- Identification of existing BSS stations or, if necessary, the addition of new e-BSS stations in each sub-area.
- Define the proper criteria for evaluating the feasibility of upgrading a BSS station to an e-BSS station.
- Formulation of a hybrid multi-criteria evaluation/ranking. The multi-criteria ranking is prepared by combining the AHP method and the DEA method. The AHP method is used to reduce and aggregate features related to the same efficiency aspect of the e-BSS station ratings. Then, the technical efficiency of the e-BSS stations in each sub-region is assessed using the DEA method.

3.1. Subdivision of the Urban Area Region into Sub-Areas around Landmarks Points

An efficient definition of an e-BSS system in an urban area is principally based on a rational location of the sharing stations, according to the potential "users" distribution or demand and the spatial definition of the city area regions [17,18].

In this section, a method is proposed to divide the urban area where the e-BSS systems are to be placed into sub-areas using predefined landmark points.

The e-BSS is an extension of the public transportation system that efficiently connects people from the public transit network to their final destination. Landmarks are, therefore, of great importance and need to be defined based on the literature review (Table A1, Urban-related criteria) and urban mobility experts based on a detailed analysis of the urban plan and migration flows classified as geological and meteorological, biological, or human-made [19].

The landmarks used in this work to select from the existing set of BSS stations are those that can be reasonably upgraded to e-BSS stations, such as shopping malls, primary/secondary schools, commercial buildings, recreational areas, campuses, cultural elements/tourism/social life, industrial areas, public administration buildings, hospitals or health centres, hub parking areas, and public transportation intersections.

For the general model definition, let $V = \{v_1, v_2, \ldots, v_n\}$ be the set of points that will be used as landmarks in a metric space $\left(R^3, d\right)$, where R^3 is the Euclidian space and the metric d is the Euclidian distance $d(x, y) = \sqrt{\sum_{i=1}^{3}(x_i - y_i)^2}$, $x = (x_1, x_2, x_3)$, and $y = (y_1, y_2, y_3)$. These points are used to construct the Voronoi diagram and solve the nearest neighbour problem [20].

The Voronoi diagram of V is defined as a collection of n Voronoi cells $\Omega = \{\Omega_i\}_{i=1}^{n}$, where cells are defined as:

$$\Omega_i = \left\{ x \in R^3; d(x, v_i) \leq d\left(x, v_j\right), \forall j \neq i \right\}. \tag{1}$$

Each Voronoi cell Ω_i is the intersection of a set of 3D half-spaces, delimited by the bisecting planes of the Delaunay edges incident to the site v_i and are convex polytopes [21].

Thus, given an arbitrary landmark in the city area, it is possible to define a polytope of points closer to this landmark than to the others. Therefore, it makes sense to use this partition of the urban area to define and evaluate the locations of e-BSS stations separately in each polytope, as these regions are separate and independent from each other. Figure 2 is presented an example of the Voronoi diagram in two dimensions [20,22].

The time complexity of the construction of a Voronoi diagram of n uniform distributed pints in a unit square is $O(n \ln \ln n)$ [23].

In most cases, the time complexity of the Voronoi diagram in R^3 construction is $O(n)$. The running time of these algorithms is related to the following statements: the complexity of the kernel used to insert a new point into the existing topology, the search algorithm used to detect the sub-tessellation that needs to be changed, and the order/distribution of the set of points that needs to be added. Generally, the Bowyer–Watson algorithm is used [24].

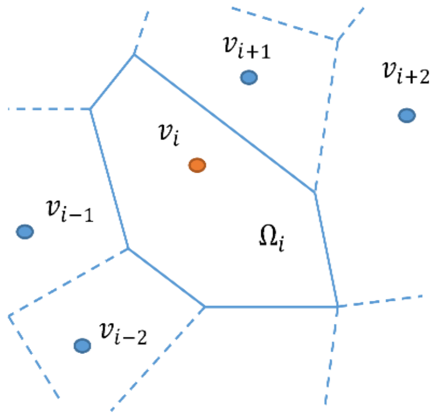

Figure 2. The Voronoi of cell Ω_i in R^2.

3.2. Identification of Existing BSS Stations, or if Necessary, Add New e-BSS Stations

Let $\Omega = \{\Omega_i\}_{i=1}^{n}$ be the Voronoi diagram formed by n Voronoi cells, defined in the previous section, that produces the partition of the examined urban area. Let $BSS = \{BSS_i\}_{i=1}^{m}$ be the set of BSS stations located in the studied urban area. Let $\delta_j(\Omega_i)$ be a binary function that can be used to check whether the BSS_j station is located in sub-area Ω_i. The function is defined as:

$$\delta_j(\Omega_i) = \begin{cases} 1; & d\left(BSS_j, v_i\right) \leq d\left(BSS_j, v_k\right), \forall k \neq i,\ 1 \leq k \leq n \\ 0; & otherwise \end{cases}, 1 \leq j \leq m. \quad (2)$$

Thus, it is possible to perform partitioning of the BSS set of existing stations and define $eBSS_i^j$ station sets in each sub-region Ω_i, taking into account the partitioning of the urban area. These sets consist of BSS stations that are eligible for upgrading to stations with additional e-bike-sharing. The sets of the partition are defined as:

$$eBSS_i^j = \left\{BSS_j; \delta_j(\Omega_i) = 1; 1 \leq j \leq m\right\}, 1 \leq i \leq n. \quad (3)$$

In the case where there are no pre-existing BSS stations in a selected region Ω_i, a candidate e-BSS station is placed as the centroid of a polytope Ω_i and the coordinates are calculated as the average value of all vertices of the boundary of the polytope Ω_i.

3.3. Defining the Criteria Set to Evaluate the Feasibility of Upgrading a BSS Station to an e-BSS Station

This section presents an organised set of criteria that enables the selection of the existing BSS stations which make sense to be upgraded into e-BSS stations. The set of criteria is based on the extensive list of criteria presented in Table 1, which has undergone the following aggregation procedure and principles:

- Criteria that are associated with the same property were aggregated;
- Criteria that explain positive (negative) efforts were aggregated, but mixed efforts were not aggregated;
- Aggregation also considers the relationships between criteria and their independence, although, in practice, it is difficult to define the relationships between criteria; and
- Some criteria have been omitted because they are difficult to quantify or do not have continuous real values, so they cannot be used effectively in the DEA analysis.

