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Deploying Battery Swap Stations for Electric Freight Vehicles based on Trajectory Data Analysis

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***Abstract*— This paper proposed a bi-objective model to deploy battery swap stations for Electric Freight Vehicles (EFVs) based on big data analysis. We particularly extracted trip, parking and charging information of EFVs in Beijing from a one-week dataset containing trajectories of 17,716 EFVs (with a sample rate of 99.8%) in 2019 to define rules in the model and parameterize the model, so as to improve the model realism and accuracy. The bi-objective model aimed to minimize the total cost of building battery swap stations and maximize operational efficiency of EFVs. The model was solved by a genetic algorithm. Parameter sensitivity analysis was also conducted. The test case of Beijing suggested that the bi-objective model, together with genetic algorithm, could help freight companies find a set of Pareto Optimal solutions to the deployment of battery swap stations. Among the solutions, the one with the highest investment in battery swap stations could reduce the average charging time of EFVs by 96.56%. In addition, the sensitivity analysis results suggested that the parameters related to battery, infrastructure and number of EFVs were influential to both the total costs and operational efficiency of EFVs, and should be considered carefully in the deployment of battery swap stations.**

***Index Terms*— Freight Transport; Electric Vehicle (EV); Trajectory Data; Battery Swap Station; Infrastructure Deployment; Bi-Objective Model.**

I. Introduction

THE emerging concept of green logistics, which is aimed at introducing Electric Freight Vehicles (EFVs) into freight transport systems, has received increasing attention across the globe [1-3]. According to the forecast by Global EV Outlook [4], EFVs were mostly produced as light-commercial vehicles (LCVs), which reached 250,000 in 2018, with around 80,000 sold in 2017. The sale of medium-sized trucks ranged from 1,000 to 2,000 in 2018, and most of them were sold in China. Under the EV30@30 Scenario (all Electric Vehicles (EVs) except for two-wheelers will reach 30% market share by 2030), the number of EFVs would reach 3,300,000. Different from passenger EVs, EFVs are mainly used by freight companies who tend to more care about the costs and benefits. Due to supportive policies (e.g., financial subsides) by both local and central governments, attempts have been made by freight companies to introduce EFVs into their vehicle fleets.

The lack of charging infrastructure has been one of the main barriers to the development of EVs, including EFVs [5-7]. This could further influence the decision-making of freight companies. Specifically, medium-freight trucks and heavy-freight trucks generally have a battery capacity of around 300 kWh and 990 kWh, respectively. This requires EFVs to get recharged through a charging facility (e.g., charging post) with high power, so as to finish recharging within an acceptable time to freight companies. For example, it takes around six hours to get an EFV with a battery capacity of 300 kWh fully charged through the DC fast charging with a power of 50 kW [4].

Battery swap stations tend to be a promising type of charging infrastructure which can meet the requirements of freight companies in terms of charging time [8, 9]. At a battery swap station, EV drivers can quickly replace the used on-board batteries with a fully charged one [10-12]. This would help freight companies to improve the operational efficiency of EFVs, and thus reduce operational costs. Further, this would make EFVs attractive to freight companies and promote the adoption of EFVs in freight transport [13].

Attempts have been made by several companies, such as Better Place in Israel, Tesla in America, and China State Grid, to promote the development of battery swapping technologies for EVs, but most of them failed. The main barriers to the development included the high upfront investment and the lack of battery standardization. However, the battery swapping technology is becoming mature because of the improvement in battery swap standards, the reduction in construction costs, and supportive policies. For example, the upfront investment is now less than 10% of that in 2008, which makes battery swap station economically feasible.

Previous studies have attempted to deploy battery swap stations for passenger EVs, but paid significantly less attention to EFVs. In response, this paper aims to propose an approach to deploy battery swap stations for particularly EFVs. Specifically, the trip, parking and charging patterns of EFVs will be extracted from GPS trajectory data on actual EFVs and will be further used to develop a bi-objective model for the

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deployment of battery swap stations. The empirical findings from the trajectory data would help to better estimate charging demand of EFVs and thus more properly locate battery swap stations.

