Case Studies on Transport Policy 13 (2023) 101052

Contents lists available at ScienceDirect

Case Studies on Transport Policy

journal homepage: www.elsevier.com/locate/cstp

Optimising shared electric mobility hubs: Insights from performance analysis and factors influencing riding demand

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ARTICLE INFO

Keywords:
Shared mobility
Electric mobility
Mobility hubs
E-bike
E-bike sharing system
Data envelopment analysis

ABSTRACT

In order to decarbonise the transport networks, systemic change is needed. One manifestation of this transformation is shared electric mobility, seeking to curtail car usage and ownership. This current case study aims to measure and optimise the operational performance of shared electric mobility hubs (eHUBs). From the performance results of eHUBs, one can get helpful insights to develop appropriate future planning and management policies for improving the transport chain. Incorporating data from September 2021 to October 2022, this research developed a novel dynamic two-stage data envelopment analysis (DEA) framework to assess the performance of the eHUB network in Inverness, Scotland. In the first stage, the DEA model computes relative efficiency scores related to the operational performance of the stations. The second stage focuses on network analysis and examining the factors that may influence the high or low obtained performance scores. Scrupulous analysis shows that the population in the catchment area of the eHUBs and the weather conditions (specifically, temperature) are among the most important factors influencing riding demand. The study also finds a weak association between eHUBs efficiency and proximity to public transport stops, suggesting that electric-assist bikes (e-bikes, pedelecs) may not strongly complement public transport, unlike bike-sharing systems. It indicates that e-bikes serve rather as a standalone mode for longer journeys. The findings of the case study can be used to improve sustainable mobility strategies, particularly related to e-bikes in other cities and urban areas.

1. Introduction

1.1. Background

Adopting sharing economy solutions, which emphasise possessing less and sharing more, is one of the key strategies to tackle overconsumption, achieving sustainability, and mitigating emissions (Schanes et al., 2016; Miramontes et al., 2017). Shared mobility is recognised as a sharing solution to substitute for private automobility in the transportation sector (Sopjani et al., 2020; Coenegrachts et al., 2021; Della Mura et al., 2022). This substitution may decrease traffic congestion (Bösehans et al., 2021) and, if electrified, can contribute positively to reducing air pollution (Machado et al., 2018) and GHG emissions (Martin and Shaheen, 2016; Caulfield and Kehoe, 2021) in urban settlements. Shared mobility can also be a beneficial tool for the progressive redistribution of wealth to the more vulnerable parts of society underserved by existing transport provisions (Hosseini and Stefaniec, 2023).

Shared mobility hubs are increasingly gaining popularity and investment at research and policy levels (Rongen et al., 2022). These hubs offer integrated multimodal shared transport services and facilitate intermodal transfers by providing an array of mobility options in proximity (Miramontes et al., 2017). What distinguishes them from free-floating car-sharing and bike-sharing systems is the specific geographical location of a hub, making multimodal trips more convenient and creating a sense of a designated place for travel. A fixed site can also provide a suitable location for installing charging infrastructure where shared electric vehicles can be recharged while parked (Liao and Correia, 2022).

Whether the added value of multimodal hubs is abundant (Bösehans et al., 2023) or insubstantial compared to the monomodal car-sharing scheme (Claasen, 2020), its potential to replace private car trips should not be underestimated (ITF, 2018). This research focuses on shared electric mobility hubs (eHUBs), which are on-street locations that simultaneously build on multimodal and electric mobility services. As an

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https://doi.org/10.1016/j.cstp.2023.101052
Received 17 January 2023; Received in revised form 19 July 2023; Accepted 21 July 2023
Available online 22 July 2023

innovative pilot low-carbon mobility project, the eHUBS project[1] aims to deploy various electric micro-mobility options, such as e-bikes, e-cargo bikes, and e-scooters. Currently, pilot eHUB networks are operating in ten cities in Europe. The goal of pilot projects such as the eHUBS project is to modify mobility behaviour in society by replacing private car trips with trips made by electric and micro-mobility means of transport.

This work offers a unique framework for evaluating shared electric mobility hubs and e-bike sharing systems. The presented analysis in this research is informative in that it assesses the eHUB network by investigating multiple indicators, which recognises efficiency improvement directions within the mobility sector. The performance of eHUBs is examined over 12 months extending the analysis to incorporate the time factor. Furthermore, this study is the first to measure the performance of an e-bike sharing system using a data envelopment analysis (DEA) framework and explore the factors influencing the obtained efficiency scores. The dynamic slacks-based measure DEA approach (SBM) is selected as a suitable model to provide an informative and comprehensive picture of the eHUB system, which can assist mobility decision-makers in future developments and rearrangements. additionally, this study contributes to a topical issue, given the concerted efforts made by many governments towards shared mobility and electrifying transportation. While policymakers are often sceptical about the outcomes of the untested new forms of mobility, this research provides evidence for the effective implementation of eHUB networks. Through these improvements and implications, the transport chain can advance toward implementing challenging goals of climate neutrality and reducing private car usage and ownership.

1.2. Previous work

The transportation sector serves as the backbone of the modern economy. Due to its massive energy consumption, waste production, and emission generation, it is necessary to appraise the efficiency and sustainability of different segments and aspects of this sector. Since DEA's inception, dozens of studies have utilised it to estimate efficiency and sustainability in different parts of the transportation sector (Cavaignac and Petiot, 2017). DEA has been applied for the sustainability assessment of various transport case studies within a country (Chutiphongdech and Vongsaroj, 2022; Gandhi et al., 2022; Stefaniec et al., 2020) and between several countries (Güner, 2021; Stefaniec et al., 2021). In relation to the public transport domain, Caulfield et al. (2013) employed DEA as an appraisal tool to examine optimal public transport investment strategies. Suguiy et al. (2020) considered the quality of service, satisfaction of the passengers, and operation efficiency index to measure the performance of the public transport network in 50 Brazilian cities by using DEA. Including daily shared-bicycle ridership and the number of shared-bicycle stations as indicators in their proposed DEA framework, Tamakloe et al. (2021) analysed transit-oriented development in Seoul.

