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A Data-Driven Approach

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DOI
10.3390/app13031984

Publication date
2023

Document Version
Final published version

Published in
Applied Sciences (Switzerland)

applied sciences

MDPI

Article

Optimizing Electric Taxi Battery Swapping Stations Featuring Modular Battery Swapping: A Data-Driven Approach

Zhengke Liu [1], Xiaolei Ma [1], Xiaohan Liu [1,*], Gonçalo Homem de Almeida Correia [2], Ruifeng Shi [3] and Wenlong Shang [4]

[1] School of Transportation Science and Engineering, Beihang University, Beijing 100191, China
[2] Department of Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, 2628 CN Delft, The Netherlands
[3] School of Control and Computer Engineering, North China Electric Power University, Beijing 102206, China
[4] Beijing Key Laboratory of Traffic Engineering, College of Metropolitan Transportation, Beijing University of Technology, Beijing 100124, China
* Correspondence: xiaohan1994@buaa.edu.cn

Abstract: Optimizing battery swapping station (BSS) configuration is essential to enhance BSS's energy savings and economic feasibility, thereby facilitating energy refueling efficiency of electric taxis (ETs). This study proposes a novel modular battery swapping mode (BSM) that allows ET drivers to choose the number of battery blocks to rent according to their driving range requirements and habits, improving BSS's economic profitability and operational flexibility. We further develop a data-driven approach to optimizing the configuration of modular BSS considering the scheduling of battery charging at the operating stage under a scenario of time-of-use (ToU) price. We use the travel patterns of taxis extracted from the GPS trajectory data on 12,643 actual taxis in Beijing, China. Finally, we test the effectiveness and performance of our data-driven model and modular BSM in a numerical experiment with traditional BSM as the benchmark. Results show that the BSS with modular BSM can save 38% on the investment cost of purchasing ET battery blocks and is better able to respond to the ToU price than to the benchmark. The results of the sensitivity analysis suggest that when the peak electricity price is too high, additional battery blocks must be purchased to avoid charging during those peak periods.

Keywords: battery swapping station configuration; modular battery swapping mode; electric taxi; data-driven approach; trajectory data

Citation: Liu, Z.; Ma, X.; Liu, X.; Correia, G.H.d.A.; Shi, R.; Shang, W. Optimizing Electric Taxi Battery Swapping Stations Featuring Modular Battery Swapping: A Data-Driven Approach. *Appl. Sci.* **2023**, *13*, 1984. https://doi.org/10.3390/app13031984

Academic Editor: Konstantinos Gkoumas

Received: 24 November 2022
Revised: 30 January 2023
Accepted: 31 January 2023
Published: 3 February 2023

1. Introduction

1.1. Background

The transportation industry faces pressing challenges in reducing the carbon emissions of internal combustion engine vehicles (ICEVs). In recent years, the development of electric vehicles (EVs) has become part of the critical pathway to effectively alleviating energy pressure and achieving the dual carbon goal (e.g., achieving peak emissions before 2030 and carbon neutrality before 2060 in China). Governments worldwide are developing policies to boost transport electrification in order to reduce vehicle emissions, with one of such policies being the replacement of ICEVs with EVs [1,2]. For example, all new passenger vehicles in the Netherlands must be zero-emissions by 2030 [3]. However, there are several limitations and concerns for taxi drivers in replacing their ICEVs with EVs, which create impediments for the electrifications of such fleets. It is fairly quick for ICEVs to refuel at gas stations, whereas EVs require specific equipment and a significant amount of charging time (in the order of hours) even considering the new fast charging stations, which provide 80% of the battery in about 20 to 60 min [4]. Furthermore, although it is easy to park EVs at a workplace or home for a few hours or overnight, it is challenging for electric taxi (ET) drivers to recharge during their daily business without losing clients [5–8].

There are two energy refueling modes for EVs: battery charging mode (BCM) and battery swapping mode (BSM). Compared with BCM, BSM can accomplish energy refueling for ETs in a shorter time, which can be comparable to the time currently consumed by ICEVs [9–11]. The BSM is more suitable and applicable for public transport vehicles such as buses and ETs with uniform battery blocks due to the requirements of battery block standardization and specialized supporting infrastructure [12,13]. Moreover, the recycling process of batteries can decrease the environmental impacts of battery production [14,15]. BSM can facilitate this process better than BCM. Therefore, battery swapping is a compelling choice to accelerate taxi fleet electrification when these fleets are relatively uniform. The high accessibility and flexibility of battery swapping stations (BSSs) allow taxi drivers to arrive at BSSs easily and ensure empty batteries are swapped with fully charged batteries in only one minute [5]. The depleted batteries are then recharged at the BSSs and are later used by other taxis [7].

Due to high upfront investment costs [13,16], BSSs must be configured to respond to market dynamics appropriately and efficiently, i.e., the battery swapping demand (*BSD*) of ET drivers and the time-of-use (ToU) price. Furthermore, current BSSs only offer a single type of battery for swapping, but not all ET drivers need that specific driving range. Cloud-based smart battery management systems have recently emerged as a better solution for battery condition monitoring and optimization, allowing for the implementation of novel battery management strategies [17]. In order to match the dynamic *BSD* and ET drivers' driving range requirements, this study proposes a novel operational strategy in which ET drivers can choose the varying number of battery blocks (its rated capacity is less than the standard battery in current BSSs) to rent at modular BSSs according to their driving range requirements and habits, as illustrated in Figure 1. Moreover, the abundant traffic data in urban areas makes it possible to develop a data-driven approach to estimating the *BSD* by mining the GPS dataset of taxi trajectories, which are a proxy to power consumption [18,19]. The abovementioned considerations motivate this research to propose a data-driven framework for configuring and operating ET BSS featuring modular battery swapping.

