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# Are shared electric scooters energy efficient?

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ABSTRACT

Shared electric scooters (e-scooter) are booming across the world and widely regarded as a sustainable mobility service. An increasing number of studies have investigated the e-scooter trip patterns, safety risks, and environmental impacts, but few considered the energy efficiency of e-scooters. In this research, we collected the operational data of e-scooters from a major provider in Gothenburg to shed light on the energy efficiency performance of e-scooters in real cases. We first develop a multiple logarithmic regression model to examine the energy consumption of single trips and influencing factors. With the regression model, a Monte Carlo simulation framework is proposed to estimate the fleet energy consumption in various scenarios, taking into account both trip-related energy usage and energy loss in idle status. The results indicate that 40% of e-scooter battery energy was wasted in idle status in the current practice, mainly due to the relatively low usage rate (0.83) of e-scooters. If the average usage rate drops below 0.5, the wasted energy could reach up to 53%. In the end, we present a field example to showcase how to optimally integrate public transport with e-scooters from the perspective of energy efficiency. We hope the findings of this study could help understand and resolve the current and future challenges regarding the ever-growing e-scooter services.

## 1. Introduction

Developing sustainable transportation systems has become a common goal across the world. The shared purpose drives countries to promote mobility systems that are powered by clean energy, such as electric buses (Qu and Wang, 2021). However, the UN's yearly report shows that only half of the world's urban population have access to public transportation by 2019, and renewable energy accounts for merely 3.4% of the total consumption in the transport sector by 2018 (Sachs et al., 2021). The recent emergence of shared electric scooters (e-scooters) provides a promising solution to relieve those two concerning problems. On the one hand, e-scooter enters the market initially as a first/last mile service that could improve the accessibility of public transport (Smith and Schwieterman, 2018); on the other hand, it naturally relies on an electric power system and is probably the first fully electrified large transport system.

The modern form of shared e-scooters was first introduced to the market in the United States in 2017. By the end of 2018, more than 85,000 e-scooters were deployed in U.S. cities and used in 38.5 million trips, while dockless bicycles, which have a much longer history, were involved only in 9 million trips (NACTO, 2019). In addition, more than 70% of people in major cities in the United States were reported to have positive attitudes towards e-scooters (Clewlow, 2019; Sellaouti et al., 2020). Albeit with the growing popularity and promising outlook, there is one crucial question that has yet to be answered: are e-scooters energy efficient? This problem is vital because fossil fuel is still the major source of electricity in today's world (Liddle and Sadorsky, 2017). Thus, energy efficiency should be taken into account in the judgment of whether a mobility service is truly sustainable. The present paper is devoted to this topic and shedding light on the energy efficiency of e-scooters with field evidence.

Specifically, we look into the dockless and shared e-scooters, which typically have a design with a deck, a handlebar, and two-wheelers propelled by small electric motors (see Fig. 1). Although with different vehicle appearances and power systems, e-scooters and shared bikes usually have similar subscription systems, positioning and unlocking technologies, parking rules, and thus similar travel experiences (Bao et al., 2017). However, for service providers, e-scooter fleet management and operation are arguably more challenging due to the limited battery capacity. To maintain a desired level of service, shared bike providers focus mainly on the imbalance between the spatiotemporally varying demands and vehicle supplies. E-scooter companies nevertheless have additional concerns about the battery state of charge (SoC). The battery

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**Fig. 1.** Electric scooter sharing (source: https://commons.wikimedia.org/w/index.php?curid=90168905).

SoC of an e-scooter drops not only during usage but also in idle status. The energy loss in idle status for one e-scooter seems deceptively small and thus has been overlooked in existing studies, while the cumulative effect of a large e-scooter fleet over a long time span is nontrivial. To provide a comprehensive understanding of the energy efficiency of shared e-scooter systems, we collected the largest and densest data for this topic in the literature, built upon which the structure and influencing factors of e-scooter energy consumption are investigated.

The remainder of the paper is structured as follows. Section 2 reviews related studies in the shared mobility area. In Section 3, we introduce the data collection method and statistical summaries. Section 4 and 5 present the model and case studies, respectively. Section 6 includes an example in which we integrate buses and e-scooters to minimize trip energy consumption. Section 7 concludes the paper with discussions.

## 2. Literature review

Before the e-scooter's debut, the shared bike is arguably the most prevailing micro-mobility service in most urban areas. Considering that shared bikes and e-scooters target the same user group, cities that have successful bike-sharing systems will most likely be fertile grounds for e-scooters as well. This naturally leads to follow-up studies in the shared mobility community that investigate the differences between the two modes (Curl and Fitt, 2020; McKenzie, 2019; Zhu et al., 2020). McKenzie (2019) investigated when and where the e-scooters are used and compared the spatiotemporal usage patterns of e-scooter with the bike-sharing system in a major urban center. Younes et al. (2020) analyzed and compared the contributing factors of dockless e-scooters and station-based bikes based on a negative-binomial regression model. The result indicated that the weather is less of a disutility for e-scooter users than for shared bike users. Lazarus et al. (2020) found that the major difference between e-scooter trips and other shared services is that e-scooters have more usages in communities with lower population density. Albeit with those notable differences, e-scooters are currently following the same business model of shared bikes, especially dockless shared bikes. Moreover, compared with the abundance of bike-sharing studies, research on e-scooters is rare. Therefore, we first review seminal studies on dockless bike-sharing systems to present the context of shared mobility systems and then focus on recent e-scooter studies.

### 2.1. Dockless bike-sharing research

With the development of information communication technologies, it is estimated that more than 23 million shared bikes have been deployed around the world in 2019 (Svegander, 2020). Compared to traditional station-based bike-sharing systems, dockless bike-sharing is more convenient and accessible as sharing bikes could be parked in any proper location (Chen e.t al., 2020). A majority of studies have investigated the mobility pattern of dockless bike-sharing systems, such as the relationship between trip frequency and contributory factors. Ma et al. (2020) compared the performance of docked bike-sharing systems with dockless ones in riding distance, usage frequency, spatial and temporal patterns. Shen et al. (2018) reviewed the usage of dockless bike-sharing in Singapore by spatial autoregressive models. The results indicated that a large fleet size, convenient access to public transportation, and supportive cycling facilities have positive impacts on the use of dockless sharing bikes. Link et al. (2020) applied discrete choice models to understand dockless bike-sharing characteristics and usage patterns. They found that the primary objective of the dockless bike-sharing trips is leisure activities, followed by commuting purposes.

Demand prediction for dockless shared bikes is another widely studied topic. Xu et al. (2018) developed a deep learning model to predict the dynamic demand of dockless shared bikes. The results are informative in rebalancing bikes in the system. Ai et al. (2019) employed a convolutional LSTM network to predict the short-term spatial and temporal distribution of the dockless bike-sharing system. Hua et al. (2020) predicted the real-time usage and distribution of dockless bike-sharing by random forest models and found it more challenging to predict the distribution of bicycles than the usage demand.

In addition, considerable efforts have been made to improve the dockless bike-sharing system through vehicle relocation. Pan et al. (2019) conducted a novel deep reinforcement learning framework to rebalance the dockless bike-sharing systems considering spatial and temporal features. Barabonkov et al. (2020) simulated and evaluated the rebalancing strategies for dockless bike-sharing systems with a mixed-integer program to generate the optimal relocation solution. As for the environmental impact, Luo et al. (2019) conducted a life cycle assessment of dockless and docked bike-sharing systems, respectively. The results showed that rebalancing is essential in terms of reducing greenhouse gas emissions.

### 2.2. E-scooter studies

E-scooters have the potential to relieve the increasingly severe traffic congestions and greenhouse gas emissions (Browne et al., 2020; Hardt and Bogenberger, 2019). In this area, the literature has been focused on travel behavior (Bai and Jiao, 2020; Caspi et al., 2020; Jiao and Bai, 2020; Severengiz et al., 2020), safety (Che et al., 2020; Dhillon et al., 2020; Sikka et al., 2019; Yang et al., 2020), and environmental impacts (Hollingsworth et al., 2019).