Tavassoli et al. (2014) proposed a model based on the SBM to analyse the technical efficiency and service effectiveness of 11 Iranian airlines. Gong et al. (2019) utilised an SBM-based model to compare 26 major shipping companies. Tomikawa and Goto (2022) measured the efficiency of the Japanese railway system before and after privatisation by combining both radial and nonradial DEA. Using SBM, Quintano et al. (2020) assessed the eco-efficiency of 24 ports in Europe. In line with other studies (Rashidi and Cullinane, 2019; Liu et al., 2017; Lee et al., 2014; Cook et al., 2013), they confirmed that outcomes generated from SBM are more precise and reliable compared to radial DEA models when dealing with complex case studies. To effectively deal with complex dynamic applications (when the system runs over separated time periods), Tone and Tsutsui (2010) introduced the dynamic SBM model, which investigates and evaluates DMUs in separated periods.

A few research papers also concentrate on the performance measurement of shared mobility in urban settlements from different points of view. Focusing on the efficiency evaluation of Malmö's public bike-sharing stations and their determinants, Caggiani et al. (2021) employed DEA to identify the best-performing stations in the system. In their model, they considered the usage trends of each station as outputs and the characteristics of stations are among their inputs. They concluded that their outcomes could assist service planners in reallocating existing resources in the bike-sharing system. The turnover rate of bike-sharing stations is defined as both the daily number of bikes rented from a station divided by the same station's capacity and the daily number of bikes returned to a station over the same station's capacity (Jiménez et al., 2016). Aiming to improve the efficiency of the bike-sharing system in Seoul, Hong et al. (2020) utilised turnover rate and balancing rate as outputs in their two-stage DEA-based framework. Also, the number of bicycle racks and the ratio between the bicycle paths and vehicle lanes are selected as inputs. They mentioned their short study period (one month) as the main limitation of their work. In an effort to reduce the occurrence of accidents involving micro-mobility, Prencipe et al. (2022) employed input-oriented radial DEA to assess the safety of urban areas. Their study was conducted in the city of Bari, Italy and involved the consideration of various inputs including population size, number of educational institutions, hospitals, and bus stops.

Apart from DEA, a number of studies explored electric micro-mobility from diverse angles, using different analytical tools. For instance, Bardi et al. (2019) constructed an ordered probit model to identify the determinants of satisfaction levels and usage patterns in e-bike sharing systems. De Kruijf et al. (2021) employed binary regression analysis to investigate the relationship between e-cycling and weather conditions in Noord-Brabant, the Netherlands. They concluded that e-bike trips decrease at higher air temperatures. Noland (2021) analyzed the effect of weather conditions on three shared micro-mobility modes, namely e-scooters, e-bikes, and bicycles, in Austin, Texas, using Prais-Winsten regression analysis. The author noted that higher average temperatures increase the duration and distance of e-bike travel, while lower temperatures, rain, and wind have an adverse effect on e-cycling.

1.3. Structure of the paper

The central aim of the current study is to provide quantitative empirical evidence to handle policy-related concerns on the adoption of shared mobility. This work develops an evaluation framework to measure the relative efficiency of the eHUBs and identify the factors which determine their performance to assist local authorities in the future planning and management of these sites.

The rest of the research paper is organised as follows. Section 2 presents the methodology. Section 3 describes the case study, dataset, our new proposed framework, and variables. Section 4 interprets the study's outcomes and discusses key factors influencing the operational performance of eHUBs. Section 5 concludes the paper and provides recommendations for policymakers.

2. Methodology

To measure the performance of eHUBs, the current study employs the SBM-DEA approach for the following reasons. DEA and stochastic frontier analysis (SFA) are two well-established quantitative approaches for performance assessment. However, SFA, as a parametric method, is suitable for single-output case studies. Thus, SFA is unfit to appraise complex systems such as the eHUB network when several outputs exist. Conversely, as a nonparametric methodology, DEA can measure relative performance in multi-input and/or multi-output cases (Wu et al., 2016). Charnes et al. (1978) introduced radial DEA to measure the productivity of the decision making units (DMUs). DEA is able to produce a single

[1] eHUBS project website: https://www.nweurope.eu/projects/project-search/ehubs-smart-shared-green-mobility-hubs/.

measure of performance for each DMU with multiple inputs consumed to produce multiple outputs. It should be noted that DEA is a relative efficiency appraisal model. This means that DEA can assist decision-makers in learning how well a DMU performs compared to its peers.

2.1. Dynamic slacks-based measure approach

Tone (2001) developed the nonradial efficiency measure in DEA called SBM. Unlike the radial model, the SBM model deals concurrently with the input surpluses and the output shortfalls. The inefficiency components called slack variables are deducted from the unity, giving each DMU a performance score (Tomikawa and Goto, 2022). In addition, SBM possesses greater discriminatory power than radial models to rank DMUs (Rashidi and Cullinane, 2019). There are n DMUs that utilise input $X = (x_{ij}) \in R^{m\times n}$ and output $Y = (y_{ij}) \in R^{s\times n}$. The SBM methodology is unit-invariant and also monotone decreasing in each slack of input $s_i^-(i = 1, \cdots, m)$ and output s_r^+ $(r = 1, \cdots, s)$ that represent input surplus and output shortfall, respectively.