II. Literature Review

A. Adoption and Usage of EVs in Freight Transport

Adoption and usage of EVs are of great importance to the development of EVs, and thus have received attention in the studies of electrifying freight transport.

In terms of adoption of EFVs, previous studies tended to be focused on the barriers to the adoption of EFVs and potential environmental benefits of the EFV diffusion. For example, a comparative study of Denmark, Germany, the Netherlands, Sweden and the UK was conducted by Taefi *et al.* [14] to investigate the potential barriers and enablers to the diffusion of EVs in freight transport. It was found that barriers and enablers were in general similar in these countries. Altenburg *et al.* [15] analyzed the factors influencing the decision-making of freight companies using a qualitative method. They conducted 14 interviews with freight companies in the city of Amsterdam, and the results suggested that both reformation and early users benefited from the positive influences of EFVs on society or the environment. Mirhedayatian *et al.* [16] developed a framework incorporating an optimization model and economic analysis to explore the optimal behavior of a freight company and social influence, in response to those EFV-related policies, such as zone fee to congestion and low-carbon areas with exemptions for EFVs. The results suggested that the area fee enhanced the company's social welfare while increasing the company's total cost.

Another group of EFV studies looked at the travel behavior of EFVs, with a focus on routing strategies of EFVs and charging behavior of EFVs. For example, Schiffer *et al.* [17] proposed a positioning-route selection method for a strategic design of the EFV fleet, considering both EFV routing strategies and the layout of charging stations. Hoed *et al*. [18] carried out an analysis of the EFVs in Amsterdam, and found that EFVs needed to get recharged during those long trips with additional waiting time and detour. As a result, most EFVs were suitable for short trips. To address this problem, battery swap stations would be a promising solution, as EFVs can replace the used batteries with fully charged ones at battery swap stations within a short time (e.g., 3 minutes), which can effectively improve the operational efficiency of EFVs.

B. Deployment of Battery Swap Stations

As aforementioned, battery swap stations have been increasingly viewed as a promising type of charging infrastructure, as they can help to significantly reduce the recharging time [19], on one hand, and could also be coupled with renewal energy (solar and wind energy) system, on the other hand [20, 21].

Many models and methods have been developed to locate battery swap stations for different EV types, including passenger EVs [5], EFVs [22], electric buses [23], electric taxies [24, 25], and electric scooters [26]. In general, these models tried to deal with different optimization problems. For example, Almuhtady *et al*. [22] introduced a battery swapping plan in the EFV fleet using a degradation-based optimization strategy to minimize maintenance costs. Liang *et al*. [27] developed a linear programming model to deal with the battery swapping demand and battery charging-discharging balance at battery swap stations, intending to maximize the daily operating profit. Sun *et al*. [11] investigated the charging plan at battery swap stations in those cases where the battery swapping demand and the charging price changed over time, using a periodic fluid model. Huang [26] paid more attention to the design of the swap stations, and explored the effect of visual perception on user preferences through interactive experiments with both users and facilities involved. Besides, some studies additionally considered the power system in the deployment of battery swap stations. Yu Zheng *et al.* [28] introduced a design system of battery charging/swap stations to optimize infrastructure supply and charging schedule on the basis of the life cycle cost theory. Sarker *et al.* [29] built an optimization model to estimate the system cost considering the relationship among customers, battery swap stations, electricity market, and power system. Adegbohun *et al.* [30] introduced an automated swap technology to increase the market share of swap stations considering power system reliability and cost.

In order to solve the models, several algorithms have been developed. For example, Yang and Sun [31] proposed an EV battery swap stations location routing method based on a four-phase heuristic named SIGALNS (involving modified sweep heuristic, iterated greedy, adaptive large neighborhood search and improvement heuristic) and a two-phase Tabu Search-Modified Clarke and Wright Savings heuristic (TS-MCWS), which can be used to figure out the location strategy of battery swap stations and the routing plan of an EV fleet. Hof *et al*. [32] used the Adaptive Variable Neighborhood Search (AVNS) algorithm to deploy the battery swap stations based on the parking behavior of EVs. Yang *et al.* [33] proposed a model for deploying battery swap stations considering the EFV driving behavior and the drivers' psychology. Furthermore, a heuristic algorithm that combined Tabu Search and GRASP was proposed to solve the model.