Following the bike-sharing research paradigm, recent studies have estimated the usage patterns and influencing factors on the ridership of e-scooter sharing systems. Bai & Jiao (2020) analyzed the e-scooter usage characteristics and the relationship between e-scooter ridership and related factors in the U.S. cities based on a negative binomial regression model and GIS hotspot spatial analysis. Caspi et al. (2020) explored the travel behavior patterns of e-scooter sharing systems and conducted spatial regression models to evaluate the effects of land-use characteristics, built environment, and demographics on e-scooter travel generation. Besides, the result found that student is the primary source of trips. Similarly, there are studies to understand the impacts of weather on e-scooter usage. Mathew, Liu and Bullock (2019) conducted a study to examine the effects of weather factors on urban e-scooter utilization by statistical models. The result found that users would be more sensitive to temperatures below freezing and snowfall than rain.

There are also raising concerns that e-scooters may induce safety risks for pedestrians and riders. The crashes and fatalities have been increasing since the e-scooters companies are expanding rapidly across the world. For example, the e-scooter parking and riding on the sidewalk could impair and threaten pedestrians' safety. The safety impacts on e-scooter riders have been measured in several studies (Fang et al., 2018; Gössling, 2020; James et al., 2019; Maiti et al., 2020). The results indicated that the leading causes of e-scooter rider injuries include falls and collisions with objects or vehicles (Trivedi et al., 2019). Other studies were focused on the safety impacts of e-scooter sharing systems. Allem and Majmundar (2019) examined the degree that e-scooter companies emphasize safety on Instagram and found that the protective gear is rarely used with the e-scooters. Badeau et al. (2019) quantified and characterized the e-scooter-related injuries based on electronic medical records. They found that major head injuries and musculoskeletal injuries account for a large proportion of patients.

The body of literature related to the environmental impact of e-scooter is relatively small. Severengiz et al. (2020) assessed the ecological effects of the e-scooter in Berlin by conducting a life cycle assessment. Hollingsworth et al. (2019) conducted a Monte Carlo analysis to estimate the average value of life cycle global warming impacts of shared e-scooters. Severengiz et al. (2020) utilized quantifiable environmental indicators to determine the shared e-scooters' ecological impact. The result has also been compared with private cars, public transport, biking, and walking. Few studies have investigated the relationship between the energy consumption of e-scooter trips and contributing factors. Questions remain as to how to quantify the energy consumption of an e-scooter fleet in various scenarios.

## 3. Data

In this section, we introduce the data collection procedure and present preliminary summaries of e-scooter trip characteristics. The analysis of field data lays an evidence-based foundation for the analytical models to be built in Section 4.

### 3.1. Data collection

The e-scooter data was collected in Gothenburg, the second-largest city in Sweden. E-scooters were mainly deployed in the central zone of Gothenburg, as shown in Fig. 2, with exceptions in forest and lake areas. We developed a web crawler for a major e-scooter company which arguably dominated the local market during the study period and recorded the geolocation and battery SoC of each available scooter (those not currently in use nor fully depleted) in Gothenburg.

Specifically, we collected the fleet information periodically from 5 a.m. to 12 p.m. every day between November 16, 2020, and November 22, 2020. The update frequency is set up as 120 s. In total, we collected 635 million data samples, each including the time stamp, location, and SoC of an e-scooter. Based on this log data, we identify e-scooter trips by comparing the appearances and disappearances of identical e-scooters at different time stamps. We noticed that there were always significant battery SoC drops when e-scooters changed their positions, which indicates that vehicle relocation was not performed for the studied e-scooter fleet. In this regard, a new trip for an e-scooter will always start at the same place where the previous trip ended. Due to errors and package losses during data collection, we remove trips that have travel time over 40 min and those with trip distance less than 80 m, as McKenzie (2019) did in his research. In total, we have identified 13547 trips.

Since we had no access to the information of e-scooters that were being used, the trajectories of e-scooter trips could not be directed obtained. However, the origin and destination (OD) locations of e-scooter trips are accurate, although the start/end time has a 1-min error on average (because the data update frequency is 2 min). To facilitate the energy consumption analysis later in this paper, we estimate the travel distance and duration of each e-scooter trip with the following approach. To begin with, we extract the OD geolocations of every trip we have identified. Afterward, we use the OD data as inputs to the Distance Matrix Service from Google Maps, which could return the shortest path for each trip assuming that the bicycle mode is taken. We consider this approximation reasonable because e-scooters have a similar speed to that of bicycles and use bicycle lanes in Gothenburg. Based on the shortest path trajectories, the average speed of each e-scooter trip is calculated. An overview of the collected data is shown in Table 1.

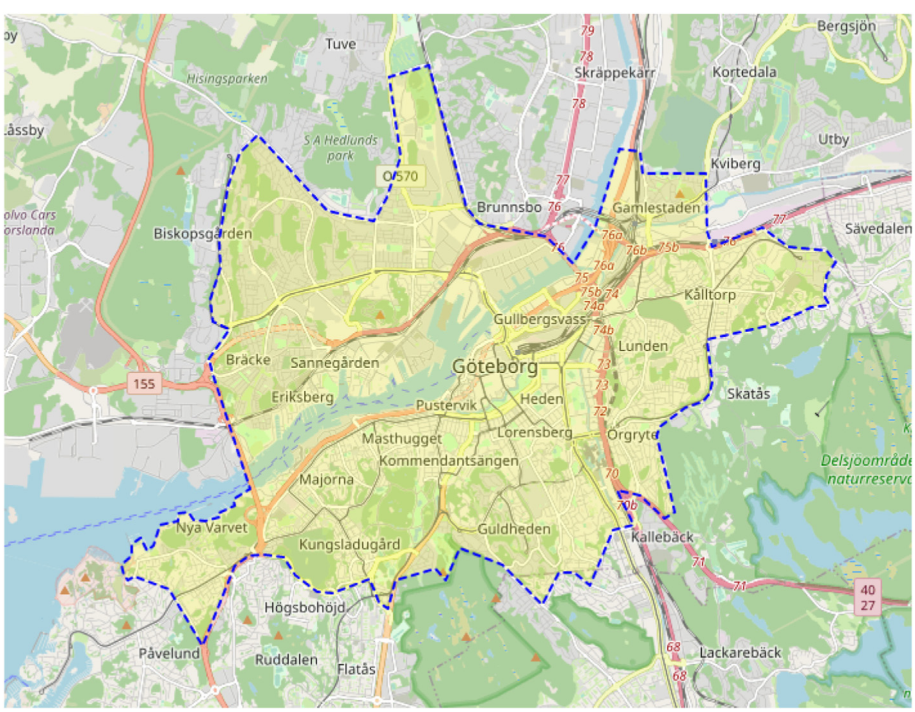


**Fig. 2.** The central area of Gothenburg, Sweden (source: OpenStreetMap.org).

**Table 1**
Summary for the scooter samples.

| | Weekends | Weekdays |
|---|---|---|
| Total number of trips | 2883 | 10664 |
| Average trip distance (m) | 1535 | 1735.1 |
| Average trip duration (s) | 677.4 | 648 |
| Average number of e-scooters used per day | 741.5 | 954.4 |
| Average number of trips per day | 1441.5 | 2132.8 |

### 3.2. Spatiotemporal trip patterns

To illustrate the energy consumption intensity, we first summarize the temporal distribution of trips as shown in Fig. 3. One can observe significantly different patterns between weekdays and weekends. For example, the e-scooter usage was relatively intensive during 7 a.m.–9 a.m. and 4 p.m.–5 p.m. on weekdays, corresponding to the normal commuting hours. On the weekend, a large portion of trips occurred in the afternoon between 1 p.m.–7 p.m. without visible peaks. This contradicts the results of studies conducted in U.S. cities, which found that the shared e-scooters were not often used for commuting (Mathew et al., 2019; Noland, 2019). This indicates that e-scooter usage can differ from case to case and general conclusions cannot be drawn yet.