Based on the technology set, the relative efficiency of the focal DMU_o may be generated from the linear program. We select output-oriented SBM to calculate the operational performance scores of eHUBs, since it is assumed that the regulators wish to enhance the electric mobility system output and maximize profit. The efficiency score of DMU_o under the constant returns to scale assumption is obtained by:

$$\frac{1}{\rho_o} = \max_{\lambda,\, s^-,s^+} 1 + \frac{1}{s}\left(\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}}\right) \text{s.t. } x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \quad (i = 1, \cdots, m),\ y_{ro} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \quad (r = 1, \cdots, s), \lambda_j \geq 0\,(\forall j),\ s_i^- \geq 0\,(\forall i),\ s_r^+ \geq 0\,(\forall r) \tag{1}$$

A DMU is classified as SBM-output-efficient if the value of ρ_o is equal to unity. That is equivalent to having output slacks of size zero. The model enables us to obtain projections onto the frontier for inefficient DMUs. Based on the optimal solutions for λ^*, s^{-*}, and s^{+*}, the input surplus and output deficiency are computed.

To demonstrate the changes in performance over time, we apply the modified dynamic SBM to measure the performance of each station during each month of the 12-month sample. The selected input and output are computed in T periods indexed $t = 1, \cdots, T$. DMUs, indicators, and parameters are identified by subscript or superscript t, which relates them to the term. The model does not consider any additional carry-over activities due to the absence of link indicators in the eHUB system dataset. The dynamic system possibility set is defined as follows:

$$x_{it} \geq \sum_{j=1}^{n} x_{ijt}\lambda_j^t (i = 1, \cdots, m; t = 1, \cdots, T),\ y_{rt} \leq \sum_{j=1}^{n} y_{rjt}\lambda_j^t \quad (r = 1, \cdots, s;\ t = 1, \cdots, T),\ \lambda_j^t \geq 0 \quad (j = 1, \cdots, n; t = 1, \cdots, T). \tag{2}$$

The output-oriented efficiency τ_{ot} for period t can be computed from the program below (Tone and Tsutsui, 2010):

$$\frac{1}{\tau_{ot}} = \max_{\lambda,\, s^-,s^+,s^{u+}} 1 + \frac{1}{T}\left[\frac{1}{s}\left(\sum_{r=1}^{s}\frac{s_{rt}^+}{y_{rot}}\right)\right], \text{s.t. } x_{iot} = \sum_{j=1}^{n} x_{ijt}\lambda_j^t + s_{it}^- (i = 1, \cdots, m; t = 1, \cdots, T),\ y_{rot} = \sum_{j=1}^{n} y_{rjt}\lambda_j^t - s_{rt}^+ (r = 1, \cdots, s;\ t = 1, \cdots, T),\ \lambda_j^t \geq 0\,(\forall j, t),\ s_{it}^- \geq 0\,(\forall i, t),\ s_{rt}^+ \geq 0\,(\forall r, t). \tag{3}$$

Because of the reciprocal of τ_{ot}, the output efficiency score ranges between zero and unity. To calculate the SBM estimates, we employ R software.

2.2. Network representation

Network analysis is a tool that detects patterns in complex systems such as bike-sharing systems (Wu and Kim, 2020; Xin et al., 2022; Builes-Jaramillo and Lotero, 2022) and thus suits our case study. A representation of the network of eHUB stations was constructed as a graph and visualised using open-source software Gephi version 0.9.7 (Gephi, 2022). The network consists of nodes that represent the eHUB stations, and edges that link these stations. The network is directed, meaning that the flow of e-bikes into and out of each station was taken into account. Round trips were also included in the analysis, ensuring a comprehensive view of network operation. The weight of the edge represents the bidirectional flow between a pair of stations, while the node's weight reflects the number of round trips. The distance between stations was not considered in this analysis. To measure the connectivity of the stations, a degree centrality metric was applied (Wu and Kim, 2020). It is the sum of the in, out, and round trips from and to a given station.

The application of network analysis provides a comprehensive understanding of the dynamics and usage patterns inherent to the eHUB network. It offers a clear depiction of the system's key strengths and weaknesses, guiding future enhancement and effective planning for the service providers. For instance, identifying the most active stations or routes can provide insights for potential infrastructure upgrades or more efficient redistribution of e-bikes across the network.

3. Case study

3.1. Study area

This case study develops a framework to evaluate the operational performance of eHUB networks. The proposed framework is based on dynamic DEA, which can compare units that utilise and produce the same sets of inputs and outputs. The method is applied to evaluate the performance of the eHUB system in Inverness (known as Hi-Bike Inverness, developed by HITRANS company) covering the 12 months of operation from its inception in October 2021 to September 2022. During the study period, the network offered only one type of electric vehicle: e-bikes.

Inverness, the capital of the Scottish Highlands, is home to almost 50,000 inhabitants (The Scottish Government, 2022). By the end of September 2022, there were three docking eHUBs in Inverness: Inverness Campus, Inverness Railway station, and NatureScot Great Glen House station (See Fig. 1). A docking eHUB has physical docks available, and e-bikes can recharge their batteries there (Fig. 2). The Inverness Campus station is situated nearby several higher education institutes. Inverness Railway is located close to the central transit node of the city, and NatureScot Great Glen House is in proximity to a large business centre. Also, Inverness had three virtual (dockless) eHUBs available: Eden Court Theatre station, Inverness Leisure station, and Raigmore Hospital station (Fig. 1). A virtual eHUB is a GPS-defined zone where e-bikes can be taken out or returned to the system, but there are no charging facilities. The system has another virtual station (School of Forestry station), but we do not consider it in our DEA analysis because of data inconsistency. The Eden Court Theatre station operates beside a cultural centre. Inverness Leisure station is on the doorstep of a community sports centre, and Raigmore Hospital station is located within a hospital area. This diversification in the locations of current stations can offer helpful information about the impact of the surrounding vicinity on the performance of each station and provide insights for choosing sites for new stations.