C. Big Data Analysis in the Studies of Freight Vehicles

Recently, big data become an important data source for transport studies [34, 35]. GPS trajectory data tend to be one of the most-used data sources in the studies of freight transport, and have been used to provide insights into trip patterns of freight vehicles, such as analyzing driving behavior, monitoring fuel consumption, measuring operational efficiency of vehicles and optimizing delivery routes. However, previous studies mostly looked at Conventional Freight Vehicles (CFVs) and paid little attention to EFVs. Therefore, we here only reviewed those CFV studies with big data.

Previous studies tended to be focused on trip and parking patterns of CFVs. Yang *et al*. [36] proposed a robust learning method based on support vector machine (SVM) to extract parking time, the distance between parking stop and sports center, and the distance between parking stop and its closest major bottleneck, using the trajectory data on CFVs. Huang *et al*. [37] proposed a method to identify CFV trips and classify delivery areas (including intra-province delivery and inter-province delivery) with the trajectory data on CFVs. Tian *et al*. [38] investigated the break-taking behavior of CFVs during those long-distance trips, providing new insight into behavioral patterns of CFVs. Specifically, based on trajectory data, stopping points were selected as parking locations for the long-haul trucks, which were divided into three types according to different parking durations. An exponential distribution and a power-law distribution could fit the three types well. By analyzing the connections among the distribution of the three types, they found that the combination of the three separate classes was Gaussian.

In addition, some studies used big data to evaluate the freight transport system. For example, Yang *et al*. [39] developed procedures and methods for evaluating urban freight performance with the GPS trajectory data, using three measures, namely mobility, fuel consumption, and emissions. Hadavi *et al*. [40] identified a set of specific, measurable, and policy-oriented indicators for CFVs, which could be quantified with trajectory data. The indicators could be used in the further analysis of urban transport activities. Yanhong and Xiaofa [41] used the trajectory data on CFVs to analyze the utilization of vehicles.

D. Research Gaps and Aims

As reviewed above, attempts have been made to introduce EVs into freight transport. However, previous studies of EFVs were limited in the following two aspects:

First, previous studies of EFVs tended to be focused on general charging infrastructure, such as charging posts, and paid significantly less attention to the role of battery swap stations, which is a promising type of charging infrastructure in the electrification of freight transport. Although attempts have been made to deploy battery swap stations for passenger EVs, the travel and charging behaviors of EFVs and passenger EVs are different, and the approaches for passenger EVs could not be applied to EFVs directly. Specifically, EFVs generally need to follow a fixed timetable; whereas there is more uncertainty around trip and charging behaviors of passenger EVs; Furthermore, EFVs are profit-oriented, and their travel and charging behaviors are more associated with time value and operational efficiency, compared to passenger EVs; Battery standardization is one of the main barriers to the development of battery swap stations. However, it would be easier to apply the same battery standard to all EFVs. In other words, battery swap stations tend to be more feasible to EFVs than passenger EVs in practice.

Second, GPS trajectory data on freight vehicles was an important data source in previous studies of freight transport. However, trajectory data on actual EFV was seldom used, in part because EFVs have not been widely introduced in freight transport yet. It would be problematic to investigate EV-related problem (e.g., deployment of charging infrastructures) using trajectory data on conventional freight vehicles, as the trip and parking patterns of conventional and electric freight vehicles could be different [1, 42]. In general, EFVs need to get recharged through charging posts at parking lots, and their parking behaviors might be influenced by charging [43]. For example, EFVs might have to get parked for a longer time than usual, in order to get more electricity through charging. Also, EFV drivers tend to be more willing to choose a parking lot with charging facilities available. Furthermore, due to the limited driving range and range anxiety, trip patterns of EFVs might also be influenced [44]. For example, EFVs would not take a risk and try those long trips when their State of Charge (SOC) is low. Moreover, estimating electricity consumption and further charging demand is of great importance to the deployment of charging infrastructures [45]. However, it would be rather difficult to do such estimations with trajectory data on conventional freight vehicles, as it does not contain any information on electricity consumption or charging behavior.