The spatial distribution patterns of e-scooter trips are also compared in Fig. 4, where red dots indicate zones with high trip density, and green dots denote areas with low trip density. Fig. 4 shows distinct e-scooter usage patterns on different days of the week. It can be found that numerous trips occurred during 6:00–11:00 on weekdays, while e-scooters were not heavily used during this period on the weekend, which supports the previous inference in Fig. 3. Besides, during 15:00–20:00, there were numerous trip attractions both on weekdays and weekends. Areas with a high density of trips were mainly distributed in the prosperous commercial regions and transportation hubs. The result indicates that e-scooters could be a competitive transport mode against walking and cycling in the urban transportation system. The electric scooter might also be a potential feeder mode for public transport, as demonstrated in previous studies (Pavone et al., 2012).

Trip length is naturally an influencing factor to the energy consumption of e-scooter trips. The Empirical Cumulative Distribution Functions (ECDFs) of the travel distance per trip during weekdays and weekends are illustrated in Fig. 5. Almost 90% of scooter trips are less than 4 km both on weekends and on weekdays, which is consistent with the conclusion in previous studies (Chang et al., 2019; Ciociola et al., 2020; McKenzie, 2019). Nearly 70% are shorter than 2 km on weekends, and the number is more than 60% on weekdays.

## 4. Methodology

In this section, we present the analytical framework used to evaluate the energy consumption of e-scooter systems in various scenarios, as shown in Fig. 6. In the first step, we develop a multiple logarithmic regression model based on field data to identify influencing factors to trip energy consumptions. In the second step, we analyze the fleet energy consumption performance through a Monto Carlo simulation approach considering both trip energy consumptions and energy loss in idle status.

### 4.1. Multiple logarithmic regression

Linear regression analysis is commonly used to reveal the relationships between interested variables (Mehmanpazir et al., 2019). However, when the variables in regression analysis are highly skewed, the existence of these variables would undermine the performance of the regression model. Transforming variables logarithmically is an effective solution to resolve the nonlinear relationship between the independent and dependent variables (Benoit, 2011).

As for the linear regression model $Y = \alpha + \beta X + \varepsilon$ there are three types of logarithm formulations as follows:

a. Log-linear model

$$\log(Y) = \alpha + \beta X + \varepsilon \tag{1}$$

b. Linear-log model

$$Y = \alpha + \beta\log(X) + \varepsilon \tag{2}$$

c. Log-log model

$$\log(Y) = \alpha + \beta\log(X) + \varepsilon \tag{3}$$

The coefficients indicate the change in the dependent variable for a one-unit change in the independent variable in the linear regression model. However, the interpretation of the coefficients in logarithmic models is distinct. Specifically, in the log-linear model, with a one-unit increase in $X$, the $\log(Y)$ will increase $\beta$ units. In the linear-log model, $Y$ will increase $\beta$ units if there is a one-unit increase in the $\log(X)$.In the log-log model, the dependent variable and independent variables are both log-transformed, and thus the coefficients should be also interpreted in the same way.