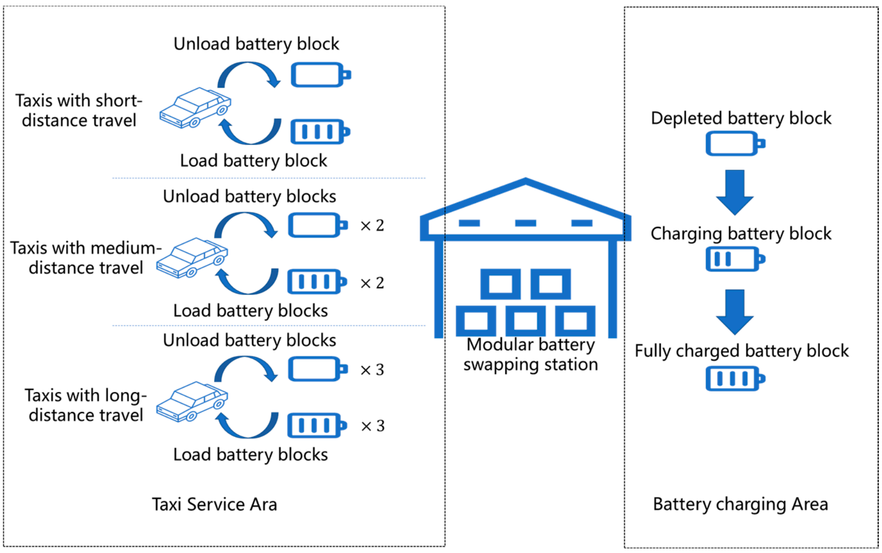


Figure 1. A typical modular battery swapping station.

1.2. Literature Review

Although the research idea of this study is intuitive, there are only a few studies on data-driven BSS configurations in the literature, let alone modeling the configuration problem of modular BSS. Due to the lack of detailed EV trajectory data, the existing optimization models for configuring BSSs are usually solved with the assumption that the *BSD* satisfies the uniform or empirical distributions [7,20]. This ideal assumption simplifies the analysis of the performance of BSSs that have battery-to-grid (B2G) capability or that cooperate with microgrids. However, it does not match the real-world *BSD* patterns that demonstrate temporal fluctuations [13]. Therefore, Wang et al. [21] and Yang et al. [22] highlighted the significance of dynamic *BSD* and proposed data-driven approaches for deploying BSSs using GPS trajectory data on actual electric freight vehicles and shared electric vehicles. They extracted the trip and *BSD* patterns to parameterize the BSS configuration model, so as to help improve the model's realism and accuracy. With advances in data collection and storage technology for ETs, Li et al. [23] characterized the driving behavior of ETs by mining and modeling the trajectory data and proposed a joint modeling approach for user charging behavior decision making and charging station planning. However, few studies use a data-driven approach to configure the ET BSS.

The EV charging stations and BSSs often contribute with heavy power loads to the public grid. Under the scenario of ToU price, it is necessary to consider the battery charging scheduling at the operating stage before configuring the BSS. For example, Sun et al. [24], Tan et al. [25] and Wu et al. [26] have proposed scheduling methods for battery charging at BSSs, considering *BSD* and charging costs. However, the practicality of these studies is limited by assuming that *BSD* is predetermined.

Although extensive literature studies on BSS document positive results and insights into BSS operations, they have to consider ET drivers' heterogeneous driving range requirement and then make active responses on the supply side. A handful of related studies mined and analyzed ETs trajectory data to incorporate vehicle heterogeneity into charging infrastructure planning [1]. However, they only passively adjusted the number of charging piles and did not respond regarding the battery swapping or charging service. Moreover, the concept of modular battery swapping is similar to the concept of individual battery cell replacement, which has been validated to be viable and more economically beneficial than replacing the entire battery, given that the design requirements are fulfilled [27].

1.3. Contributions

This study aims to fill the aforementioned methodological gaps by developing a data-driven approach to configuring and operating ET BSSs with modular battery blocks. The contributions of this study are summarized as follows:

- We propose a data-driven approach for the configuration problem of ET modular BSSs using the travel patterns of taxis extracted from GPS trajectory data on real-world taxis.
- We present a set of state–transition equations for battery blocks between adjacent time slots based on the dynamic inventory theory. It can describe the controlled charging scheduling of batteries to respond to the ToU price at the operating stage.
- We validate our model and approach in a real-world numerical experiment and create a benchmark to evaluate the performance of modular BSSs.

The remainder of this paper is organized as follows. Section 2 describes the data and introduces the data-driven approach. A numerical experiment is analyzed in Section 3. Section 4 concludes the paper and points to future research.

2. Materials and Methods

To develop a data-driven optimization model, first, it is necessary to clean the GPS dataset of taxi trajectories and extract useful information, such as travel patterns and behaviors. With the extracted information, it is possible to estimate the battery-swapping demand for ETs. Finally, an optimization model can be developed to configure ET BSS with modular battery blocks.

2.1. Data Description

The *BSD* estimation in our study is performed using the GPS dataset of gasoline taxi trajectories in Beijing, China, which were collected from 8–15 October 2018, and the location information was recorded every five seconds. For a city with a steady population, established economic structures, and a well-developed road network, travel patterns within the urban transportation system can be assumed to stay constant during the midterm. Therefore, in a near future scenario, a taxi's average daily travel mileage could be determined in line with current drivers' travel behaviors, regardless of whether a taxi is powered by electricity or gasoline.