The obtained criteria set is not associated with specific characteristics of an urban region, the nation, or particular users. It can therefore be considered general enough to be part of the algorithm without losing generality.

Table 1. Criteria structure and variable definition in the DEA model.

	Criteria/(Unit of Measure)	Variable Classification: Inputs (I) Desirable Outputs (O+)/Undesirable Outputs (O−)
C_1	User Count-Related Criteria	I
C_{11}	Population density (aged 15–25 years)/(per cent)	
C_{12}	Population density (aged 25–65 years)/(per cent)	
C_{13}	Population density (aged 66 or more years)/(per cent)	
C_2	Transportation Network Criteria	I
C_{21}	Proximity to a bike lane/(meter)	
C_{22}	Proximity to the subway network/(meter)	
C_{23}	Proximity to the bus transport network/(meter)	
C_{24}	Proximity to the tramway network/(meter)	
C_{25}	Proximity to transit hubs and intersections/(meter)	
C_{26}	Proximity to road networks/(meter)	
C_{27}	Proximity to ferry ports/(meter)	
C_{28}	Proximity to high traffic density roads/(meter)	
C_{29}	Proximity to the parking area/(meter)	
C_3	Terrain-Related Criteria	I
C_{31}	The slope of the terrain/(maximum slope of a hill in per cent)	
C_{32}	Possibility of expansion in the future/(per cent)	
C_4	Environment-Related Criteria	O+
C_{41}	Emission reduction due to e-bike-sharing system (e-BSS)/(kg CO2eq)	
C_{42}	Proximity to repositioning trucks depot location/(meter)	
C_5	Battery-Related Criteria	O+
C_{51}	Number of batteries at the station/(number of batteries)	
C_{52}	Number of charging piles at the station/(piles)	
C_{53}	E-bike battery autonomy under regular use/(minutes)	
C_6	E-bike-Related Criteria	O+
C_{61}	Number of e-bikes at the station/(number of e-bikes)	
C_{62}	Number of e-bikes slots/(number of e-bikes)	
C_7	Economic Criteria	O−
C_{71}	Infrastructure and updating costs/(EUR)	
C_{72}	Annual/operation and maintenance costs/(EUR/bike station)	
C_{73}	Investment payback period/(years)	
C_{74}	Land occupation/acquisition costs/(EUR/m2)	
C_8	Electricity-Related Criteria	I
C_{81}	The power supply capacity of transmission and distribution network/(Volts)	
C_{82}	Availability of existing electric network of the city/(meter)	
C_{83}	Sustainable energy potential/(per cent).	
C_{84}	Proximity to an electric substation/(meter)	

The number of criteria at the aggregation level is within the limits that allow later effective use of the DEA analysis—respecting the consistency of the results obtained and the number of existing e-BSS candidate stations (decision-making units; DMUs) in the used subdivision of the urban area in cells.

Meaningful assignment of the set of criteria to a landmark is made using the AHP method. Only criteria that are closely related to the characteristics of the selected landmark and its potential e-BSS users are then marked with high weights and thus assigned to the landmark. The final criteria hierarchical structure of the AHP is presented in Table 1.

3.4. Formulation of a Hybrid Multi-Criteria Evaluation Method

Multi-criteria ranking is composed of two steps: The AHP weighting method, which is used to evaluate the importance of the criteria, and the DEA method, which is used to evaluate the technical efficiency of the electric bike-sharing station candidates.

The AHP method is a robust and flexible MCDM tool for dealing with complex decision-making problems that many large companies use in their Six Sigma projects. It eliminates bias in the decision-making process and ensures that the decision made reflects the values and priorities of the decision makers. The AHP method has built-in checks and balances that allow for logical consistency. The AHP divides a complicated system into a hierarchical system of elements, usually including objectives, evaluation criteria, and alternatives. The evaluation criteria level can be composed of different evaluation criteria, which can also be organised in a multi-layered structure [25].

The AHP method is used in the first step to aggregate features related to the same efficiency aspect of the e-BSS station rating. This approach is necessary since the second step of the multi-criteria e-BSS candidates ranking is executed with the DEA method. The DEA method allows the assessment of the technical efficiency of the e-BSS station candidates in each sub-region of the examined urban area, but the discrimination capacity of the method is related to the ratio between the number of decision-making units (DMU) and the number of input and output variables. In the proposed methods, the e-BSS stations are DMUs. The most commonly used paradigm assumes that the discriminatory power of the DEA method is reliable if at least twice more DMUs are considered than the sum of the number of inputs and outputs of the model [26,27].

The criteria used to evaluate the e-BSS candidates presented in Table 1 are organised in a hierarchy structure that is the standard output, together with related weights, of the AHP method [28].

The judgement scale plays a significant role in the AHP decision-making process since it influences the consistency of the decision making and variances of priorities. The proposed model focuses on the values of priorities and highlights the most important criterion, so in this case, the use of the Power-Geometric scale is appropriate [29]. With the Power- Geometric scale, priority discrimination is improved. This is because it widens the weight range and makes priority discrimination more significant compared to the most commonly used Linear scale. The Power-Geometric scale is also preferable compared to the Power Scale because it has a lower weight uncertainty and also a lower weight dispersion [30].

Furthermore, in the process of peer comparison, it is necessary to highlight that the requirements of all stakeholders (e-bike users and investors) must be considered. The process of upgrading the existing set of BSS stations into an e-BSS set of stations can only be considered effective if it meets the expectations of e-bike users and investors [27].

These requirements may reduce the consistency of the AHP method, as e-bike users and investors have different priorities. Therefore, it is necessary to pay more attention and define a group of experts able to take into account these differences. Moreover, it is necessary to find a compromise between them. In order to minimise the lack of consistency of the AHP method, it was applied separately for each landmark since the landmarks determine the e-BSS users.

The AHP method can be used separately at each subtree of the structure, and then the results are aggregated into an overall assessment at the aggregation level for the selected landmark. The main steps of the AHP method are as follows:

Step 1—Using the Power-Geometric scale defines the pairwise comparison matrix A, that is reciprocal, with a unit diagonal, rational matrix. The dimensions of the matrix are related to the number of examined criteria. The entries of the matrix are values of the pairwise comparison of criteria using the power scale [31].