3.2. Data description

For operational efficiency measurement of eHUBs based on previous literature and the available data, the capacity of each station at the

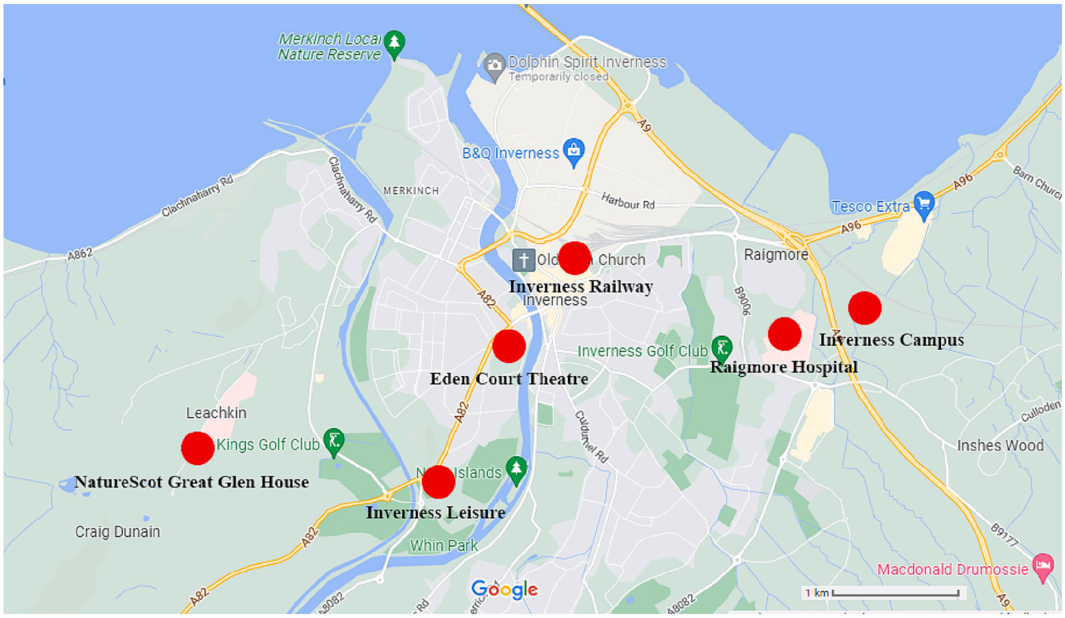

Fig. 1. Map of the eHUB network in Inverness.

Fig. 2. Inverness Campus eHUB with physical docks and shared e-bikes. (Photo credit: Highlands and Islands Enterprise). Reprinted with consent.

eHUB system is considered as the sole input (Fig. 3). The eHUB network in Inverness utilises a fleet of 30 e-bikes circulating across all stations. Each virtual station accommodates up to six e-bikes, while each docking station has a capacity for 15. Outputs include the turnover station rate based on arrival, balancing station rate, and monthly total length of trips per station (in km). The turnover station rate (TO) expresses the station's popularity as a destination point. In other words, it shows how often the capacity of an eHUB is used by riders. Jiménez et al. (2016) calculated it as the total number of daily arrivals *(AR_i)* to the station *i* divided by the station's capacity (C_i).

$$TO_i = \frac{AR_i}{C_i} \tag{4}$$

The balancing station rate (BL) demonstrates the daily average occupancy of each eHUB. It shows whether there is a balance between the number of e-bikes taken out from a station and put into a station within a day. It is defined as the ratio between daily departure *(DP_i)* and daily arrival (Hong et al., 2020) of e-bikes at each station in the eHUB network.

$$BL_i = 1 - \left|\frac{DP_i - AR_i}{AR_i}\right| \tag{5}$$

Finally, to compute the monthly total length of trips per station (LT_i) in km, we multiply the number of monthly departures from station *i* by the monthly average distance of the trips started from station *i*. A summary of the descriptive statistics of the relevant data is shown in Table 1. The current research used data from six operating eHUBs in Inverness, covering the 12 months from October 2021 to September 2022. To evaluate the performance based on the proposed framework, we treat each eHUB in a particular month as an eHUB-month unit; hence, we have 72 DMUs. High construct validity is concluded for our DEA model because the number of eHUB-month units meets the rule of thumb (Hosseini and Stefiniec, 2019) that the number of DMUs should be bigger than triple the number of variables used for the DEA analysis.

As shown in Table 1, the minimum amount of monthly total length of trips per station travelled in the system is zero, which is the case for Inverness Leisure station in December 2021. Tone (2002) mentioned two possible reasons for a DMU, having an output of size zero. First, the DMU may never produce that specific output during the studied period, in which case the indicator must remain untouched (zero). Second, the DMU can generate that output, but incidentally, its observed value is

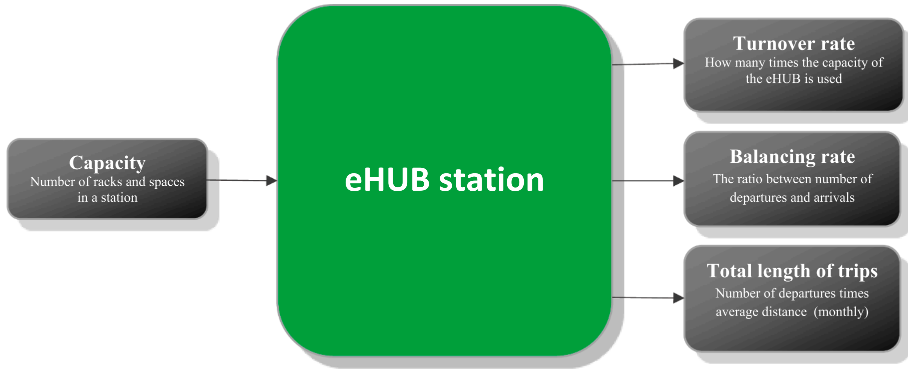

Fig. 3. Illustration of the proposed dynamic framework.