The dataset (sample data are shown in Table 1) includes the desensitized taxi ID, longitude, latitude, vehicle speed (km/h), passenger load state, and timestamp. This information can describe the operating status of ETs: taxi ID can uniquely identify the vehicle; longitude and latitude can be combined with electronic maps to determine the location of the vehicle in driving, which is used to calculate the daily travel mileage; remaining data can be used to infer the ET drivers' travel behaviors, such as daily departure time and average travel speed.

Table 1. An example for the GPS trajectory data.

Taxi ID	Longitude	Latitude	Speed	Load State [1]	Timestamp
488115	116.357784	40.034022	32	1	10 October 2018 06:00:01;
214157	116.483694	39.942724	68	1	10 October 2018 06:00:01;
164927	116.233147	39.76826	76	1	10 October 2018 06:00:01;
470325	116.2453	39.861894	57	0	10 October 2018 06:00:01;
191485	116.484017	39.874658	20	0	10 October 2018 06:00:01;
21184	116.44534	40.002848	108	1	10 October 2018 06:00:01;

[1] The passenger load state equals 1 when the ET is carrying passengers and 0 when the ET is empty.

2.2. Assumptions

We made the following key assumptions to facilitate our data-driven approach for modular BSS configuration:

- The daily driving mileage of a city taxi driver is stable, but there may be shorter or longer driving mileage on certain days. Therefore, we choose the median of multi-day driving mileage to represent the daily driving mileage of a taxi driver, i.e., the driving range requirement of an ET.
- Charging an annual battery rental fee to EV users is a potentially effective way to ensure the profitability of BSS [16]. We assume the modular BSS can provide one to three battery blocks for ET drivers to rent according to their driving range requirement for one year. The modular BSS only provides the number of rented battery blocks for each ET battery-swapping.
- Different automakers will have different battery designs and different battery management systems. Taxi fleets are relatively uniform; thus, we assume that the battery blocks in the electric taxis and BSS are identical. The driving range of ETs increases in equal proportion to the number of battery blocks rented.

2.3. Daily Travel Mileage Distribution Estimation

Driving range requirement is an essential indicator of travel behavior for ET drivers. We can obtain each taxi's daily travel mileage by mining the GPS dataset of taxi trajectories. The multi-day travel mileage for a vehicle is sorted in ascending order, and the median is taken as the driving range requirement for the driver. A modular battery swapping service allows ET drivers to choose the number of battery blocks to rent to cater to their driving range requirements and habits; thus, we can divide ET drivers into different groups according to the number of battery blocks they rent.

In our study, one battery block can provide a 150 km driving range for the ETs, and an ET driver with a specific driving range requirement can install one to three battery blocks into an ET. For economy, they will rent the minimum number of battery blocks that can meet their driving range requirement. Hence, we classify the ET drivers into three groups according to the capacity of the battery block:

- Short-distance travel (driving range requirement is less than 150 km);

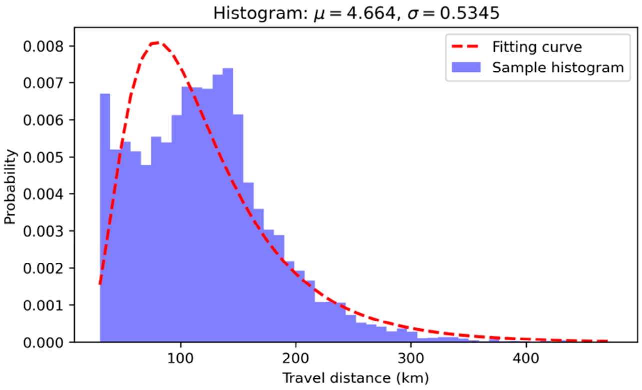
- Medium-distance travel (driving range requirement is larger than 150 km and less than 300 km);
- Long-distance travel (driving range requirement is larger than 300 km).

The minimum distance for our sample is 30 km. As shown in Figure 2, the multi-day travel mileage of ET drivers of short-distance travel satisfies the truncated log-normal distribution (Equation (1)). Moreover, the multi-day travel mileage of ET drivers of medium- and long-distance travel satisfies the truncated normal distribution in Equation (2).

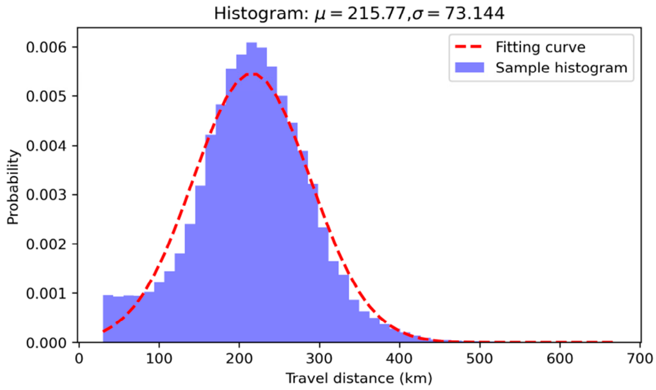
$$f_{short}(d) = \frac{1}{d\sigma_{short}\sqrt{2\pi}} \exp\left[-\frac{(\ln d - \mu_{short})^2}{2\sigma_{short}^2}\right] \quad , d \geq 30 \tag{1}$$

$$f_{medium/long}(d) = \frac{1}{\sigma_{medium/long}\sqrt{2\pi}} \exp\left[-\frac{\left(d - \mu_{medium/long}\right)^2}{2\sigma_{medium/long}^2}\right] \quad , d \geq 30 \tag{2}$$

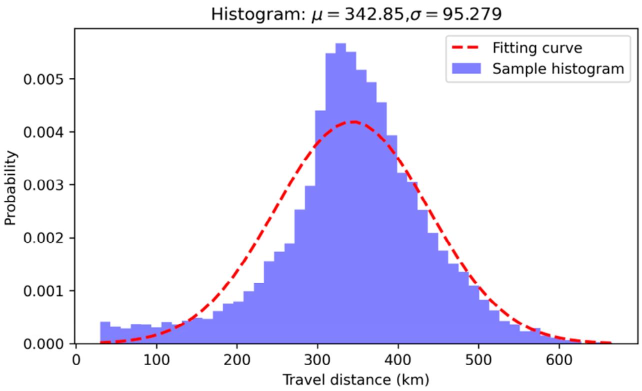
We estimate the parameters μ and σ in Equations (1) and (2) by the multi-day daily travel mileage of taxis that have been grouped.