Step 2—In case of full consistency of matrix A, it has only one eigenvalue λ_{max}, so it is possible to write $Aw = \lambda_{max}w$, where w is the associated right eigenvector that is formed by the weights. Eigenvalue components can be efficiently approximated using Saaty's method [32]:

$$w_i = \frac{1}{n} \sum_{j=1}^{n} \frac{a_{ij}}{A_j}\ ;\ A_j = \sum_{i=1}^{\mathrm{n}} a_{ij} \text{ for } i = 1,\ \ldots,\ n. \tag{4}$$

The maximum eigenvalue λ_{max} is approximated as:

$$\lambda_{max} = \sum_{i=1}^{n} A_i \cdot w_i. \tag{5}$$

Step 3—The consistency of the method can be checked using the maximum eigenvalue technique [33]. Consistency is defined using the consistency ratio $CR = CI/RI$, where $CI = (\lambda_{max} - n)/(n-1)$. Consistency is proved if $CR \leq 0.1$, where RI is the appropriate Random Index used with the Power-Geometric scale [28,29,34].

Step 4—Final weights on the lives are obtained by aggregation, using a product of weights on the path to the root in the tree structure.

Step 5—A sensitivity analysis can also be performed at each level of the AHP criteria hierarchy to assess the stability of the optimal solution and to determine which is the most critical criterion (weight).

The most critical criterion C_k is the one with the smallest absolute $\delta_{i,j,k}^{abs}$ or relative $\delta_{i,j,k}^{rel}$ change in weight w_k by the amount of $\delta_{i,j,k}^{abs}$ that reverses the ranking between the alternatives (DMUs of the model) DMU_i and DMU_j [35]:

$$\begin{gathered} \delta_{i,j,k}^{abs}\left(DMU_i, DMU_j, w_k\right) = \frac{P_j - P_i}{b_{jk} - b_{ik}}; \\ \left|\delta_{i,j,k}^{abs}\left(DMU_i, DMU_j, w_k\right)\right| < w_k;\ i < j;\ i,j = 1,\ldots,\ n. \\ \delta_{i,j,k}^{rel} = \frac{\delta_{i,j,k}^{abs}\left(DMU_i, DMU_j, w_k\right)}{w_k}. \end{gathered} \tag{6}$$

where the preference P_i of alternative DMU_i is the weighted sum of weights w_k and performance measures b_{ik} of alternative DMU_i with respect to the criterion $C_k,\ k = 1,\ldots,n$. Performance values are normalised.

Obtained final weights can be used to define the input and output variables of the DEA model separately for each landmark. The DEA method can evaluate the technical efficiency of e-BSS candidates (DMUs of the model), evaluating the ratio between the inputs and the outputs [36].

Linearisation of the DEA model is executed as the output-oriented Charnes, Cooper, and Rhodes (CCR) model [27,37]. In the model formulation, let $X = \left[x_{ij}\right] \in R^{m \times n}$ be the input matrix and $Y = \left[y_{ij}\right] \in R^{s \times n}$ be the output matrix that can be composed of desirable and undesirable entries.

For positive effort inputs or outputs, normalisation is achieved by dividing the variable value by the maximum value of the examined category. For negative effort inputs or outputs, normalisation is performed by dividing the minimum value of the investigated category by the variable value [38].

DMU_0 is the target DMU, and $x_0 = (x_{10},\ \ldots, x_{m0})$, $y_0 = (y_{10},\ \ldots, y_{s0})$ are the input and output vectors.

In the proposed formulation, the efficiency of DMUs is measured using non-radial models based on slacks for inputs and outputs. They are integrated into an efficiency measure called efficiency slacks-based measure (SBM), with high discrimination and the capacity to discover sources of inefficiencies [39,40].

First, the convex hull of inputs and outputs is defined and split into desirable outputs y^D and undesirable outputs y^U, as a Production Possibility Set (PPS) [39]:

$$PPS = \left\{ (x,y);\ \begin{matrix} x \geq \sum_{i=1}^{n} \lambda_i x_i; y \leq \sum_{i=1}^{n} \lambda_i y_i; y = y^D \cup\ y^U; y^D \in R^{s_1 \times n}; \\ y^U \in R^{s_2 \times n};\ s_1 + s_2 = s;\ \lambda_1, \ldots, \lambda_n \geq 0 \end{matrix} \right\} \tag{7}$$

Then, the target decision-making unit DMU_0 is described as:

$$x_0 = \sum_{i=1}^{n} \lambda_i x_i + s^- \text{ and } y_0 = \sum_{i=1}^{n} \lambda_i Y y_i - s^+, \tag{8}$$

where $s^- \in R^m$ and $s^+ \in R^s$ are positive slack vectors, expressing the input excess and the output shortfall. The output slack vectors are also split into desirable s^{D+} and undesirable s^{U+} output shortage [27].

The slack-based efficiency output-oriented measure ρ_{SBM} with a constant return to scale of variables is defined as [41,42]:

$$\rho_{SBM} = \min_{\lambda,\, s^-, s^+} \left\{ \frac{1}{1 - \frac{1}{s}\left(\sum_{i=1}^{s1} \frac{s_i^{D+}}{y_{i0}} + \sum_{i=1}^{s2} \frac{s_i^{U+}}{y_{i0}}\right)} \right\}. \tag{9}$$

Subject to constraints:

$$\begin{array}{l} x_0 = \sum_{i=1}^{n} \lambda_i x_i + s^- \text{and } y_0 = \sum_{i=1}^{n} \lambda_i Y y_i - s^+, \\ \sum_{i=1}^{n} x_{ji}\lambda_i + s_j^- = x_{i0}, j = 1, \ldots, m; \\ \sum_{i=1}^{n} y_{ki}{}^D \lambda_i - s_k^{D+} = y_{k0}, k = 1, \ldots, s_1; \\ \sum_{i=1}^{n} y_{ki}{}^U \lambda_i - s_k^{U+} = y_{k0}, k = 1, \ldots, s_2; \text{ and} \\ \lambda \geq 0,\ s^- \geq 0,\ s^+ \geq 0. \end{array} \tag{10}$$