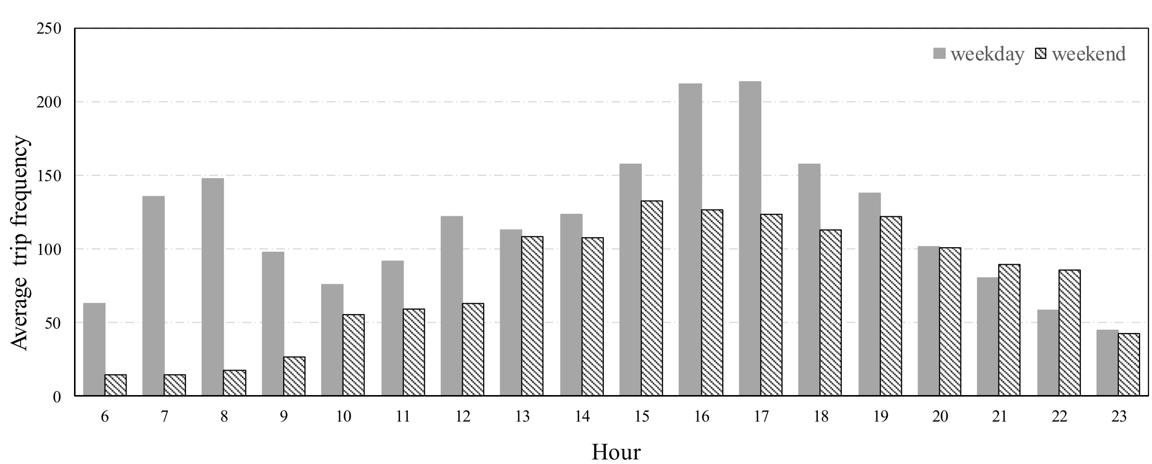


**Fig. 3.** Average trips frequency per hour on weekday and weekend.

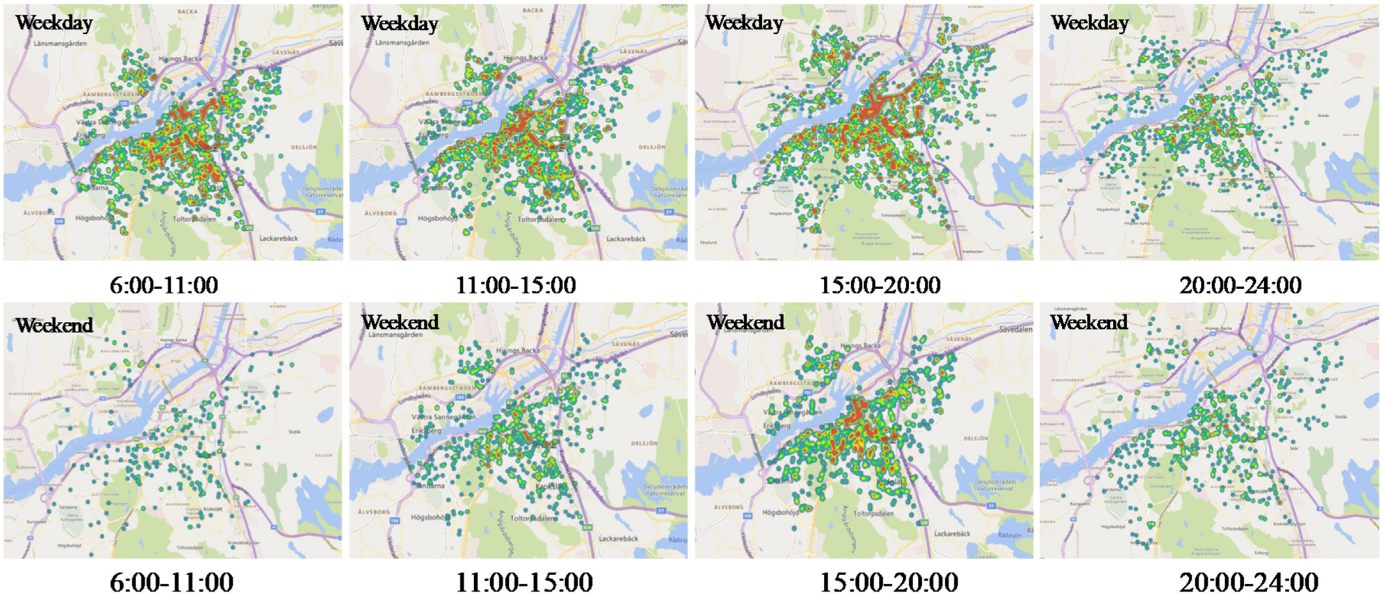


**Fig. 4.** The spatial distribution of e-scooter trip origins.

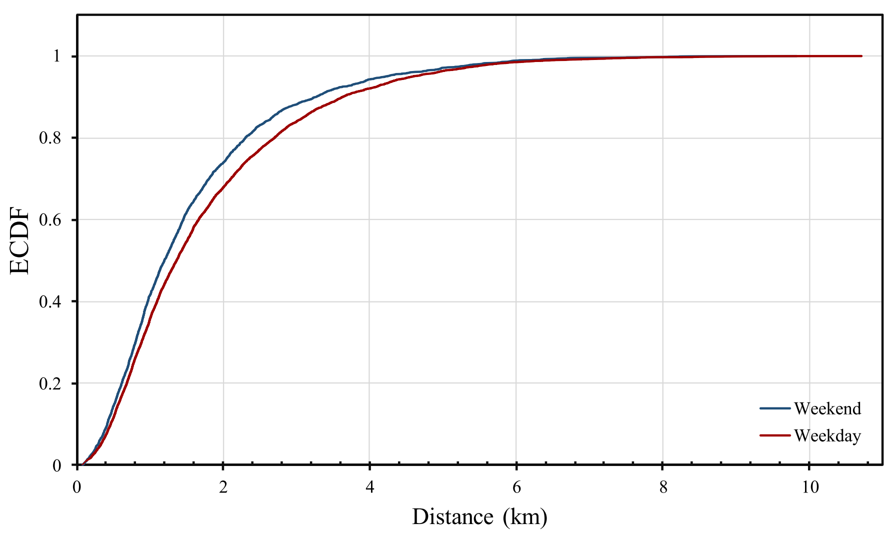


**Fig. 5.** ECDFs for electric scooter trips distance and duration on weekends and weekdays.

*4.2. Monte Carlo simulation*

In this section, the empirical distributions of influencing variables and the results of the multiple logarithmic regression are embedded into a Monte Carlo simulation framework to investigate the overall performance of the fleet energy consumption in various scenarios. In the simulation, the value of each variable is obtained by sampling randomly according to their respective distributions. The Probability Density Function (PDF) is used to describe the range of the Monte Carlo analysis output. Generally, there are parametric and nonparametric methods to estimate the PDF. With parametric methods, the output range could be presented by a probability density function of the contributing variables. With the nonparametric methods, the PDF could be constructed by probability density function estimators with a large number of samples (Leontaritis et al., 2020). Therefore, when the information regarding the PDF is insufficient, the nonparametric methods are more suitable for our study.

The kernel density estimator is a widely applied nonparametric method to approximate the PDF, estimating the function at discrete points (Burke and Kiedrowski, 2018). The formulation is as follows:

$$\hat{f}(x) = \frac{\sum_{j=1}^{M} k\left(\frac{x-x_j}{p}\right)}{Mp} \tag{4}$$

*where* $x_1, \ldots, x_j, \ldots, x_M$ are the samples; $p$ represents the bandwidth; $k$ is the kernel function; and the optimal value is calculated by minimizing the mean integrated square error (Bashtannyk and Hyndman, 2001). In this research, k satisfies the following properties (Silverman, 2018).

$$\begin{cases} \int \omega k(\omega) d\omega = 0 \\ \int k(\omega) d\omega = 1 \\ \int \omega^2 k(\omega) d\omega = k^2 \neq 0 \end{cases} \tag{5}$$

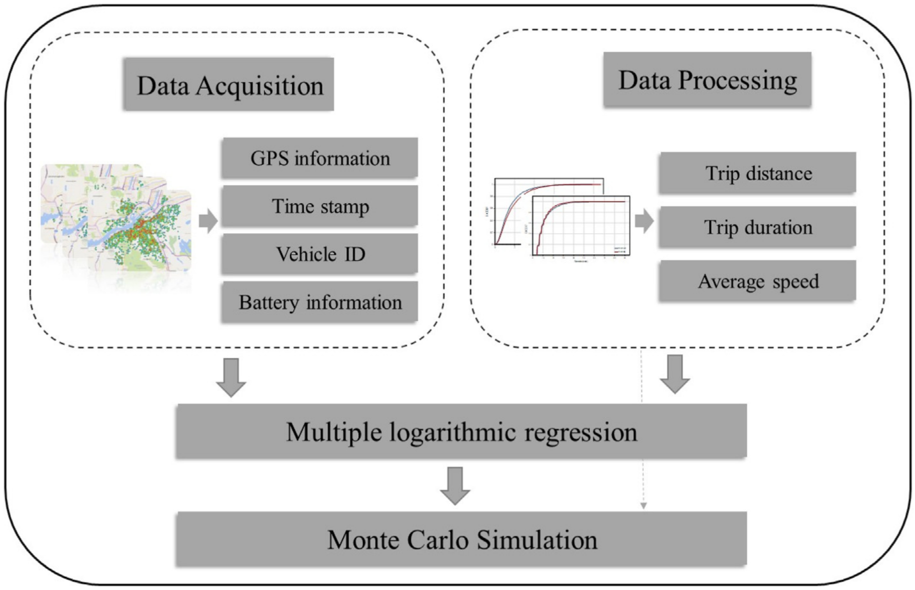


**Fig. 6.** The structure of the hybrid framework.

## 5. Results

In this section, we show the results of the proposed models in Section 3 based on the field data introduced in Section 2.

### 5.1. Trip energy consumption

In Fig. 7, we illustrate the distribution of e-scooter trip distance before and after the logarithmic transformation. As shown in the figure, the empirical distribution of trip distance is highly skewed while the transformed distribution exhibits a normal distribution. Therefore, the logarithmic transformation of trip distance is applied in the regression model instead of empirical data. The descriptive statistics for the variables are summarized in Table 2. Table 3 shows the results of the regression model which has the following formulation.

$$q = -7.290 + 0.953\ln(D) + 1.267v + 0.493t \tag{6}$$

To demonstrate the quality of the regression model, we examine the residual distribution as shown in Fig. 8. In Fig. 8(a), the histogram of the regression standardized residual largely follows the normal distribution, and, in Fig. 8(b), the normal P–P plot also follows the diagonal line, both indicating a reasonably good fitting result.

### 5.2. Fleet energy consumption

In practice, the fleet energy consumption is affected by both the macroscopic e-scooter usage intensity and the microscopic energy consumption of each trip. In previous sections, we have addressed the energy consumption estimation of single trips. In this section, we first present the distribution of the fleet usage intensity, based on which the fleet energy consumption analysis is conducted.

Fig. 9 illustrates the usage frequency of e-scooters during the study period. It can be found that a large proportion of the fleet was not used during the day. On weekdays, the e-scooters were used more frequently but still at a relatively low rate. Considering the obvious patterns in Fig. 9, we model the usage frequency of the fleet with an exponential distribution. The fleet energy consumption in a typical day could then be formulated as Eq. (7), where $\delta_i$ is the usage frequency of e-scooter $i$; $y_i$ is the idle energy loss of e-scooter $i$; $N$ is the fleet size; and $Q$ is the fleet energy consumption. Values and distributions of other key variables used in the Monte Carlo simulation are listed in Table 4.

$$Q = \sum_{i=1}^{N} (\delta_i q_i + y_i) \tag{7}$$

Calibrated by the field data, the simulation result shows that the energy consumption on weekdays and weekends were 30653.1% and 23999.1% fully battery capacity, respectively. The average energy consumption of each trip were 16.81% (SoC) on weekends and 14.50% (SoC) on weekdays, which can be explained by that e-scooters were used more frequently on weekdays than weekends. The energy consumption per passenger per kilometer (ECPP) were 9.72% (SoC) and 7.47% (SoC) on weekends and weekdays, respectively. The ECPP was higher on weekends mainly because more energy was wasted in idle status. We demonstrate the accuracy of our simulation models by comparing the empirical ECPP with the simulation results using the same set of parameters. The ECPP on weekends and weekdays equal 9.397% (SoC) and 8.333% (SoC), respectively, indicating a reasonably good simulation accuracy.

In addition, the energy loss in idle status is 32.8% on weekdays and 41.9% on weekends according to the field data mainly due to the relatively low usage frequency. This considerable energy loss in idle status will heavily affect the fleet availability which not only reduces the profits and undermines the level of service but also requires frequent charging. Unfortunately, this issue has been largely overlooked in the literature. To further estimate the influence of different usage intensities on the overall energy consumption performance, we conduct the Monte Carlo simulation by changing the usage rate parameter $\lambda$ ($1/\lambda$ denotes the average number of usages for each e-scooter in the fleet) in the exponential distribution from 0.5 to 2.6 with an interval of 0.1, and the results are provided in Table 5.