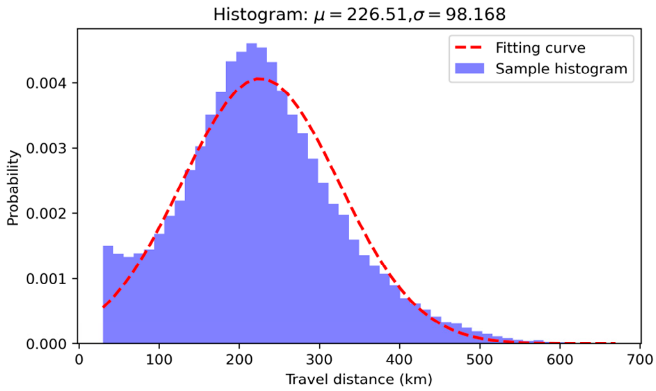
(a) Daily mileage distribution of short-distance travel ET drivers



(b) Daily mileage distribution of medium-distance travel ET drivers



(c) Daily mileage distribution of long-distance travel ET drivers



(d) Daily mileage distribution of all ET drivers

Figure 2. Probability distributions of daily mileage for different types of ET drivers.

2.4. Approach to Quantifying Battery Swapping Demand (BSD)

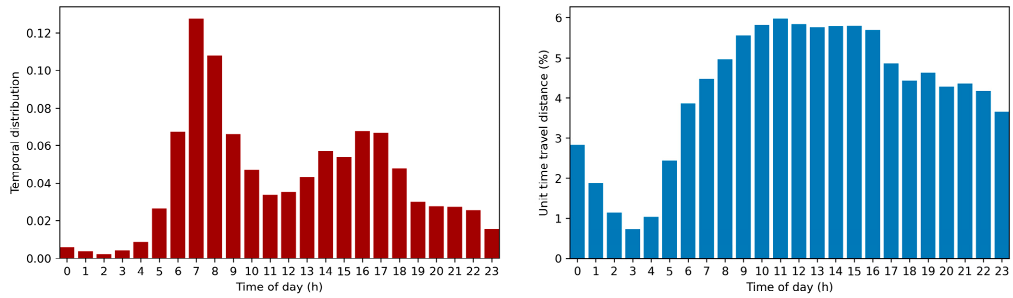
Before estimating the *BSD*, it is necessary to calculate the state of charge (*SoC*) of ETs at the beginning of each time slot [22]. Figure 3a shows the departure time distribution of taxi drivers over a day. Figure 3b shows the percentage of travel distance by taxi per hour. According to multi-day GPS trajectory data, we obtain Figure 3a,b, and the results are consistent with the experience knowledge. Since the end-time distribution of taxi drivers over a day is uneven, we use the dataset to determine the average speed and to calculate the end time by summing the average travel time (daily travel mileage d_v divided by the average speed u_a) to the departure time $t_v^{departure}$, according to Equation (3).

$$t_v^{end} = t_v^{departure} + \frac{d_v}{u_a} \tag{3}$$

Given the departure time, end time, and daily mileage of ETs, the energy consumption and *SoC* of ETs at each time slot t can be approximated based on the percentage of travel distance per unit time to the total distance. The *SoC* of the ET v at time slot $t+1$ $SoC_v(t+1)$ can be expressed as follows:

$$SoC_v(t+1) = SoC_v(t) - p(t) \cdot d_v \cdot E^{um} / \left(E_B \cdot N_v^B\right) \tag{4}$$

where $p(t)$ denotes the percentage of travel distance at time slot t to the total travel distance, d_v indicates the daily total travel distance of ET v, E^{um} indicates ET electricity consumption per kilometer (kWh/km), E_B indicates the battery capacity of one battery block, and N_v^B indicates the number of battery blocks that ET v rents.



(a) Departure time distribution of taxi drivers over a day (b) Percentage of travel distance by taxi each hour

Figure 3. Departure time distribution and percentage of travel distance per hour in this study.

The battery swapping price includes the electricity price and the battery swapping service fee, which is higher than the residential charging price; thus, drivers will choose the battery swapping service when the remaining battery electricity of ETs cannot satisfy the remaining daily travel. Otherwise, they will charge the ET at home to save money. Hence, the battery swapping decision for ET drivers is made according to the following two conditions:

(1) If the remaining battery electricity of the ET cannot meet the remaining daily travel, drivers will choose to swap the battery.
(2) The anxiety threshold of *SoC* is set at 0.2 (20%) [23]. If the remaining battery electricity drops below the threshold, drivers will choose to swap the battery.

Therefore, the *BSD* of ET v at the beginning of time slot t $BSD_v(t)$ is calculated as Equation (5):

$$BSD_v(t) = \begin{cases} N_v^B, & SoC_v(t) \le SoC_{v,r}(t),\ SoC_v(t) \le SoC_{st} \\ 0, & otherwise \end{cases} \quad \forall t \in T \tag{5}$$

where $SoC_{v,r}(t)$ represents the minimum *SoC* required for the remaining travel distance of ET v at the beginning of time slot t, and SoC_{st} indicates the anxiety threshold of *SoC*.