The slack-based efficiency output-oriented measure is greater than or equal to 1. The low discrimination power of the SBM DEA model between the optimal solutions requires introducing a new super-efficiency measure, defined in a restricted Production Possibility Set $\overline{PPS} = PPS \setminus (x_0, y_0)$. The super-efficiency output measure δ is defined as an a-dimensional measure computed using the Charnes–Cooper linear programming formulation [39,40,43,44]:

$$\delta = \min\left\{ \frac{1}{m} \sum_{i=1}^{m} \frac{x_i}{x_{i0}} \right\}. \tag{11}$$

Subject to constraints:

$$\begin{array}{l} \frac{1}{s}\sum_{i=1}^{s} \frac{y_i}{y_{i0}} = 1; \\ x \geq \sum_{\substack{i=1 \\ i \neq 0}}^{n} \Lambda_i x_i; \\ y \leq \sum_{\substack{i=1, \\ i \neq 0}}^{n} \Lambda_i y_i; \\ x \geq t x_0;\ y \leq t y_0; \\ t > 0 \text{ and } y,\ \Lambda \geq 0. \end{array} \tag{12}$$

Using the SBM DEA model, it is first possible to identify among the e-BSSs under consideration those that are technically efficient enough to be upgraded to true e-BSSs. Then, the super-efficiency DEA is performed among them to create a ranking. In this way, the decision makers can select those with the best characteristics if this is decisive in regard to remaining within their budget.

4. Numerical Example: The City Centre of Ljubljana

The proposed method is tested on the existing BSS in the city centre of Ljubljana, which is the cultural, educational, economic, political, and administrative centre of Slovenia. The area of the capital is 163.8 km^2 (the metro area is 2334 km^2), the height above sea level is 295 m, and the population in the capital is 295,504 inhabitants (the metro area has 537,893 inhabitants), so the density is 1712/km^2 [45].

The existing BSS in the metropolitan area is composed of 86 stations, and 860 bikes are available for the users [46].

In practice, in the DEA method, the number of criteria is related to the number of DMUs by the paradigm that there must be at least two times more DMUs than the sum of the number of inputs and outputs of the model. Thus, the small number of stations of the examined BSS forces us to consider the city centre as a single cell so that the bike-sharing system consists of more stations, allowing the DEA to have high discriminatory power.

The criteria from Table 1 are assessed by experts and researchers working with the municipality of Ljubljana and other municipalities in Slovenia that are interested in the issue of upgrading the existing BSS into an e-BSS. The data collection took place from 5 May 2020 to 24 June 2020. The survey is part of the data and opinion collection conducted by Bajec et al. [27]. A total of 350 people participated in this survey (93 municipal staff and 257 users or potential users of e-BSS). For the purpose of this article, researchers in the field (10 researchers from Slovenia) were also included among the potential users of e-BSS. Before the survey was launched, a pre-test was conducted by two researchers familiar with e-BSS and four users of e-BSS to avoid bias. Some questions were revised to be more precise. A recall was required after the first contact [27].

The evaluation of criteria is performed in relation to the landmarks v_1 = "campus" and v_2 = "public administration buildings", as the city centre of Ljubljana is both an administrative area and an area where there are university campuses. This non-uniqueness in defining the most important landmark in an area is not that unusual. Especially in the city centres, there are several different landmarks concentrated in the same area. The proposed methodological approach is verified on the above-defined numerical example and uses two variants of the new e-BSS upgrade for verification. The choice of the most relevant variant is left to the Ljubljana city administration.

Table A2 presents the criteria weights obtained by the two-stages AHP method using the power scale, see Equation (4), considering landmarks: v_1 = "campus" and v_2 = "public administration buildings". At all levels, a consistency check is performed, and the consistency ratio CR is always less than 0.1. At the main level of the AHP criteria hierarchy, a sensitivity analysis is also carried out to determine which is the most critical criterion (weight) in the case of the landmark under consideration. In the case of v_1 = "campus", the most critical weight is C_1 (User Count-Related Criteria), which can reverse the AHP ranking between alternatives DMU_3 and DMU_7 by a change of 0.05, see Equation (6). In the case of v_2 = "public administration buildings", the most critical weighting is C_2 (Transportation Network Criteria), which can reverse the AHP ranking between alternatives DMU_3 and DMU_9 by a change of 0.4, see Equation (6). This does not affect the results obtained, as the final ranking of the alternatives is made by the DEA super-efficiency measure, but makes it clear that the age of the users is a critical criterion when the area is considered a campus area, while the transportation network criterion becomes critical when the area is considered an administrative area. It is also noted that the sensitivity of the weights is higher in the case of the campus area than in the case of the administrative area.

In Table A3, the weighted and normalised values of the input and output variables are presented. According to the DEA method discriminatory power paradigm, 16 BSS stations were selected as the examined DMUs in the Ljubljana city centre cell to achieve the high discriminatory power of the output-oriented DEA model.

The DEA evaluation is made in two stages: first, using the output-oriented and constant return to scale DEA model to detect DMUs feasible for an upgrade; then, using the DEA super-efficiency approach, optimal DMUs are ranked to discriminate between them. Table 2 shows decreasingly ranked optimal DMUs.

Table 2. DEA super-efficiency scores of optimal DMUs.

Landmark v_1= "Campus"		**Landmark v_2= "Public Administration Buildings"**	
DMU16	0.9987	DMU16	0.9999
DMU13	**0.9986**	DMU9	0.9999
DMU9	0.9985	DMU10	0.9987
DMU3	0.9979	DMU3	0.9979
DMU10	0.9975	DMU1	0.9958
DMU15	0.9948	DMU15	0.9902
DMU1	0.9941	DMU11	0.9599
DMU11	0.9719	DMU12	0.9223
DMU5	0.9335	DMU5	0.9061
DMU12	0.8239	DMU2	0.6206
DMU2	0.5759		

It can be seen that landmark affects the selection of BSS stations that can be effectively upgraded to e-BSS, as DMU$_{13}$ is optimal for a campus area but is not selected when the city centre is considered as a region around public administration buildings. It is also possible to note that super-efficiency scores and the order of DMUs differ according to the selected landmark.

Variable return to scale and super-efficiency DEA models were found to be infeasible in this numerical example.