In the table, it can be found that when the usage frequency of each scooter is large, a larger fleet energy consumption and a smaller ECPP are observed. For example, when $\lambda$ is equal to 2, the proportion of the energy loss in idle status would account for 53% of the total energy consumption in the system. This means that, if the average usage frequency of each e-scooter ($1/\lambda$) in the system is lower than 0.5, more than half of the energy consumption in the sharing e-scooter system will be wasted in idle status. In such cases, e-scooters are hardly energy efficient.

## 6. The integration of bus and e-scooter

Since both e-scooters and public transport may suffer from low usage rates, we here show the possibility to achieve a system optimum of

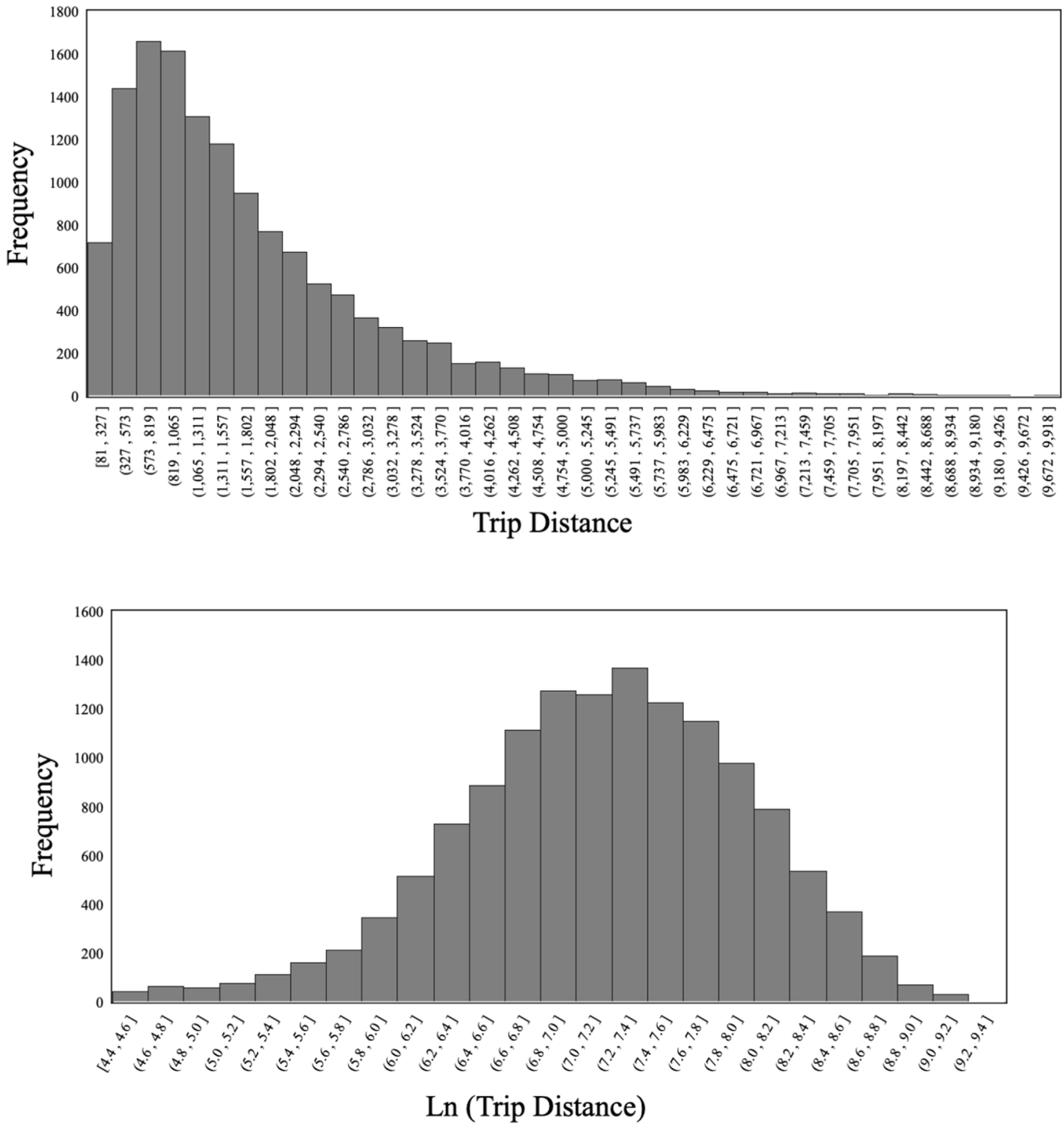


**Fig. 7.** The distribution of trip distance before and after logarithmic transformation.

**Table 2**
Descriptive statistics for variables in the model.

| Variable | Description | Mean | S.D. |
|---|---|---|---|
| $q$ | The battery energy consumed per trip, measured by SoC (%) | 8.23 | 5.61 |
| Ln($D$) | The logarithm of the travel distance per trip (m) | 7.14 | 0.81 |
| $t$ | The travel duration per trip (minutes) | 10.90 | 6.87 |
| $v$ | The average speed per trip (m/s) | 2.64 | 1.16 |

energy consumption by integrating e-scooters with public transport, taking bus as an example. The basic idea is to confine the service zone of e-scooters to increase the usage rate and reduce the length of bus lines so that the barely used end stations are replaced by e-scooters. In this approach, e-scooters could make the bus network more accessible as an efficient first/last mile service.

Specifically, we present a field example to showcase how to optimally combine e-scooters and buses from an energy consumption perspective. We select a bus route in Gothenburg, from Storgatan to Annedalskyrkan, which has 10 bus stations along the route (see Fig. 10). We assume that e-

**Table 3**
Estimation results of the model.

| | Estimates | Std. Error | t | Sig. | 95.0% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| Intercept | −7.290 | 0.526 | −13.868 | .000 | −8.320 | −6.259 |
| Ln($D$) | 0.953* | 0.103 | 9.236 | .000 | 0.751 | 1.156 |
| $v$ | 1.267* | 0.062 | 20.534 | .000 | 1.146 | 1.388 |
| $t$ | 0.493* | 0.008 | 59.954 | .000 | 0.477 | 0.509 |

Note: *significant at 95% confidence level.

**Table 4**
Monte Carlo simulation inputs.

| Variables | Range or (scale, shape factors) | | Distribution |
|---|---|---|---|
| | Weekend | Weekday | |
| Duration | 3.15–39.97 | | Uniform |
| Distance | (mean=7.14,SD=0.81) | | Lognormal |
| Average speed | (mean=2.64,SD=1.16) | | Lognormal |
| Average use rate for each e-scooter | λ = 1.23 | λ = 0.83 | Exponential |

scooters could replace several end stations where the passenger loads of buses are typically low. Therefore, the problem is how to determine the new end stations of the bus route to optimize the energy consumption of the whole trip. The notations used in the case study are summarized in Table 6. The objective function can be formulated as Eq. (8):

$$\min Q = \begin{cases} \gamma\left(\sum_{i=1}^{m} p_i d_i + \sum_{j=n}^{9} p_j d_j\right) + \alpha \sum_{k=m+1}^{n-1} d_k + \beta \sum_{k=m+1}^{n-1} p_k d_k, \text{if } m \geq 1, n \leq 9 \\ \alpha \sum_{k=1}^{9} d_k + \beta \sum_{k=1}^{9} p_k d_k, \text{if } m = 0, n = 0 \end{cases}, \forall i,j,k \in Z^+ \quad (8)$$

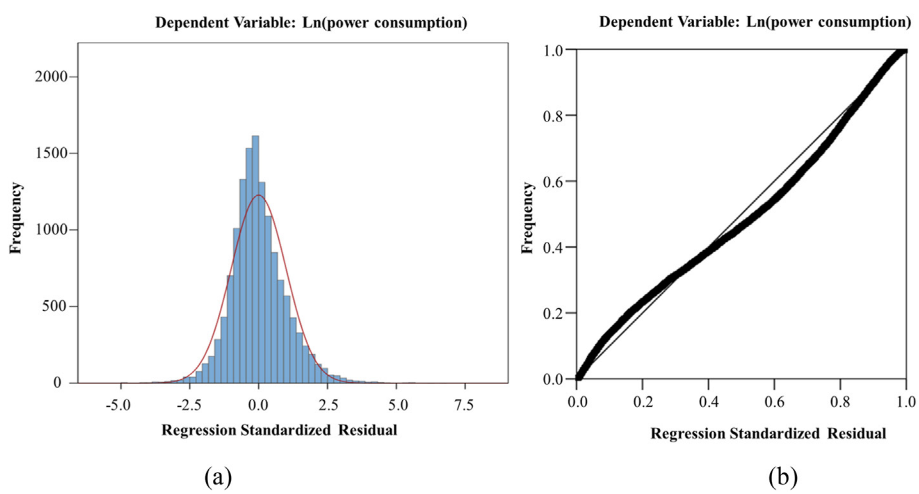


**Fig. 8.** Residual distribution (a) histogram of the regression standardized residual; (b) P–P plot of regression standardized residual.