Table 1
Descriptive statistics of inputs and outputs for the proposed performance measurement model.

	Min	Max	Mean	Std. Dev.
Station capacity	6.000	15.000	10.500	4.532
Turnover rate	0.005	0.753	0.174	0.163
Balancing rate	0.333	1.000	0.870	0.141
Monthly total length of trips (km)	0.000	2049.520	359.309	468.487

zero. In this case, we must change the amount of the variable from zero to a small positive number (for instance, 0.1). December 2021 is the only month in which the average trip distance from Inverness Leisure station was zero. Thus, we adjusted the average distance for Inverness Leisure station in December from zero to 0.1 (see Hosseini and Stefaniec, 2019 for an opposite case).

Moreover, correlation analysis for the selected indicators was also calculated and is presented in Table 2. The correlation coefficients are significantly positive at the 1% level, showing that the indicators are significantly related and suitable for use in the proposed dynamic SBM model.

4. Results and discussion

4.1. Empirical results

The core target of this study is to propose a comparative framework to measure the operational performance of electric shared mobility hubs and to offer quantitative evidence-based responses to policy-related questions on adoption of shared mobility. To compare the eHUBs on the real dataset, one specific input and three specific outputs were used in the dynamic SBM model (Equation (3). In this study, we focus on the eHUB network in Inverness, and during the study period, that network offered just one type of electric vehicle: e-bikes. Using the most recent data from the eHUBs, this research develops a dynamic two-stage DEA framework to profoundly explore this mobility service over 12 months. The performance scores generated from our model represent how successfully each eHUB in the network utilises available facilities.

Table 2
Spearman correlation coefficients matrix of indicators.

	Station capacity	Turnover rate	Balancing rate	Monthly total length of trips
Station capacity	1			
Turnover rate	[a] 0.350	1		
Balancing rate	[a] 0.395	[a] 0.365	1	
Monthly total length of trips (km)	[a] 0.739	[a] 0.798	[a] 0.395	1

[a] Correlation is significant at 1%.

Furthermore, these scores are relative, indicating the performance of each station in comparison to its peers. Therefore, low average performance scores do not represent the low performance of the whole system but rather the low performance of some stations compared to others within the network.

Table 3 reports the assessment outcomes generated from the proposed dynamic framework. The operational performance scores, ranging between 0 and 1, are used to rank the 72 eHUB-month units. In the dynamic SBM model, DMUs obtaining a score of 1 are efficient. In general, higher efficiency values represent better performance among the DMUs. In this way, our proposed model can distinguish among DMUs to identify the better performers. In other words, the higher their score, the more relatively efficient they are. Conversely, a lower score means poorer relative performance. Using arithmetic means, we also computed the average efficiency score by stations and average monthly efficiency scores to obtain the ranking (Table 3).

The following conclusions can be extracted from Table 3. Out of the 72 station-month DMUs, three were relatively efficient: Inverness Campus in October 2021 and September 2022, and Raigmore Hospital in November 2021. This shows our proposed model's high discriminatory power, which can detect inefficiencies in complex transportation systems such as an eHUB network. Although Inverness Railway was not fully efficient during any month of the study period, it has the highest average efficiency performance among the eHUBs. The Inverness Campus station obtained the second-highest average efficiency score. The first two more relatively efficient stations are docking stations. Raigmore Hospital station ranked as the third-best performer among all stations and the most efficient virtual station. Two virtual stations, Eden Court Theatre and Inverness Leisure, obtained lower efficiency scores than their peers and ranked fourth and fifth, respectively. Finally, NatureScot Great Glen House appeared to be the most inefficient station.

Moreover, looking at time periods, Inverness' eHUB network performed better in September 2022, November 2021, and August 2022 than in other studied months. The first six months of running the project happened during the COVID-19 pandemic, and the other half occurred after the pandemic restrictions were lifted in Scotland. The average performance score of eHUBs in the pandemic period was slightly lower (0.339) than in the post-pandemic period (0.439), however, no statistically significant difference in performance was observed between the means of the two periods based on the results of the T-test (Banker et al., 2010). The eHUB network started operating in September 2021, which might be a reason for slightly lower scores during the first few months. For an established shared mobility network, periods of pandemic could elicit an increased demand for such services. Wang and Noland (2021) suggest that when public apprehension and the imposition of social distancing detrimentally affect public transportation usage (Sogbe, 2021), alternatives such as shared bikes and other shared micro-mobility solutions can serve as suitable substitutes for private cars. They demonstrate that these alternatives could potentially avoid the switch

Table 3
Performance score of eHUBs from October 2021 to September 2022.