In Figure 3, the Voronoi cell of Ljubljana city centre is presented. All detected optimal DMUs are marked with a bike icon in a red square. A bike icon in a blue square represents DMU$_{13}$, positioned near the National and University Library of Ljubljana, which is the most important Slovenian library and a popular study space among students in Ljubljana. All other BSS stations are located near buildings that are close to both landmarks.

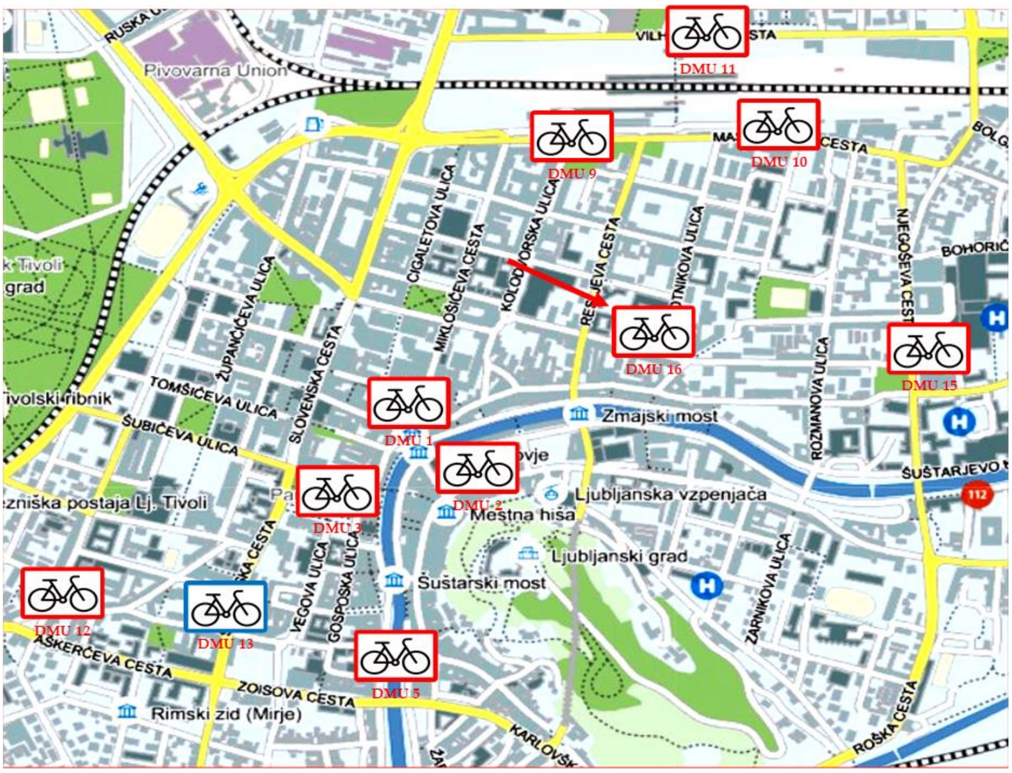

Figure 3. Optimal DMUs in the city centre cell of Ljubljana [47].

DMU_{16}, which has the highest score in both evaluations, is located at an intermediate point between landmarks (see Figure 3, red arrow), near administrative buildings, health facilities, and university campuses. This makes it optimal for both considered landmarks.

It is also important to emphasise that the considered zone is within a radius of 2 km from both landmarks. For this reason, the municipality may decide not to upgrade all detected optimal BSS stations. This further confirms the usefulness of the super-efficiency DEA, which ranks optimal BSS stations and allows the municipality decision makers to make the most appropriate selection of stations to be upgraded.

5. Discussion

The first contribution of this paper is a criteria system for evaluating the adequacy of existing BSS stations to be upgraded with e-bikes and piles, covering all aspects of sustainability and all stakeholders' needs (investors, users, and providers). The final criteria set is generally applicable since it is obtained from highly ranked international scientific literature and is not limited only to the proposed case study. The reason for designing a criteria system is the claims of researchers who argue that analysis of BSS cannot be fully completed by considering single and not multiple perspectives. Thus, a BSS needs to be integrated into urban development to serve several target groups [48]. Similarly, Andreassen et al. [49] think that matching different stakeholders' preferences is critical for a long-lasting and sustainable relationship. They suggest making any selection by defining the "right" criteria, setting a strict selection process, and applying the method able to match all stakeholders' needs.

Thus far, various methods and mathematical models have been proposed by researchers (queuing theory, cost–benefit analysis, agent-based simulation, mixed-integer linear programming, genetic algorithms, and particle swarm optimisation). These methods are, on the one hand, remarkable, but have several weaknesses:

- It is difficult to implement them in practice due to the complexity of real-world modelling problems [50].
- Models cannot consider qualitative (e.g., social influences, sustainable benefits) but only quantitative criteria [50,51].
- Charging stations' suitable location selection problem considers many conflicting criteria [16,52,53].

The MCDM approach (hybrid DEA), which is the second contribution of this paper, was found to be suitable due to its many criteria with different and even conflicting characteristics [50,52,54,55].

The added value of the algorithm proposed in this paper is the two-stage AHP assessment performed separately for each of the selected landmarks. Therefore, the evaluation results reflect the needs/desires of the users of a selected landmark, which are different from the needs of the users of another landmark. The landmarks have a strong influence on the selection of BSS stations that can be effectively upgraded to e-BSS. This reduces the risk of inadequate upgrading of BSSs within a landmark (inadequate selection of BSS station and upgrading with e-bikes and poles), and which allows decision makers to make a decision that is strongly linked to the potential users of the BSS to be upgraded and to the spatial and technical feasibility of upgrading existing BSS stations. For example, DMU_{13} is optimal for a campus area but is not chosen when the city centre is considered a region around public administration buildings. DMU_{16}, which has the highest score in both assessments, is located at an intermediate point between landmarks (administrative buildings, health facilities, and university campus) and is thus clearly relevant for both landmarks considered.

Finally, a super-efficiency measure enables ranking optimal BSS stations according to suitability so that decision makers can decide which stations should reasonably be upgraded, if not all can be. In the city centre of Ljubljana, the super-efficiency ranking of BSS stations differs when the city centre is considered as a campus area or as a region around public administration buildings (see Table 2). This allows investments to be targeted to specific potential users depending on the definition of the urban area. This possibility reduces the risk of unnecessary or wrong investments in stations.