Finally, we can obtain the new *BSD* for the BSS at time slot t by Equation (6).

$$N_{BSD,t}^{new} = \sum_{v=1}^{V} BSD_v(t) \quad \forall t \in T \tag{6}$$

2.5. Battery Swapping Station (BSS) Configuration Optimization Model

In this section, we optimize the configuration of ET BSSs with modular battery blocks (i.e., the number of stock battery blocks in BSS) by considering the impacts of ToU price and time-dependent *BSD*. Table 2 lists all the parameters used in the optimization model.

Table 2. The parameters in the optimization model.

Notation	Definition
Sets	
T	Set of discrete time slots, $T = \{1, 2, \ldots, \lvert T \rvert\}$
Indices	
t	Index of time slot, $t \in T$
F	Fully charged state of battery
C	Charging state of battery
W	Waiting-charged state of battery
Parameters	
c_B	Unit capacity cost of the ET battery block (USD/kWh)
E_B	Rated capacity of a block battery (kWh)
r	Discount rate
L_B	Life cycle of a block battery (year)
c_{Bm}	Annual operation and maintenance costs of the unit capacity of batteries (USD/kWh/year)
c_t	Electricity price at time slot t (USD/kWh)
$N_{BSD,t}^{new}$	Number of new *BSD* at time slot t
P_c	Rated power of a charging pile (kW)
T_{full}	Depleted battery fully charged time (h)
SoC_{end}	SoC of batteries in F-state (%)
SoC_{ini}	SoC of batteries in W-state (%)
N_{CP}	Number of charging piles
Variables	
N_B	Total number of stock batter blocks in BSS
$N_{F,t},\ N_{C,t},\ N_{W,t}$	Number of battery blocks in $F,\ C$ and W states at the beginning of time slot t
$N_{C,t}^{b},\ N_{C,t}^{f}$	Number of battery blocks that begin and finish charging at time slot t
$N_{BSD,t}^{total}$	Total number of *BSD* at time slot t
$N_{BSD,t}^{real}$	Total number of *BSD* satisfied at time slot t
$N_{Q,t}$	Total number of unsatisfied *BSD* at time slot t

2.5.1. ET Battery Blocks State–Transition Equations

At any time slot t, there are three states of the battery blocks in a BSS according to SoC and the charging behavior characteristics:

- Battery blocks in fully charged state (F-state) are available for battery swapping service;
- Battery blocks in the charging pile are in charging state (C-state);
- Battery blocks unloaded from ETs in the awaiting-charging inventory are in waiting-charging state (W-state).

During the entire operating horizon, the battery in the three states can maintain the original state or transfer to other states, and the state–transition relationship is shown in Figure 4.

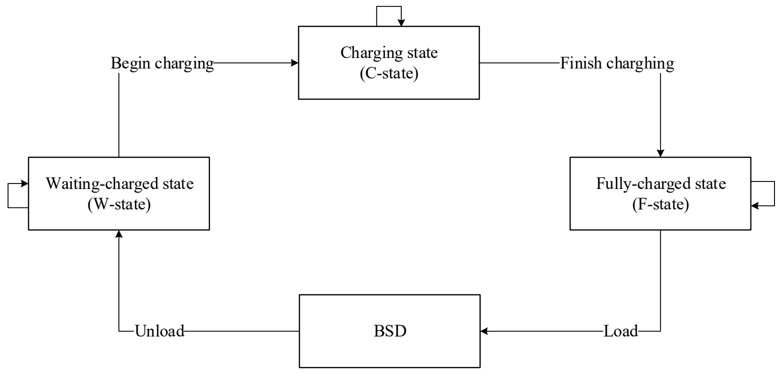


Figure 4. State–transition diagram of battery blocks in the BSS.

$N_{W,t}$, $N_{C,t}$, and $N_{F,t}$ represent the number of battery blocks in three states at the beginning of time slot t, respectively. According to Figure 4, the number of battery blocks in the F-state at the beginning of time slot $t+1$ depends on the number of battery blocks in the F-state, the number of finishing charging battery blocks, and the number of battery blocks swapped at time slot t. The conservation of states can be calculated as per Equation (7).

$$N_{F,t+1} = N_{F,t} + N^{f}_{C,t} - N^{real}_{BSD,t} \tag{7}$$

Similarly, we can calculate the number of battery blocks in the W-state and C-state at the beginning of time slot $t+1$ by Equations (8) and (9).

$$N_{W,t+1} = N_{W,t} + N^{real}_{BSD,t} - N^{b}_{C,t} \tag{8}$$

$$N_{C,t+1} = N_{C,t} + N^{b}_{C,t} - N^{f}_{C,t} \tag{9}$$

where $N^{real}_{BSD,t}$ is the total number of battery blocks swapped by BSS at the time slot t. $N^{b}_{C,t}$ and $N^{f}_{C,t}$ are the number of battery blocks beginning and finishing charging, respectively.

Because it is possible that the available battery blocks in F-state can only meet part of the BSD at time slot $t+1$. The total number of BSD, the total number of BSD being satisfied, and the total number of unsatisfied BSD at time slot $t+1$, are defined as follows:

$$N^{total}_{BSD,t+1} = N^{new}_{BSD,t+1} + N_{Q,t} \tag{10}$$

$$N^{real}_{BSD,t+1} = min\left(N_{F,t+1} + N^{f}_{C,t+1},\ N^{total}_{BSD,t+1}\right) \tag{11}$$

$$N_{Q,t+1} = N^{total}_{BSD,t+1} - N^{real}_{BSD,t+1} \tag{12}$$

Beginning and finishing charging are boundary states that belong to the C-state. Equation (13) indicates that the number of battery blocks beginning charging depends on the number of battery blocks in the W-state and the number of idle charging piles at the time slot $t+1$. Furthermore, Equation (14) describes the relationship between $N^{b}_{C,t}$ and $N^{f}_{C,t}$, which indicates that the depleted battery blocks that start charging at time t will finish charging at time $t+T_{full}$.

$$N^{b}_{C,t+1} \le min\left(N_{W,t+1},\ N_{CP} - N_{C,t} + N^{f}_{C,t+1}\right) \tag{13}$$

$$N^{f}_{C,t+(T_{full})} = N^{b}_{C,t} \tag{14}$$

$$T_{full} = \lceil E_B(SoC_{end} - SoC_{ini})/P_c \rceil \tag{15}$$

where T_{full} is related to SoC_{end} in F-state and SoC_{ini} in W-state of the battery blocks, as in Equation (15).