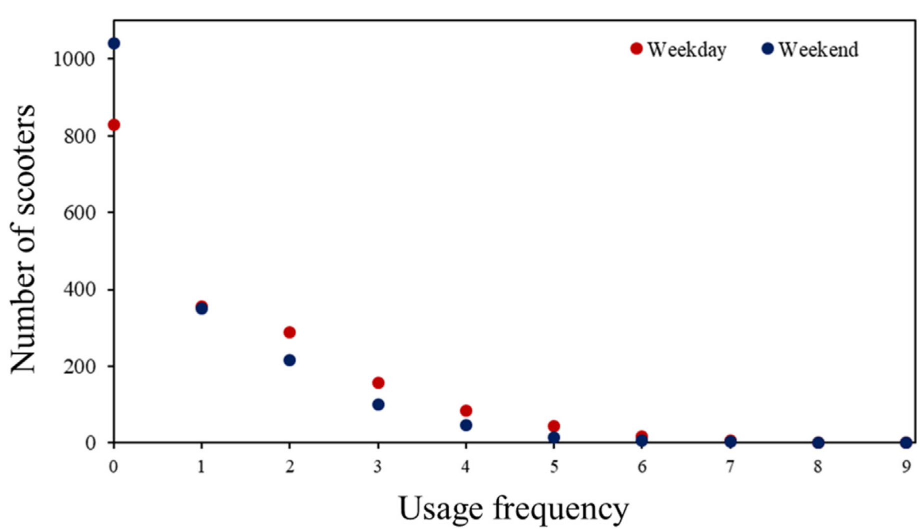


**Fig. 9.** The usage frequency of scooters on weekdays and weekends.

**Table 5**
The results of different simulation scenarios.

| λ | Total consumption (SOC %) | The proportion of the energy loss in idle status | The proportion of trip energy consumption | The energy consumption per passenger per kilometer ( SOC % ) |
|---|---|---|---|---|
| 0.5 | 44264.95 | 0.227 | 0.773 | 6.998 |
| 0.6 | 39086.07 | 0.257 | 0.743 | 7.034 |
| 0.7 | 35567.09 | 0.283 | 0.717 | 7.756 |
| 0.8 | 31038.30 | 0.324 | 0.676 | 8.333 |
| 0.9 | 29190.51 | 0.344 | 0.656 | 8.486 |
| 1.0 | 27779.54 | 0.362 | 0.638 | 8.622 |
| 1.1 | 26245.01 | 0.383 | 0.617 | 8.931 |
| 1.2 | 24510.90 | 0.410 | 0.590 | 9.397 |
| 1.3 | 23340.59 | 0.431 | 0.569 | 9.896 |
| 1.4 | 23190.08 | 0.433 | 0.566 | 10.186 |
| 1.5 | 21581.79 | 0.466 | 0.534 | 10.455 |
| 1.6 | 20316.16 | 0.495 | 0.505 | 10.537 |
| 1.7 | 20538.59 | 0.490 | 0.510 | 10.659 |
| 1.8 | 23463.01 | 0.429 | 0.571 | 9.302 |
| 1.9 | 22643.55 | 0.444 | 0.556 | 9.861 |
| 2.0 | 18985.47 | 0.530 | 0.470 | 11.239 |
| 2.1 | 18412.93 | 0.546 | 0.454 | 12.425 |
| 2.2 | 18242.73 | 0.551 | 0.449 | 12.098 |
| 2.3 | 17599.02 | 0.571 | 0.429 | 12.850 |
| 2.4 | 17058.65 | 0.589 | 0.411 | 13.270 |
| 2.5 | 17041.32 | 0.590 | 0.410 | 13.483 |
| 2.6 | 16871.65 | 0.596 | 0.404 | 13.475 |

In this study, we assume the capacity of the battery in the e-scooter is 0.48kwh. As introduced in the previous section, the energy consumption per passenger per kilometer on weekends is 9.72% (SoC). Thus, $\gamma$ equals 0.047kwh in this case study. As for the value of $\alpha$ and $\beta$, we use the operational data of another electric bus as a reference, of which we have access to the field data. Specifically, we select an electric bus route in Meihekou, Jilin province, China, where we collected the operating data of 15 buses, including the energy consumption of each trip, timestamp, the number of passengers on the bus at each station, and the latitude and longitude of each bus station. With this field data, the estimated values of $\beta$ and $\alpha$ are $6.15 \times 10^{-6}$ kWh and $5.83 \times 10^{-4}$ kWh, respectively. Besides, the number of passengers on the bus when the electric bus is leaving each station was {17, 14, 18, 25, 29, 32, 25, 19, 17, 14} according to the field data. Eventually, the optimal solution for Eq. (8) is found as $m = 1$ and $n = 9$. Specifically, bus station $s_1$ is removed, and passengers take the electric bus after riding e-scooters to station $s_2$. The bus services are cut to station $s_8$, and the region near stations $s_9$ and $s_{10}$ are serviced by e-scooters.

**Table 6**
Notation list.

| Notations | Description |
|---|---|
| Sets: | |
| **D** | The set of distance between adjacent stations, $\{d_1, d_2, \ldots, d_9\} \in \mathbf{D}$ |
| **S** | The set of the bus station in the bus route, $\{s_1, s_2, \ldots, s_{10}\} \in \mathbf{S}$ |
| **P** | The set of the number of passengers on the bus when leaving each station, $\{p_1, p_2, \ldots, p_{10}\} \in \mathbf{P}$ |
| Parameters: | |
| $A$ | The energy consumption of the system when an electric bus travels 1 km (kWh). |
| $B$ | The energy consumption of the system when a passenger travels 1 km (kWh). |
| $\Gamma$ | The energy consumption of the system when an e-scooter travels 1 km (kWh). |
| $M$ | The number of successive bus stations that are replaced by e-scooters at the beginning of the bus route, $0 \le m \le 10$, $m \in \mathbf{Z}$. |
| $N$ | The new end station for the bus, $1 \le n \le 10$, $n \in \mathbf{Z}$. The $s_n, \ldots, s_{10}$ are replaced by e-scooters. |