Investors usually do not have unlimited sources of funding, but at the same time, it is risky to invest in all stations in the initial phase of e-BSS implementation, as it is difficult to predict the future use of the system.

Managerial decisions resulting from the proposed approach strengthen three crucial pillars of sustainability: environmental, economic, and social. Offering e-bikes at BSS stations may encourage users who have not previously used BSS services, further contributing to economic efficiency and the often neglected pillar of social sustainability (economic efficiency depends on the frequency of e-bike use, which in turn depends on the degree of flexibility for users—proximity to the station, number of bikes, number of batteries, characteristics of the bikes, etc.). In addition, upgrading existing BSSs reduces the need to build new stations, which may reduce the cost of building the station as well as the negative environmental impact of building the station. At the same time, retaining old BSS users may also reduce advertising costs and is likely to provide economic eligibility in the initial phase of the project as well as long-term success. This upgrades the article by Campbell et al. [6], which is the only research that mentions the possibility of creating e-BSS on extant BSS or extending such BSS with e-bikes.

Moreover, to determine the criteria weights, the Power-Geometric scale was used, which highlights the most relevant criterion considering a selected landmark. Landmarks characterise users of each defined cell. In this way, a model additionally contributes to social and, therefore, economic sustainability, as it proposes to expand only those stations in each sub-region that are useful to users. Frequent use of bikes, however, ensures the economic viability of the project.

Despite the fact that the DEA evaluation has to be made separately for each landmark to include in the evaluation of potential users' requirements, the methods are not complex for the users. However, there are also software solutions for the subdivision of the urban area in sub-areas (Voronoi diagram), the AHP and the DEA methods.

5.1. Managerial Implications

The proposed model is primarily helpful for upgrading BSS in city centres and other areas, which are multi-purpose, so it is difficult to determine which landmark is the most relevant. However, the idea of involving key stakeholders in the planning phase and a customised algorithm can also be used in the planning of a new e-BSS or BSS. The proposed approach supports the idea of Turoń [56], who claims that it is worthwhile to check the expectations of the users of the systems and rebuild the system accordingly to create a service oriented towards the real needs of the customers.

The algorithm suggests to decision makers, investors, or legal entities that make decisions about the installation of e-BSS to see which stations make sense depending on the landmark and to what extent (how many e-bikes and/or piles) they should be upgraded. The stations for which the algorithm suggests upgrading are targeted at BSS users and their needs at this location and not at other locations. Other landmark users may have different needs or importance of requirements. Our proposed approach is customer-centric, which may lead to higher satisfaction of BSS users and, thus, better use of the system. The algorithm not only strengthens the already existing cooperation with local authorities and planners (they had to agree to the location of the BSS), but also builds cooperation with BSS users. Such an approach can reduce some of the risks and problems faced by planners of BSSs who have ignored users' opinions when considering different landmarks.

Moreover, in case an e-BSS designer has limited finances, the proposed solution even allows upgrading only those technically efficient stations that are most favourable from the point of view of the user and the investor. In a later stage, those that are less favourable but still technically efficient may also be upgraded. This solution is not only favourable to those designers who have a limited budget but also encourages other designers to invest more rationally in this area.

Our proposed criteria system for e-BSS siting is more comprehensive than other lists of criteria published in previous studies, meets some of the targets of the United Nations Sustainable Development Goal 11, and reflects the wishes of key stakeholders. This brings advantages for potential users of our algorithm but also for decision makers or designers of BSSs who want to check the profitability and also customer orientation of solutions. The criteria system is also generally useful and is not written on the skin of the Slovenian case study or investors, as it is based on the findings of the authors of international highly ranked scientific literature.

5.2. Policy Contribution

This study is a step forward in developing a business model for open innovation that does not yet exist in the field of BSSs. BSSs and e-BSSs are customer-centric business models. Our model gives a BSS user the opportunity to actively transform a system into an open, accessible, and efficient system for the user. Thanks to the collaboration between designers and users used in the proposed model, different types of recommendations and actions can be identified that should be considered not only by designers but also by community members and policy makers. The highlighted aspects (problems, risks for e-BSS users) can help policy makers to develop measures to increase interest in e-BSS, which can also translate into more sustainable services in cities.

For example, if the lack of cycling infrastructure and concerns about road safety were mentioned as possible barriers to use, policy makers should pay attention to this problem and plan future measures to reduce the problem.

5.3. Theory Contribution

The proposed model primarily benefits the theory on business models for open innovation in e-BSS, but also for sharing systems in general. Open innovation business models are needed in BSS and e-BSS but have not yet gained acceptance. BSS and e-BSS are customer-oriented solutions, and the customer feedback that the open innovation business model enables would help to develop the needed solutions

The proposed model, which is one of the first of its kind in the field, also poses a challenge to researchers. The model, therefore, requires further critical analysis, extensions, and improvements. Some of these are presented in Section 6. Further testing of the model in different environments (larger cities) and adapting or using completely new criteria is also needed, as one solution is not suitable for all situations.

The comprehensive set of criteria can be used in its current form in future research in the field of e-BSS. As a basis, it is also useful for research in the field of other e-sharing systems, such as e-scooter sharing systems and e-car sharing systems. Despite its comprehensiveness, the list of criteria can also be subject to critical analysis and updated according to the newly published results that are not part of this paper. Some recent research suggests that, for example, the security aspect is a major barrier to the greater benefits of BSSs and e-BSSs. Data sharing in mobility and city centre delivery solutions has also been shown to be risky from a user perspective, so it would be useful to pay more attention to this area in the future.

6. Conclusions

In order to fill the identified gaps and emphasise the sustainability of the final proposed solution, a sustainable and targeted extension approach of the existing BSSs with e-bikes and charging points is proposed. An Adaptive Multi-Criteria Hybrid DEA methodology was defined and tested in the city centre of Ljubljana, where the choice of a suitable landmark is not so obvious, as the area is used in many ways.

The paper upgrades the article by Villacreses et al. [12], which is the only one to propose a model for the optimal location for installing e-bike charging stations using an MCDM. The proposed approach is based on only seven criteria, which cover the environmental, social, and economic pillars of sustainability, but not comprehensively.