2.5.2. Objective Function

The objective function of our optimization model is to minimize the BSS annual costs F; thus, it can be formulated as follows:

$$\min F = F_P + F_O \tag{16}$$

where the first component F_P is the cost at the planning stage, and the second component F_O is the cost at the operating stage.

(1) **Costs at the planning stage**

At this stage, the decision variable N_B is the total number of stock battery blocks in BSS. The costs include the ET battery blocks' equivalent annual costs of initial investment F_{Inv} and the annual operation and maintenance costs F_{OM}.

$$F_P = F_{Inv} + F_{OM} \tag{17}$$

$$F_{Inv} = c_B N_B E_B \frac{r(1+r)^{L_B}}{(1+r)^{L_B} - 1} \tag{18}$$

$$F_{OM} = c_{Bm} N_B E_B \tag{19}$$

(2) **Costs at the operating stage**

At the operating stage, the charging scheduling of the BSS should consider the characteristics of ToU price c_t and time-dependent BSD. In Equation (20), the only term is the electricity purchase cost of BSS. The decision variable $N_{C,t}$ is the total number of battery blocks in the charging state at time slot t.

$$F_O = \sum_{t=1}^{T} c_t N_{C,t} P_c \tag{20}$$

2.5.3. Constraints

(1) **The number of stock battery blocks constraint**

To avoid charging piles being idle all the time, the number of battery blocks in the BSS should be at least the number of charging piles N_{CP}. At the same time, considering the scale of the BSS and the total number of ETs served, there is an upper limit to its number.

$$N_{CP} \le N_B \le N_{max} \tag{21}$$

(2) **Conservation constraint of battery blocks in different states**

As Figure 4 shows, the total number of battery blocks in BSS is the sum of the number of battery blocks in each state and is constant at any time slot t.

$$N_B = N_{F,t} + N_{C,t} + N_{W,t} \tag{22}$$

(3) **Maximum waiting time constraint**

Taxi drivers cannot wait outside the BSS for longer than the maximum waiting time T_w to ensure the quality of battery swapping service. Equation (23) represents that the unsatisfied BSD at time slot t should be met within T_w.

$$\sum_{t'=t+1}^{t+T_w} N_{BSD,t'}^{real} \ge N_{Q,t} \quad \forall t \in T \tag{23}$$

3. Numerical Experiments

This section presents results from numerical experiments. We first perform the experiment description and parameter settings. Then, we compare two BSS operation modes in an experiment based on real-world taxi GPS trajectory data collected from Beijing, China. The purpose of this experiment is to evaluate the performance and effectiveness of the proposed modular battery-swapping strategy. All code is written in Python and run on an Intel Core i7-11700 CPU (made in Vietnam) at 2.50 GHz with 32 GB RAM. The optimization model proposed in this study is an integer linear model that can be solved quickly by the commercial solver Gurobi (version 9.5.2).

3.1. Experiment Description and Parameter Settings

We focus on configuring a BSS, which provides modular battery swapping service for 200 ETs within one year (365 days). The empirical finding from the multi-day travel mileage of ETs shows that the percentage of ETs in the short-distance travel group, medium-distance travel group, and long-distance travel group are 16%, 69%, and 15%, respectively. The time interval is one hour, indicating that one day is divided into 24 time slots. The *SoC* of an ET at the beginning of the departure time on each day is taken as 100% because ETs are fully charged at home before each daily travel [20]. From real-world data, we estimate the fitting parameters for daily travel mileage distribution of different groups of drivers, departure time distribution, and percentage of travel distance per taxi per hour. Through the aforementioned fitted distributions, we can generate the daily travels of 200 ETs, and thus generate the *BSD* for 365 days.

Table 3 lists the relevant parameters in our experiment. As shown in Figure 5, our experiment adopts PG&E corporation's ToU price for commercial electric vehicle charging [28].

Table 3. The parameter settings in our experiment.

Parameters	Values	Parameters	Values
c_B	141.57 USD/kWh [20]	E_B	26.5 kWh
c_{Bm}	1.7 USD/kWh [20]	N_{CP}	10
r	0.06	L_B	5 years
P_c	13.25 kW	c_t^{peak}	0.38147 USD/kWh [28]
$c_t^{off-peak}$	0.16824 USD/kWh [28]	$c_t^{super\ off-peak}$	0.144497 USD/kWh [28]
E^{um}	0.177 kWh/km	u_a	35.6 km/h
μ_{short}	4.664	σ_{short}	0.5345
μ_{medium}	215.77	σ_{medium}	73.144
μ_{long}	342.85	σ_{long}	95.279
T_w	1 h	SoC_{end}	100%
SoC_{ini}	30%		

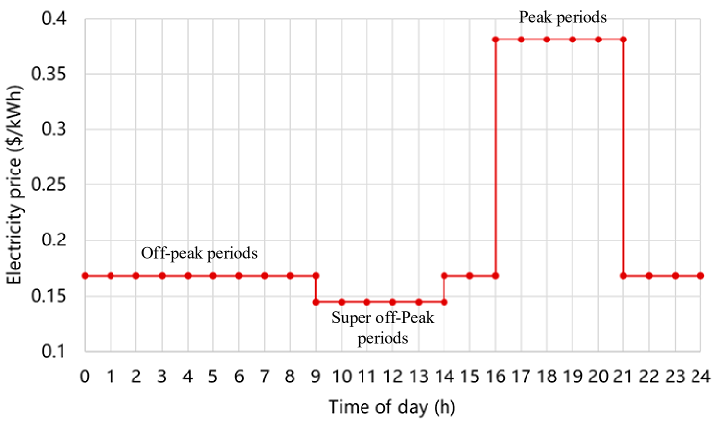


Figure 5. ToU price of PG&E corporation.