Time period	eHUBs							
	Eden Court Theatre	Inverness Campus	Inverness Leisure	Inverness Railway	NatureScot Great Glen House	Raigmore Hospital	Average (month)	Rank (month)
October 2021	0.243	1.000	0.200	0.554	0.082	0.338	0.403	6
November 2021	0.397	0.627	0.327	0.716	0.126	1.000	0.532	2
December 2021	0.125	0.277	0.004	0.307	0.014	0.590	0.219	12
January 2022	0.096	0.214	0.048	0.389	0.050	0.614	0.235	11
February 2022	0.033	0.160	0.126	0.353	0.016	0.784	0.245	10
March 2022	0.420	0.576	0.225	0.609	0.072	0.489	0.398	7
April 2022	0.137	0.522	0.320	0.605	0.225	0.754	0.427	5
May 2022	0.151	0.386	0.102	0.624	0.120	0.584	0.328	9
June 2022	0.236	0.607	0.081	0.678	0.117	0.464	0.364	8
July 2022	0.639	0.564	0.308	0.770	0.206	0.238	0.454	4
August 2022	0.307	0.824	0.633	0.888	0.105	0.123	0.480	3
September 2022	0.647	1.000	0.648	0.889	0.154	0.133	0.579	1
Average (station)	0.286	0.563	0.252	0.615	0.107	0.509	–	–
Rank (station)	4	2	5	1	6	3	–	–

from public transportation to private automobility when possible similar pandemics hit in future.

4.2. Exploring the influencing factors

As an intricate system, the low or high efficiency of the transportation chain can stem from multiple reasons. To investigate how factors outside the boundary of the eHUB system influence the performance scores, we perform a squared correlation analysis between obtained scores and the number of factors. Previous research pointed out weather conditions (De Kruijf et al., 2021; Noland, 2021), population in the catchment area (Mateo-Babiano et al., 2016; Zhang et al., 2019), and proximity to the public transport network (McBain and Caulfield, 2018; Oeschger et al., 2020; Caggiani et al., 2021) as factors which may have influence the demand for micro-mobility sharing systems.

To evaluate the impact of weather conditions on the performance of these 72 eHUB-month DMUs in Inverness, we calculate the correlation coefficient between average performance scores (Monthly) and several meteorological indicators. These weather indicators presented in Table 4 were compiled from the data collected by the nearest meteorological station in Nairn (The Meteorological Office, 2023). These indicators include monthly average temperature (°C), maximum temperature (°C), minimum temperature (°C), number of frost days, amount of rainfall (mm), and number of sunshine hours.

Weather conditions appear to importantly influence the riding demand at the studied eHUBs. The correlation coefficients related to temperature are strong, positive, and significant, representing that higher temperatures increase riding demand at eHUBs (Table 5). This finding is consistent with the results reported by Noland (2021), who found that higher temperatures increase the demand for micro-mobility. However, since the maximum recorded temperature in Inverness during the study period was 20.1 °C (Table 4), we were unable to explore the influence of excessively high temperatures on e-bike usage. Therefore, our observation does not contradict the findings of De Kruijf et al. (2021), who demonstrated that high temperatures decrease e-cycling. The maximum temperature recorded during their study period was 33.4 °C.

Furthermore, we find neither a strong nor significant correlation related to number of frost days, the amount of rainfall, and the number of sunshine hours per month. This may be attributed to the oceanic climate of Inverness, characterized by a considerable level of precipitation that persists throughout the year. It is worth mentioning that there were no occurrences of frost days in October 2022, nor in the period spanning from May 2022 to September 2022. Notably, the month of December 2022, which exhibited the weakest performance score (Table 3), recorded the highest number of frost days at 11 (Table 4). This observation potentially suggests that the frequency of frost days may have contributed to the diminished operational performance score during December 2022.

We examine the effects of indicators such as population in the catchment area of stations (within a radius of 400 m, a walkable distance), availability of public transportation (number of bus stops within a radius of 1 km), number of round and one-way trips started from each station, and weather conditions. It is worth mentioning that the population in the catchment area was estimated based on HITRANS' open-access geographic information. Also, the number of bus stops in proximity to each station was obtained from Google Maps.

The Spearman's correlation coefficient between efficiency scores and population in the catchment area of stations equals 0.670, indicating a strong significant positive association between them (Table 6). Therefore, the low performance of NatureScot Great Glen House and Inverness Leisure stations could be due to the low population in their surrounding

Table 4
Weather indicators on a monthly basis from October 2021 to September 2022 (The Meteorological Office, 2023).

	Average Temperature (°C)	Maximum Temperature (°C)	Minimum Temperature (°C)	Number of frost days per month	Rainfall (mm)	Number of Sunshine hours
October 2021	10.40	13.8	7	0	70.4	61.3
November 2021	7.30	10.4	4.2	2	56.7	35.7
December 2021	4.05	6.9	1.2	11	45.9	41.9
January 2022	6.10	8.7	3.5	2	25.3	56.1
Febuary 2022	4.65	7.7	1.6	4	95.2	76.1
March 2022	6.40	11.7	1.1	10	16.1	204.9
April 2022	7.65	11.6	3.7	3	75.4	137
May 2022	11.55	15.3	7.8	0	48.6	156.5
June 2022	13.95	18.6	9.3	0	29.4	209.6
July 2022	15.85	20.1	11.6	0	43.4	143
August 2022	15.40	19.5	11.3	0	31.8	172.1
September 2022	13.35	16.7	10	0	57.5	110.4

Table 5
Spearman's correlation coefficients between Average Performance scores and the weather indicators.

	Average Temperature	Maximum Temperature	Minimum Temperature	Number of frost days per month	Rainfall (mm)	Number of Sunshine hours
Average Performance scores (Monthly)	0.629[a]	0.580[a]	0.615[a]	−0.486	0.189	0.119

[a] Correlation is significant at 5%.

area compared to other stations. Conversely, the relatively high scores obtained by Inverness Railway and Inverness Campus correspond to a higher population in their catchment area. Also, the docks at the NatureScot Great Glen House station are tucked away from the main road and located beside the building entrance. This may cause low visibility and, as a result, low performance for this eHUB. Also, the Inverness Railway station stands beside the city's major transit point, which can be another reason for the high efficiency of this station. In the case of the Inverness Campus station, its proximity to two universities constitutes another reason for the high efficiency scores of this station, particularly in September and October. Given the above, we conclude that the population in the walkable area around eHUBs is a crucial factor to be considered when situating them.