Only a few criteria assess one aspect of sustainability, which casts doubt on the credibility of the results. Moreover, the methodology is based on the integrated approach AHP-TOPSIS to select a site for the installation of a new e-bike station rather than on the assessment of the benefits of the existing stations. Villacreses et al. [12] used a linear scale rather than a Power-Geometric scale, which is more appropriate and therefore used in this article. TOPSIS was used to rank the sites, which provides a unique ranking in common benchmarking. The method used in this article, DEA, efficiently evaluates the whole process.

The results show that upgrading an existing BSS with e-bikes and charging piles is not unique but strongly related to the use of the selected area. DMU_{13} in Ljubljana was optimal for a campus area but was not selected when the city centre was considered a region around the public administration buildings. This result answers the second question RQ2: Does the use of the selected urban area influence the upgrade of BSSs with e-bikes and piles? The proposed algorithm illustrates which stations make sense to upgrade when considering different landmarks.

Moreover, the use of the super-efficiency DEA model has shown that even the scores and the order of DMUs differ depending on the landmark selected. DMU_{16} is the only one that kept the same place (the best score) in both evaluations because it is located at an intermediate point between the landmarks. Other DMUs have changed their place in the ranking. The above results answer the question RQ3: To what extent does the upgrade with super-efficiency DEA ranking influence the upgrade and costs?

Furthermore, finally, a comprehensive criteria system for e-BSS site selection was designed to answer RQ1: What criteria are relevant to undertake a sustainable upgrade of existing BSS stations? Nine groups of criteria were identified, each including 2–12 criteria. The criteria system is synchronised with the objectives of the United Nations Sustainable Development Goal 11.

The proposed model, which is also the first such model for e-BSS, needs further critical analysis, updating, and improvement to achieve even more credible solutions. The main limitation is that the model needs to be tested on several case studies of cities of different sizes from different geographical areas. In addition, the expert panel needs to be expanded beyond Slovenia to include more general opinions and assessments. It would also be useful to analyse how the proposed MCDM approach can be integrated with linear programming, which is already widely used. The model could also bring benefits if users were willing to use e-bikes to upgrade BSS. The authors of this paper have not conducted this type of research, but in the future, it would be necessary to investigate the interest or incentives of the provider, municipality or government agency that would accelerate the use of e-bikes.

Finally, bike-sharing operators who want to switch to electric bikes need to consider the cost of switching from BSS to e-BSS, as this is not known, and to our knowledge, this type of model has not yet been implemented in the world. Therefore, we cannot say with certainty whether the conversion from BSS to e-BSS would bring savings and how much they would be. The open innovation challenges could also be a useful tool to help BSS providers gather users' opinions about the bike-sharing service and find solutions that are not only socially but also economically sustainable. Until this kind of upgrade of BSSs is implemented in the future, we can only assume that the cost of upgrading BSSs with e-bikes will be lower than the cost of setting up a new e-BSS. We hope that this article will inspire one of the project coordinators or the manager of the Living Lab in the city centre to check these assumptions.

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Appendix A

Table A1. Evaluation criteria system for the site selection of e-BSS.

Urban Life-Related Criteria	
Proximity to shopping malls	[2,50,55,57–60]
Proximity to primary/secondary schools	[60]
Proximity to commercial buildings	[2,50,53,55,57,59,61]
Proximity to tourist attractions/recreation area	[60]
Proximity to campus	[2]
Proximity to cultural elements	[12]
Walking time of the e-bike users to the bike-sharing station	[1,4,8,12,16,51,62–65]
Impact on residents' lives	[50,51,66]
Proximity to cultural and social life	[16,50,52,55,66,67]
Point of interest	[16,58,67]
Coordination level with the urban development planning	[68]
User Count-Related Criteria	
Population density	[16,52,57–60,62,67,69,70]
Proximity to a young population	[55]
Possibility of offering suitable services to the drivers at the electric vehicles charging station in the future	[69]
Transportation Network Criteria	
Proximity to a bike lane	[12,60]
Proximity to the subway network	[60]
Proximity to the bus transport network	[12]
Proximity to the tramway network	[60]
Proximity to transit hubs	[16,60,61]
Proximity to road networks	[12,52]
Proximity to ferry ports	[60]
High traffic density roads	[12,50,51,57,68]
Coordination with the entire transportation network	[51,57]
Proximity to intersections	[50,52,53,57]
Proximity to the parking area	[16,52,61]
Public transport connection	[55,57,59,66,69,70]
Terrain-Related Criteria	
The slope of the terrain	[12,16,53,57,59]
Topography	[54]
Possibility of expansion	[53,54,69]
Environment-Related Criteria	
Distance to vegetation	[16,50,52–54,57,59,60,66,68,69]
Distance to water resources/seaside	[16,50,52–54,57,60,66,68]
Distance to landslide area/to earthquake area	[16,52–54,57,59]
The emission rate of the area	[50,52,54,66,68–70]
Repositioning trucks depot location	[4,64]
Waist discharge	[50,66,69]
Battery-Related Criteria	
Number of batteries at the station	[63]
Average charging time of the battery	[4,8,71]
Voltage of the battery	[8]
Number of charging piles at the station	[4,8,50,67,72]
E-bike battery autonomy under regular use	[4,65,73]
Energy consumption rate	[4]
Drivers' comfort	[51]

Table A1. *Cont.*

E-bike-Related Criteria	
Average riding speed	[4,74]
Number of shared e-bikes at the station	[1,8,52]
Economic Criteria	
Equipment purchasing costs	[50–52,54,55,65,66,68–70,72]
Annual operation and maintenance costs	[50,51,54,66,68–70]
Investment payback period	[50,51,54,66]
Land occupation costs	[51,53,70,72]
Update and removal costs of the station	[68]
Electricity-Related Criteria	
The power supply capacity of transmission and distribution network	[50,51,54]
Impact on the load levels of the power grid	[51,54,71]
Harmonic pollution affecting the power grid	[51]
Impact on voltage/voltage stability	[50,51,68,70,72]
Electric network of the city	[2,12,16]
Sustainable energies potential	[52]
Proximity to an electric substation	[52–54]

Table A2. AHP evaluation of criteria using the power scale.