3.2. Comparison of Results between Modular BSS and Traditional BSS

One of the critical features of ET BSS is the demand-based battery rental mode to match individual travel behaviors. In this subsection, we will explore the advantages of this feature by comparing the costs and charging scheduling of the modular BSS with that of the traditional BSS.

There are some differences between traditional BSS and modular BSS in terms of parameter settings. ET drivers can only choose to rent a fixed capacity battery in traditional BSSs. We assume the battery's rated capacity in the traditional BSS is equal to that of the summation of two battery blocks in the modular BSS. Except for that, the other parameters are the same as in modular BSS. Since the input of the data-driven model in our study, i.e., the daily travel patterns of ETs, are the same in both experiments, the daily *BSD*s differ due to the different operating modes of the two BSSs, which does not lead to unfair experimental comparisons.

Table 4 represents the comparison results of annual costs of two BSS operational strategies.

Table 4. Comparison results of two BSS operational strategies.

	Annual Costs (USD)	Annual Investment Cost of Battery Blocks (USD)	Annual Operation and Maintenance Costs (USD)	Electricity Cost (USD)	Number of Purchased Equivalent Battery Blocks
Traditional BSS	170,234.52	44,530.88	2252.50	123,451.14	50
Modular BSS	113,055.47	27,609.14	1396.55	84,049.78	31

The results show that modular BSS can save investment and operating costs significantly. Under the modular battery swapping service scenario, modular BSS's annual investment cost of battery blocks is 27,609.14 USD, which is 16,921.74 USD (38%) less than the traditional battery swapping service. Specifically, we convert the batteries purchased by the traditional BSS into equivalent battery blocks, and the modular BSS can purchase 19 fewer battery blocks than the traditional BSS. Therefore, a modular BSS's annual investment cost of battery blocks is less than that of a traditional BSS. It follows that modular BSSs can reduce battery inventory at BSS by considering ET drivers' heterogeneous driving range requirement and by providing a demand-based battery rental mode to match individual travel behaviors.

As for the electricity cost, modular BSS purchases 84,049.78 USD of electricity from the grid, which is 39,401.36 USD (31.92%) less than the traditional BSS. We next analyze the operational stage. Figure 6 shows the total number of battery blocks in the charging state in each hour of a day over a year using the two operational strategies of modular BSS and traditional BSS. We can see that ET battery blocks in both BSSs are mainly charged during periods of flat and valley prices. This suggests that BSSs can reduce the burden of uncontrolled charging on the grid compared to EVs charging stations. In addition, the percentage of battery blocks in the modular BSS charged during the period of valley price is 53.7%, much higher than the 36.30% in the traditional BSS. Conversely, the percentage of battery blocks charged during peak price periods in the modular BSS is 3%, which is much smaller than the 12.86% in the traditional BSS. This indicates that modular BSSs perform better than traditional BSSs in terms of peak shaving and valley filling.

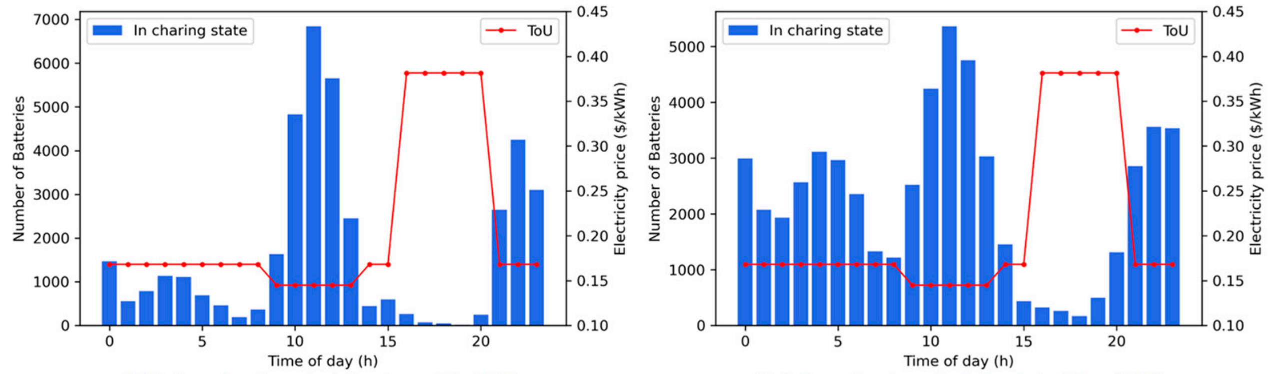


Figure 6. Battery charging schedule in two scenarios over one year.

3.3. Sensitivity Analysis

The cost of battery purchase is one of the most critical factors impacting the profitability of the BSS. Table 5 shows the effects of different unit capacity costs of batteries on the optimization results of BSS configuration and various economic indicators of the BSS.

Table 5. Configuration optimization results of BSS under different prices of battery.