Regarding proximity to public transport, this study found a weak but significant correlation coefficient (0.392) between obtained efficiency scores and the number of bus stops within a 1 km radius. However, no significant correlation was found when considering bus stops within a 400 m radius (Table 6). Therefore, this research is unable to confirm the findings of previous studies that examine bike-sharing systems and propose that these systems complement public transport (Shaheen and Chan, 2016; McBain and Caulfield, 2018; Caggiani et al., 2021). This inconsistency may necessitate treating e-bike sharing systems differently from bike sharing systems in terms of their relationship with public bus transport. Specifically, the stronger association with public transport for bikes compared to e-bikes suggests a more complementary relation with the former rather than the latter. This observation implies that e-bikes, with their motor assistance, have the potential to overcome barriers associated with traditional bike riding such as gradients and physical effort. This enables them to cover distances that may have previously required a combination of bikes and local public transport, though further research is needed to confirm this assertion. Nevertheless, the high efficiency of Inverness Railway could demonstrate a positive relationship between shared e-micro-mobility and railway services, as well as potentially other long-distance public transport modes. Situating stations near transit hubs can also provide a traveller with a means to cover the first and last mile of a journey and, in doing so, contribute to a modal shift toward sustainable transport.

4.3. Network representation of the eHUB system

Correlation analysis is also performed between the efficiency scores and the number of monthly round and one-way trips (Table 6). It indicates a very strong association with respect to one-way trips and a strong relationship to round trips. Of the total number of trips, one-way trips constituted 62.15%, while the remaining 37.85% consisted of round trips. This observation is significant because some service providers in other pilot cities are currently focused exclusively on e-bike round trips. Therefore, it is recommended that they consider including the possibility of one-way trips in their future plans to accommodate this popular travel preference. Additionally, excelling in providing both one-way and round-trip options would enhance the overall usability and appeal of the eHUB network. To more adequately investigate these observations, we perform a network analysis of the eHUB system.

A network representation of the eHUB stations provides useful information about the links between stations and the riding volume. The graphs in Fig. 4 show the cumulative network flow in the period from October 2021 to September 2022. The number of rides between stations and round trips was expressed as a percentage of all trips in the network in a given period to enable comparison over time. The number of in and out trips were calculated, and the sum of the edges for these is reported.

The graphs show that the Inverness Railway-Inverness Campus segment dominated the network and accounted for 66.30% of all trips (including round trips) in the study period. Between the two stations, the campus was more popular for round trips, which made up one-fifth of all trips taken within the network. However, the connectivity analysis found that Inverness Railway attracted the highest number of eHUB system users: 41.74% (Table 7).

A substantial number of journeys also used the route linking Inverness Railway with Raigmore Hospital. The three points – Inverness Railway, Inverness Campus, and Raigmore Hospital – are centrally located in Inverness. The least popular were connections between stations located far apart, such as NatureScot Great Glen House-Raigmore Hospital or Inverness Railway-School of Forestry. The lowest connectivity was observed for Inverness Leisure, followed by NatureScot Great Glen House and Eden Court Theatre (Table 7). School of Forestry was not used continuously throughout the study period, hence cannot be fully analysed.

5. Conclusions and policy implications

Using a novel dynamic DEA-based model, this research examines the performance of a shared mobility system known as shared electric mobility hubs (eHUBs) in Inverness, Scotland. We recognise the more relatively efficient stations in eHUB network and the determinants of their higher operational efficiency. Identifying the features of better-performance stations will assist service providers and policy makers in designing and expanding the studied network and other similar mobility systems more effectively. The findings indicate that eHUB stations located in close proximity to transit hubs and higher education institutions are more operationally efficient. The Inverness Railway and Inverness Campus locations were proven to be great trip attractors, with popularity rising on warmer days. The empirical evaluation of the eHUBs in Inverness leads to the following conclusions and mobility policies which can be generalised to e-bike-sharing systems in other regions.

First, the analysis shows that the population within the walkable area

Table 6
Spearman's correlation coefficients between performance scores and the selected indicators.

	Population within a radius of 400 m	Bus stops within a radius of 1 km	Bus stops within a radius of 400 m	Number of Round trips	Number of One-way trips	Total number of trips
Performance scores	0.670[b]	0.392[b]	0.224	0.567[b]	0.843[b]	0.806[b]

[b] Correlation is significant at 1%.

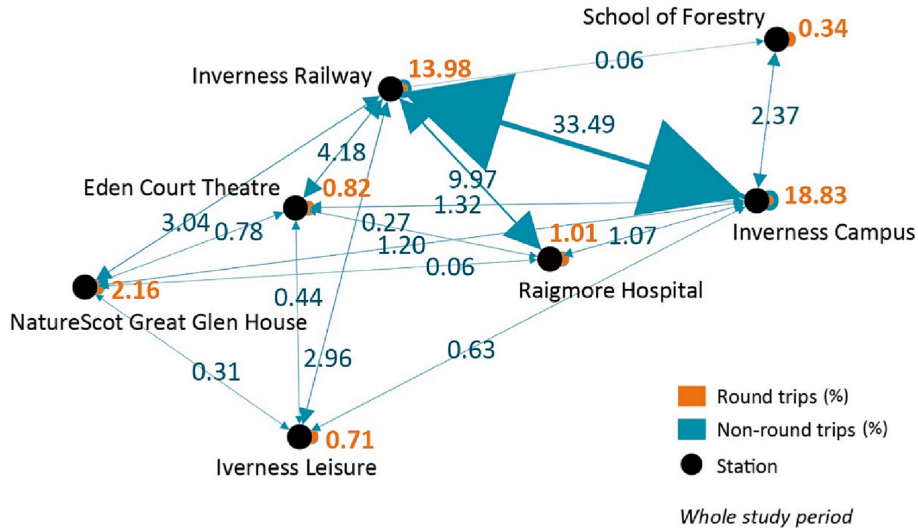

Fig. 4. Ehub stations network represented by nodes and edges.