Criteria	Landmark v_1="Campus"			Landmark v_2="Public Administration Buildings"		
	1st Stage	2nd Stage	Final Weights	1st Stage	2nd Stage	Final Weights
C_1	0.2607			0.3976		
C_{11}		0.9033	0.2355		0.2134	0.0848
C_{12}		0.0828	0.0216		0.5554	0.2208
C_{13}		0.0138	0.0036		0.2312	0.0919
C_2	0.3611			0.3365		
C_{21}		0.2384	0.0861		0.2369	0.0797
C_{22}		0.0790	0.0285		0.0437	0.0147
C_{23}		0.3193	0.1153		0.2409	0.0811
C_{24}		0.0417	0.0151		0.0314	0.0106
C_{25}		0.2240	0.0809		0.1580	0.0532
C_{26}		0.0186	0.0067		0.0848	0.0285
C_{27}		0.0067	0.0024		0.0164	0.0055
C_{28}		0.0132	0.0048		0.0636	0.0214
C_{29}		0.0592	0.0214		0.1244	0.0418
C_3	0.0216			0.0233		
C_{31}		0.3729	0.0081		0.8889	0.0207
C_{32}		0.6271	0.0136		0.1111	0.0026
C_4	0.0296			0.0340		
C_{41}		0.9412	0.0279		0.8889	0.0302
C_{42}		0.0588	0.0017		0.1111	0.0038
C_5	0.1025			0.0916		
C_{51}		0.7275	0.0746		0.5753	0.0527
C_{52}		0.2352	0.0241		0.3661	0.0335
C_{53}		0.0373	0.0038		0.0586	0.0054
C_6	0.2004			0.0703		
C_{61}		0.6667	0.1336		0.8000	0.0562
C_{62}		0.3333	0.0668		0.2000	0.0141

Table A2. *Cont.*

Criteria	Landmark v_1="Campus"			Landmark v_2="Public Administration Buildings"		
	1st Stage	**2nd Stage**	**Final Weights**	**1st Stage**	**2nd Stage**	**Final Weights**
C_7	0.0189			0.0339		
C_{71}		0.6004	0.0114		0.3258	0.0111
C_{72}		0.2748	0.0052		0.2345	0.0080
C_{73}		0.0248	0.0005		0.1075	0.0036
C_{74}		0.1000	0.0019		0.3322	0.0113
C_8	0.0051			0.0128		
C_{81}		0.2986	0.0015		0.2920	0.0037
C_{82}		0.4329	0.0022		0.4312	0.0055
C_{83}		0.0516	0.0003		0.0521	0.0007
C_{84}		0.2169	0.0011		0.2247	0.0029

Table A3. Value of the input and output variables for the selected DMUs.

Variable Classification	I	I	I	I	O−	O+	O+	O+
	C1	**C2**	**C3**	**C8**	**C7**	**C4**	**C5**	**C6**
Landmark v_1 ="campus"								
DMU1	0.2607	0.0181	0.0081	0.0046	0.0076	0.0293	0.0315	0.0752
DMU2	0.2607	0.0204	0.0081	0.0046	0.0180	0.0293	0.1025	0.2004
DMU3	0.2607	0.0292	0.0081	0.0045	0.0137	0.0292	0.0592	0.1503
DMU4	0.2607	0.1195	0.0081	0.0044	0.0117	0.0292	0.0432	0.1202
DMU5	0.2607	0.0138	0.0081	0.0043	0.0079	0.0292	0.0315	0.0752
DMU6	0.2607	0.1315	0.0216	0.0043	0.0142	0.0292	0.0592	0.1503
DMU7	0.2607	0.1269	0.0216	0.0049	0.0142	0.0293	0.0592	0.1503
DMU8	0.2607	0.1415	0.0081	0.0047	0.0142	0.0293	0.0592	0.1503
DMU9	0.2607	0.0905	0.0081	0.0049	0.0117	0.0294	0.0432	0.1202
DMU10	0.2607	0.1336	0.0081	0.0047	0.0142	0.0295	0.0592	0.1503
DMU11	0.2607	0.0331	0.0081	0.0042	0.0148	0.0295	0.0592	0.1503
DMU12	0.2607	0.0146	0.0081	0.0042	0.0142	0.0291	0.0592	0.1503
DMU13	0.2607	0.1416	0.0081	0.0043	0.0142	0.0291	0.0592	0.1503
DMU14	0.2607	0.1239	0.0081	0.0044	0.0148	0.0295	0.0592	0.1503
DMU15	0.2607	0.1255	0.0081	0.0044	0.0123	0.0296	0.0432	0.1202
DMU16	0.2607	0.0376	0.0081	0.0051	0.0148	0.0295	0.0592	0.1503
Landmark v_2 = "public administration buildings"								
DMU1	0.3976	0.0159	0.0207	0.0116	0.0164	0.0332	0.0311	0.0264
DMU2	0.3976	0.0171	0.0207	0.0116	0.0283	0.0332	0.0916	0.0703
DMU3	0.3976	0.0405	0.0207	0.0112	0.0224	0.0331	0.0569	0.0527
DMU4	0.3976	0.1483	0.0207	0.0110	0.0226	0.0331	0.0431	0.0422
DMU5	0.3976	0.0130	0.0207	0.0108	0.0183	0.0330	0.0311	0.0264
DMU6	0.3976	0.1569	0.0233	0.0107	0.0254	0.0329	0.0569	0.0527
DMU7	0.3976	0.1560	0.0233	0.0124	0.0254	0.0333	0.0569	0.0527
DMU8	0.3976	0.1865	0.0207	0.0118	0.0254	0.0332	0.0569	0.0527
DMU9	0.3976	0.0648	0.0207	0.0124	0.0226	0.0335	0.0431	0.0422
DMU10	0.3976	0.1628	0.0207	0.0118	0.0254	0.0337	0.0569	0.0527
DMU11	0.3976	0.0278	0.0207	0.0104	0.0292	0.0336	0.0569	0.0527
DMU12	0.3976	0.0142	0.0207	0.0106	0.0254	0.0328	0.0569	0.0527
DMU13	0.3976	0.1711	0.0207	0.0106	0.0254	0.0329	0.0569	0.0527
DMU14	0.3976	0.0904	0.0207	0.0110	0.0292	0.0336	0.0569	0.0527
DMU15	0.3976	0.1618	0.0207	0.0111	0.0263	0.0340	0.0431	0.0422
DMU16	0.3976	0.0297	0.0207	0.0128	0.0292	0.0336	0.0569	0.0527

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