Unit Capacity Costs of Batteries (USD/kWh)	Number of Purchased Battery Blocks	Annual Investment Cost of Battery Blocks (USD)	Electricity Cost (USD)
100	31	19,502.11	84,049.78
80	31	15,601.69	84,049.78
60	31	11,701.27	84,049.78
50	32	10,065.61	83,653.52
40	33	8304.13	83,332.93
30	34	6416.82	83,080.15
20	35	4403.70	82,882.90

Table 5 shows that when the unit capacity cost of batteries is larger than 60 USD/kWh, the optimal number of purchased battery blocks and electricity cost do not vary with unit capacity cost of batteries. This is because when the unit capacity cost of batteries is higher, the cost of purchasing an additional battery block is higher than its reduced charging cost due to charging at valley electricity prices, which makes the total annual cost of the BSS an upward trend.

In order to analyze the impact of the ToU price on the operation of BSSs, we keep the price during valley price periods constant and increase the price during peak periods in equal proportion to form different ToU price schemes.

Figure 7 shows that raising the electricity price during peak periods, i.e., increasing the difference between peak and valley electricity prices, leads to an increase in the optimal number of backup battery blocks in the BSS. This result is due to purchasing an additional battery, bringing a higher return on charging during valley price periods than its annual investment cost. Moreover, an interesting result is that when the peak electricity price growth rate is greater than 1.5, the electricity cost starts to decrease with the increasing growth rate. This indicates that the additional battery blocks are purchased to act as an energy storage battery, which is charged during the valley price periods and is then used for *BSD* during the peak price periods. BSS hardly charges the battery blocks during peak price periods.

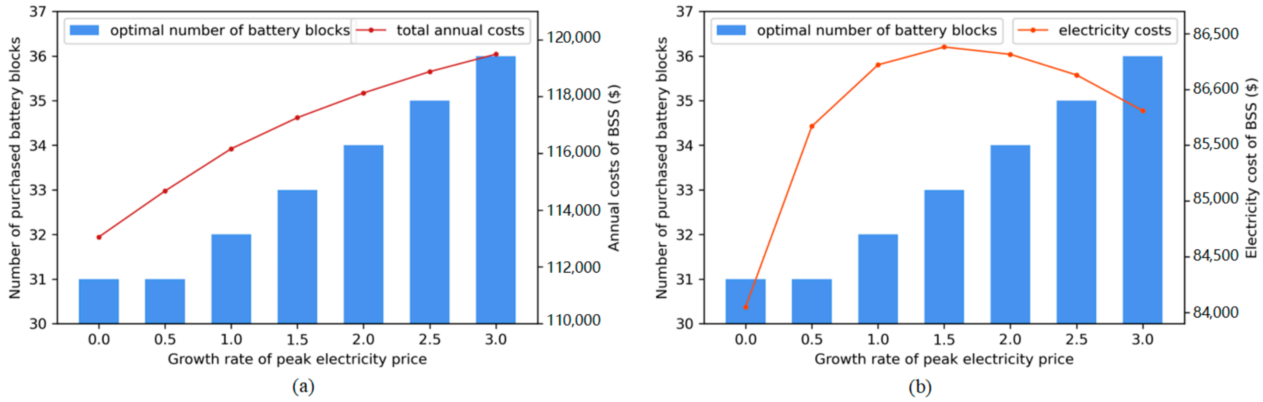


Figure 7. Configuration optimization results of BSS under different ToU prices. (**a**) impact of ToU prices on total annual costs, (**b**) impact of ToU prices on electricity costs.

4. Conclusions

This study proposes a novel battery swapping mode (BSM) for electric taxis (ETs), i.e., the so-called modular BSM, which can provide a flexible combination of battery blocks to meet different driving range requirements. Furthermore, we developed a data-driven approach to configuring and operating modular battery swapping stations (BSSs) using the taxi travel patterns extracted from the eight days of GPS trajectory data associated with 12,643 actual taxis in Beijing, China. The departure time distribution, daily mileage distribution, and percentage of travel distance per hour extracted from the trajectory data were used to define the model's rules to establish a realistic and accurate model. The trajectory data analysis indicates a strong relationship between the ET travel patterns and the dynamic battery swapping demand (*BSD*).

We performed a real-world numerical experiment with traditional BSM as the benchmark to evaluate our model and modular BSM. It was demonstrated that the BSS with modular BSM can save 38% on the investment costs of purchasing ET battery blocks and respond to the time-of-use (ToU) price better than the benchmark. Additionally, a sensitivity analysis was conducted to measure the impact of two essential model parameters on the model output: the unit capacity costs of batteries and the ToU price. Insightful findings are obtained for BSS infrastructure planning. First, battery price fluctuations within a reasonable range will not significantly impact the configuration of BSSs. Second, when peak electricity prices (grid load) are high, increasing the number of battery blocks purchased, they can be charged early at valley electricity prices, which is a good solution.

From the findings of this study, our future research will focus on the configuration and operation of modular BSSs featuring battery energy storage systems (BESS) that have the capability of battery-to-grid (B2G) or that cooperate with microgrids. Moreover, considering the stochastic *BSD* for an ET driver and evaluating the performance of modular BSSs in different regions/countries are interesting future directions. Furthermore, modeling the details of the battery swapping process will increase the model scale, and designing a customized algorithm to solve the model will also be an important research direction in the future.

Author Contributions: Conceptualization, Z.L. and X.M.; methodology, Z.L.; software, Z.L.; validation, X.L. and G.H.d.A.C.; investigation, R.S. and W.S.; resources, X.M.; writing—original draft preparation, Z.L. and X.L.; writing—review and editing, G.H.d.A.C.; visualization, R.S.; supervision, X.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, Award Number: 52072017.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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