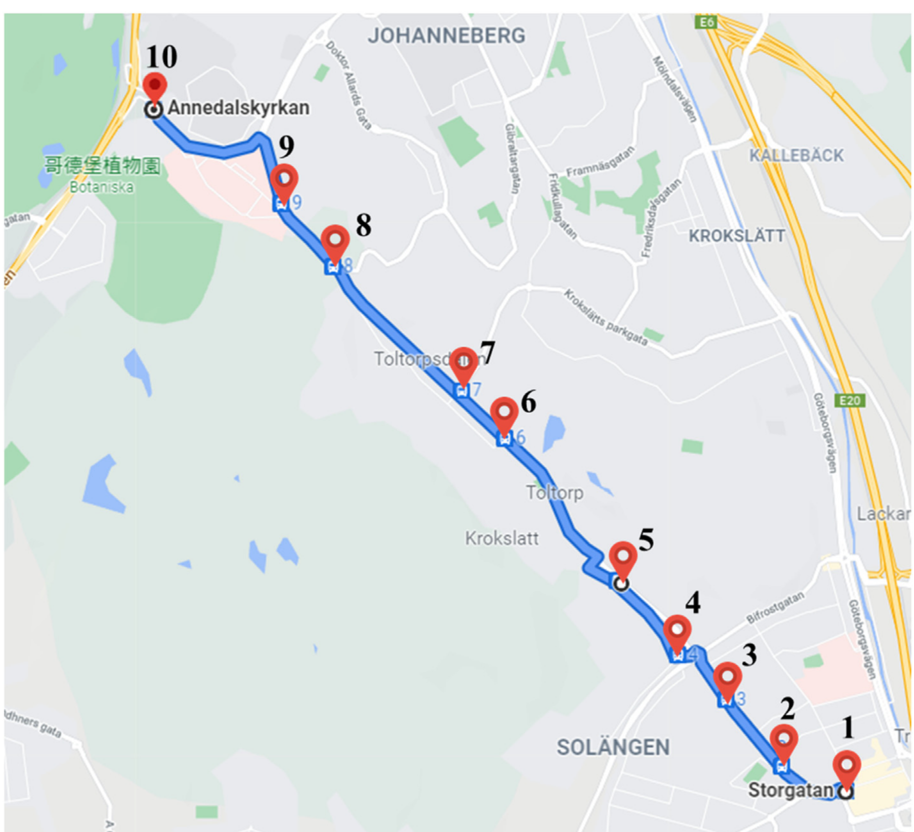


**Fig. 10.** The studied bus route in Gothenburg.

## 7. Conclusion and discussion

The shared e-scooters have been increasingly used in urban areas as an emerging shared micro-mobility service. In this study, we estimated the energy consumption of e-scooter systems based on the field data collected in Gothenburg. We revealed the spatial and temporal patterns of the e-scooter usages and found both significant commuting and recreation trips, based on which we modeled the energy consumption of single e-scooter trips by a multiple logarithmic regression approach. In addition, the Monte Carlo simulation was conducted to calculate the total energy consumption of the e-scooter system. The result indicated that the energy loss in idle status is considerable, which accounts for 32.8% on weekdays and 41.9% on weekends. Eventually, we investigated how the average usage frequency of e-scooters affects fleet energy consumption through an extensive number of case studies. The results showed that more than 50% of energy can be wasted in the idle status if the average use frequency of each e-scooter is lower than 0.5 times per day. In the end, we presented an example to demonstrate how to combine e-scooters with electric buses to minimize the energy consumption of trips and enable door-to-door travel.

We hope the results of this research could lay a foundation for better operations and regulation developments of e-scooters. There are also several notable limitations regarding this study. Firstly, the travel patterns of the e-scooter could be related to land-use characteristics and weather factors. In future studies, these factors should be considered and integrated into the model. Moreover, the vehicle relocation was not performed in Gothenburg but could happen in other cities. The influence of relocation strategies on energy consumption needs to be investigated in future research. As a new mobility service under fast expansion, more studies in diverse regions are needed to understand and better operate the e-scooter system.

## 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.

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## References

Ai, Y., Li, Z., Gan, M., Zhang, Y., Yu, D., Chen, W., Ju, Y., 2019. A deep learning approach on short-term spatiotemporal distribution forecasting of dockless bike-sharing system. Neural Comput. Appl. 31 (5), 1665–1677. https://doi.org/10.1007/s00521-018-3470-9.

Allem, J.-P., Majmundar, A., 2019. Are electric scooters promoted on social media with safety in mind? A case study on Bird's Instagram. Preventive Medicine Reports 13, 62–63. https://doi.org/10.1016/j.pmedr.2018.11.013.

Badeau, A., Carman, C., Newman, M., Steenblik, J., Carlson, M., Madsen, T., 2019. Emergency department visits for electric scooter-related injuries after introduction of an urban rental program. Am. J. Emerg. Med. 37 (8), 1531–1533. https://doi.org/10.1016/j.ajem.2019.05.003.

Bai, S., Jiao, J., 2020. Dockless E-scooter usage patterns and urban built Environments: a comparison study of Austin, TX, and Minneapolis, MN. Travel Behaviour and Society 20, 264–272. https://doi.org/10.1016/j.tbs.2020.04.005.

Bao, J., Xu, C., Liu, P., Wang, W., 2017. Exploring bikesharing travel patterns and trip purposes using smart card data and online point of interests. Network. Spatial Econ. 17 (4), 1231–1253.

Barabonkov, D., D'Alonzo, S., Pierre, J., Kondor, D., Zhang, X., Tien, M.A., 2020. Simulating and Evaluating Rebalancing Strategies for Dockless Bike-Sharing Systems. ArXiv Preprint ArXiv:2004.11565.

Bashtannyk, D.M., Hyndman, R.J., 2001. Bandwidth selection for kernel conditional density estimation. Comput. Stat. Data Anal. 36 (3), 279–298. https://doi.org/10.1016/S0167-9473(00)00046-3.

Benoit, K., 2011. Linear regression models with logarithmic transformations. London School of Economics, London 22 (1), 23–36.

Browne, K., Kaji, D., Kaplan, H., Luo, J., Tanikura, M., 2020. Utilizing E-Scooters to Reduce Carbon Emissions Attributable to the Transportation Sector in Santa Monica.

Burke, T.P., Kiedrowski, B.C., 2018. Monte Carlo perturbation theory estimates of sensitivities to system dimensions. Nucl. Sci. Eng. 189 (3), 199–223. https://doi.org/10.1080/00295639.2017.1388093.

Caspi, O., Smart, M.J., Noland, R.B., 2020. Spatial associations of dockless shared e-scooter usage. Transport. Res. Transport Environ. 86, 102396. https://doi.org/10.1016/j.trd.2020.102396.

Chang, A., Miranda-Moreno, L., Clewlow, R., Sun, L., 2019. Trend or Fad. Deciphering the Enablers of Micromobility in the U.S.

Che, M., Lum, K.M., Wong, Y.D., 2020. Users' attitudes on electric scooter riding speed on shared footpath: a virtual reality study. International Journal of Sustainable Transportation 15 (2), 152–161. https://doi.org/10.1080/15568318.2020.1718252.

Chen, Z., van Lierop, D., Ettema, D., 2020. Dockless bike-sharing systems: what are the implications? Transport Rev. 40 (3), 333–353. https://doi.org/10.1080/01441647.2019.1710306.

Ciociola, A., Cocca, M., Giordano, D., Vassio, L., Mellia, M., 2020. E-scooter sharing: leveraging open data for system design. In: 2020 IEEE/ACM 24th International Symposium on Distributed Simulation and Real Time Applications (DS-RT), pp. 1–8. https://doi.org/10.1109/DS-RT50469.2020.9213514.

Clewlow, R.R., 2019. The Micro-mobility Revolution: the Introduction and Adoption of Electric Scooters in the united states.

Curl, A., Fitt, H., 2020. Same same, but different? Cycling and e-scootering in a rapidly changing urban transport landscape. N. Z. Geogr. 76 (3), 194–206. https://doi.org/10.1111/nzg.12271.

Dhillon, N.K., Juillard, C., Barmparas, G., Lin, T.-L., Kim, D.Y., Turay, D., Seibold, A.R., Kaminski, S., Duncan, T.K., Diaz, G., Saad, S., Hanpeter, D., Benjamin, E.R., Tillou, A., Demetriades, D., Inaba, K., Ley, E.J., 2020. Electric scooter injury in southern California Trauma centers. J. Am. Coll. Surg. 231 (1), 133–138. https://doi.org/10.1016/j.jamcollsurg.2020.02.047.

Fang, K., Agrawal, A.W., Steele, J., Hunter, J.J., Hooper, A.M., 2018. Where Do Riders Park Dockless, Shared Electric Scooters? Findings from San Jose. California.

Gössling, S., 2020. Integrating e-scooters in urban transportation: problems, policies, and the prospect of system change. Transport. Res. Transport Environ. 79, 102230. https://doi.org/10.1016/j.trd.2020.102230.

Hardt, C., Bogenberger, K., 2019. Usage of e-scooters in urban environments. Transportation Research Procedia 37, 155–162. https://doi.org/10.1016/j.trpro.2018.12.178.

Hollingsworth, J., Copeland, B., Johnson, J.X., 2019. Are e-scooters polluters? The environmental impacts of shared dockless electric scooters. Environ. Res. Lett. 14 (8), 084031. https://doi.org/10.1088/1748-9326/ab2da8.