Table 7
Connectivity of eHUB stations, whole period.

Station	All trips (%)
Eden Court Theatre	4.81
Inverness Campus	36.31
Inverness Leisure	3.12
Inverness Railway	41.74
NatureScot Great Glen House	4.66
Raigmore Hospital	7.65
School of Forestry	1.71
Total	100

around the eHUB stations is a critical factor in achieving optimal demand for the service. Stations with a larger population in their catchment area appeared to have better performance. For instance, the Inverness Railway, with the highest population in its catchment area, was the most efficient during the study period. Conversely, the NatureScot Great Glen House station, located in a catchment area with the lowest population, displayed the weakest efficiency. In this study, the catchment area was regarded as comprising only residents, but it is important to acknowledge that travellers or tourists could also increase the demand for e-bike services. An underlying factor that may explain the effects of both could be the volume of pedestrian traffic; this data, however, has not been available and, if collected, could be used in future research.

Second, while previous research (Shaheen and Chan, 2016; McBain and Caulfield, 2018; Caggiani et al., 2021) indicates a complementary relationship between bike-sharing systems and public transport, this study reveals a weak association between the performance of e-bike stations and public bus services. This highlights the potential of e-bikes as a standalone mode of transportation for longer journeys. Equipped with motor support, e-bikes effectively address obstacles such as distance, gradient, and physical exertion, thereby eliminating the necessity of combining them with local public transport for complementing extended travel. Moreover, e-bikes are well-suited for complimenting long-distance travel, as evidenced by the popularity of the Inverness Railway among eHUB users. Inverness Railway was most popular among e-HUBs users indicating that long-distance travel rather than short-distance is complimented by e-bikes. This has an implication for planning multi-modal transport by locating e-bike sharing stations at the transit hubs rather than local public transport stops.

Third, the study reveals that virtual eHUB stations have lower performance scores than docking eHUBs. Additionally, the NatureScot Great Glen House station, despite being a docking station, receives the lowest efficiency score. This could be due to its location being tucked away from the main road and adjacent to the building entrance, making it difficult to find. Hence, the lack of recognisability for both the NatureScot Great Glen House station and dockless stations could be a factor contributing to their lower operational performance. Although frequent users might more readily locate virtual stations with time, this may pose a difficulty for new and sporadic riders. It is suggested that the relationship between station recognisability and attracting e-bike users requires further investigation, as existing literature does not provide sufficient evidence, and this study was not specifically designed to establish a causal relationship. Nevertheless, increasing the station's visibility in open-access geographic maps such as Google Maps or placing the stations near main roads can enlarge the recognisability of stations and may improve the system's performance.

Fourth, the impact of temperature was found to be considerable. The results revealed that higher temperature increases the riding demand at eHUBs. Interestingly, the amount of rainfall and number of sunshine hours seem not to influence the riding patterns. The oceanic climate of Inverness, with a substantial precipitation level that persists throughout the year, may be a reason for this. While no significant correlation was found between the number of frost days and the monthly performance score, it is notable that December 2022, with the weakest performance score, experienced the highest number of frost days. This observation indicates that frost days may have played a role in the low operational performance during December 2022. On the other hand, the impact of the COVID-19 pandemic on performance scores was not found to be significant. This might show that eHUBs could serve as substitutes for private cars when the restrictions reduce public transport usage during incoming pandemics.

Fifth, this study does not account for the quality of cycling infrastructure in Inverness, although it is a crucial factor in attracting e-bike users. The bicycle lanes in the city are scattered and disconnected. Also, Inverness does not have sufficient segregated cycle infrastructure, which affects the overall perception of the city's attractiveness for cyclists and e-bike users. As shown in the case of Seville, demand for shared bikes may rise if the local government invests in improving the provision of infrastructure following the guideline rules proven effective in the Spanish city (Marqués et al., 2015). Good-practice network design features include the segregation of bike lanes from motorised traffic, bidirectionality of cycling traffic, continuity of paths without gaps, uniform design and pavement, and connecting trip attractors with residential areas (Caulfield et al., 2020).

Finally, we hope that this quantitative analysis serves as a groundwork for future research and practical applications, facilitating a more rigorous examination of the interconnected implications and mechanisms of shared mobility and electric micro-mobility in transportation system development and policy formulation. This case study was conducted based on data from a small-medium-sized urban area. Therefore, future research could analyse the electric shared mobility systems in larger cities and metropolitan areas. Such future research should complement our findings by showing diverse perspectives and may bring further practical insights into implementing electric shared mobility systems.

CRediT authorship contribution statement

Keyvan Hosseini: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Agnieszka Stefaniec:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Margaret O'Mahony:** Conceptualization, Methodology, Validation, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Brian Caulfield:** Conceptualization, Methodology, Validation, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was supported by Interreg North-West Europe (Project number: NWE 826). The sponsor neither had any direct involvement in the conduct of this work nor had any influence on the decision to publish this research paper. The authors wish to acknowledge Ms Vikki Trelfer for providing data.

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