Hua, M., Chen, J., Chen, X., Gan, Z., Wang, P., Zhao, D., 2020. Forecasting usage and bike distribution of dockless bike-sharing using journey data. IET Intell. Transp. Syst. 14 (12), 1647–1656. https://doi.org/10.1049/iet-its.2020.0305.

James, O., Swiderski, J., Hicks, J., Teoman, D., Buehler, R., 2019. Pedestrians and E-scooters: an initial look at E-scooter parking and perceptions by riders and non-riders. Sustainability 11 (20), 5591. https://doi.org/10.3390/su11205591.

Jiao, J., Bai, S., 2020. Understanding the shared E-scooter travels in Austin, TX. ISPRS Int. J. Geo-Inf. 9 (2), 135. https://doi.org/10.3390/ijgi9020135.

Lazarus, J., Pourquier, J.C., Feng, F., Hammel, H., Shaheen, S., 2020. Micromobility evolution and expansion: understanding how docked and dockless bikesharing models complement and compete – a case study of San Francisco. J. Transport Geogr. 84, 102620. https://doi.org/10.1016/j.jtrangeo.2019.102620.

Leontaritis, A., Nassehi, A., Yon, J.M., 2020. A Monte Carlo analysis of the effects of geometric deviations on the performance of magnetic gears. IEEE Trans. Ind. Appl. 56 (5), 4857–4869. https://doi.org/10.1109/TIA.2020.3008115.

Link, C., Strasser, C., Hinterreiter, M., 2020. Free-floating bikesharing in Vienna – a user behaviour analysis. Transport. Res. Pol. Pract. 135, 168–182. https://doi.org/10.1016/j.tra.2020.02.020.

Liddle, B., Sadorsky, P., 2017. How much does increasing non-fossil fuels in electricity generation reduce carbon dioxide emissions? Appl. Energy 197, 212–221.

Luo, H., Kou, Z., Zhao, F., Cai, H., 2019. Comparative life cycle assessment of station-based and dock-less bike sharing systems. Resour. Conserv. Recycl. 146, 180–189. https://doi.org/10.1016/j.resconrec.2019.03.003.

Ma, X., Ji, Y., Yuan, Y., Van Oort, N., Jin, Y., Hoogendoorn, S., 2020. A comparison in travel patterns and determinants of user demand between docked and dockless bike-sharing systems using multi-sourced data. Transport. Res. Pol. Pract. 139, 148–173. https://doi.org/10.1016/j.tra.2020.06.022.

Maiti, A., Vinayaga-Sureshkanth, N., Jadliwala, M., Wijewickrama, R., Griffin, G.P., 2020. Impact of E-scooters on pedestrian safety: a field study using pedestrian crowd-sensing. ArXiv:1908.05846 [Cs]. http://arxiv.org/abs/1908.05846.

Mathew, J.K., Liu, M., Bullock, D.M., 2019. Impact of weather on shared electric scooter utilization. In: 2019 IEEE Intelligent Transportation Systems Conference (ITSC), pp. 4512–4516. https://doi.org/10.1109/ITSC.2019.8917121.

Mathew, J.K., Liu, M., Seeder, S., Li, H., other, 2019a. Analysis of E-scooter trips and their temporal usage patterns. Institute of Transportation Engineers. ITE Journal 89 (6), 44–49.

McKenzie, G., 2019. Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. J. Transport Geogr. 78, 19–28. https://doi.org/10.1016/j.jtrangeo.2019.05.007.

Mehmanpazir, F., Khalili-Damghani, K., Hafezalkotob, A., 2019. Modeling steel supply and demand functions using logarithmic multiple regression analysis (case study: steel industry in Iran). Resour. Pol. 63, 101409. https://doi.org/10.1016/j.resourpol.2019.101409.

Noland, R.B., 2019. Trip patterns and revenue of shared e-scooters in Louisville, Kentucky. Transport Findings. https://doi.org/10.32866/7747.

NACTO (National Association of City Transportation Officials), 2019. NACTO (National Association of City Transportation Officials) Shared Micromobility in the U.S.: 2019. NACTO, New York, NY, 2019. https://nacto.org/shared-micromobility-2019/.

Pan, L., Cai, Q., Fang, Z., Tang, P., Huang, L., 2019. A deep reinforcement learning framework for rebalancing dockless bike sharing systems. Proceedings of the AAAI Conference on Artificial Intelligence 33, 1393–1400. https://doi.org/10.1609/aaai.v33i01.33011393.

Pavone, M., Smith, S.L., Frazzoli, E., Rus, D., 2012. Robotic load balancing for mobility-on-demand systems. Int. J. Robot Res. 31 (7), 839–854. https://doi.org/10.1177/0278364912444766.

Qu, X., Wang, S., 2021. Communications in transportation research: vision and scope. Communications in Transportation Research 1, 100001.

Sachs, J., Kroll, C., Lafortune, G., et al., 2021. Sustainable Development Report 2021. Cambridge University Press.

Sellaouti, A., Arslan, O., Hoffmann, S., 2020. Analysis of the use or non-use of e-scooters, their integration in the city of Munich (Germany) and their potential as an additional mobility system. In: 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), pp. 1–5.

Severengiz, S., Finke, S., Schelte, N., Forrister, H., 2020. Assessing the environmental impact of novel mobility services using shared electric scooters as an example. Procedia Manufacturing 43, 80–87. https://doi.org/10.1016/j.promfg.2020.02.114.

Severengiz, S., Finke, S., Schelte, N., Wendt, N., 2020a. Life cycle assessment on the mobility service E-scooter sharing. In: 2020 IEEE European Technology and Engineering Management Summit (E-TEMS), pp. 1–6. https://doi.org/10.1109/E-TEMS46250.2020.9111817.

Shen, Y., Zhang, X., Zhao, J., 2018. Understanding the usage of dockless bike sharing in Singapore. International Journal of Sustainable Transportation 12 (9), 686–700. https://doi.org/10.1080/15568318.2018.1429696.

Sikka, N., Vila, C., Stratton, M., Ghassemi, M., Pourmand, A., 2019. Sharing the sidewalk: a case of E-scooter related pedestrian injury. Am. J. Emerg. Med. 37 (9). https://doi.org/10.1016/j.ajem.2019.06.017, 1807.e5-1807.e7.

Silverman, B.W., 2018. Density Estimation for Statistics and Data Analysis, first ed. Routledge. https://doi.org/10.1201/9781315140919.

Smith, C.S., Schwieterman, J.P., 2018. E-scooter Scenarios: Evaluating the Potential Mobility Benefits of Shared Dockless Scooters in Chicago.

Svegander, M., 2020. The Bike and Scooter-Sharing Telematics Market. Berg Insight, Stockholm, Sweden.

Trivedi, T.K., Liu, C., Antonio, A.L.M., Wheaton, N., Kreger, V., Yap, A., Schriger, D., Elmore, J.G., 2019. Injuries Associated with standing electric scooter use. JAMA Network Open 2 (1), e187381. https://doi.org/10.1001/jamanetworkopen.2018.7381.

Xu, C., Ji, J., Liu, P., 2018. The station-free sharing bike demand forecasting with a deep learning approach and large-scale datasets. Transport. Res. C Emerg. Technol. 95, 47–60. https://doi.org/10.1016/j.trc.2018.07.013.

Yang, H., Ma, Q., Wang, Z., Cai, Q., Xie, K., Yang, D., 2020. Safety of micro-mobility: analysis of E-scooter crashes by mining news reports. Accid. Anal. Prev. 143, 105608. https://doi.org/10.1016/j.aap.2020.105608.

Younes, H., Zou, Z., Wu, J., Baiocchi, G., 2020. Comparing the temporal determinants of dockless scooter-share and station-based bike-share in Washington, D.C. Transport. Res. Pol. Pract. 134, 308–320. https://doi.org/10.1016/j.tra.2020.02.021.

Zhu, R., Zhang, X., Kondor, D., Santi, P., Ratti, C., 2020. Understanding spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility. Comput. Environ. Urban Syst. 81, 101483. https://doi.org/10.1016/j.compenvurbsys.2020.101483.