To fill the research gaps above, this paper will use GPS trajectory data on actual EFVs to develop a battery swap station optimization model particularly for EFVs. Its contributions are twofold: First, the existing battery swap station optimization models were mostly for passenger EVs, and could not be applied directly to EFVs. Therefore, we will develop an optimization model particularly for EFVs, considering their unique trip, parking and charging patterns. Second, we will extract trip, parking and charging information of EFVs from a large trajectory dataset on actual EFVs. This is expected to better define the rules in the optimization model and also to parameterize the model, so as to improve its realism and accuracy.

III. Study Area, Data Source and Data Mining

A. Study Area: Beijing, China

The capital of China, Beijing, was used as a case study. Its total area was 16,410.54 km^2 in 2019 with a population of 21.5 million [46]. Its total freight volume was 273.38 million tons in 2019 and rose by 8.3% year-on-year. Road freight plays an important role and its volume was 223.52 million tons, accounting for 81.8% of the total volume [47].

Transportation electrification has also received considerable attention in the freight transport system of Beijing. The number of EFVs was 17,753 in Beijing in 2019, and rose by 15.3% year-on-year [47]. There were around 3,700 general charging stations for EFVs, as shown by Fig. 1.

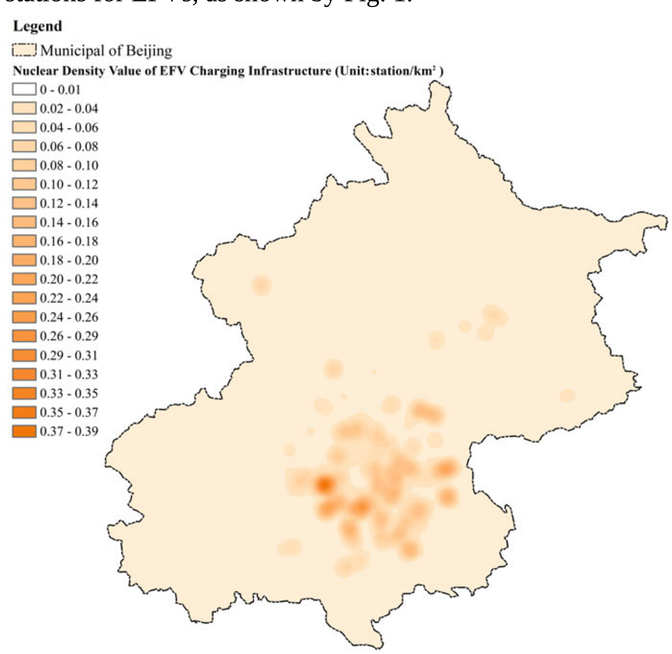

Fig. 1. The Nuclear Density of EFV Charging Infrastructure in Beijing.

B. Data Source

We used one-week GPS trajectory data on 17,716 actual EFVs in Beijing with a sample rate of 99.8%, which was collected from 11th November to 17th November 2019. In total, the dataset contained around 4 billion records. Table I shows an example of the records in the dataset. For each record, it contains vehicle ID, time, speed (unit: km/h), kilometers travelled (unit: km), SOC (the Stage of Charge of an EFV), latitude and longitude. In the dataset, around 83.0% of the EFVs had 1,000-10,000 GPS records, as shown in Fig. 2. On-board GPS devices made a record with a certain interval for each of the EFVs. The time resolution of GPS trajectories varied from seconds to minutes: most of the records (99.98%) had a time resolution from 5 to 15 seconds.

TABLE I
AN EXAMPLE OF GPS TRAJECTORY DATA FOR ONE EFV

Vehicle ID	Time	Speed	Kilometers Travelled	SOC	Longitude	Latitude
LSCA64 5633	20190823 050823	0	66302	0.99	115.9627	39.4608
LSCA64 5633	20190823 051336	58	66305	0.98	115.9584	39.48611
LSCA64 5633	20190823 142231	41	66474	0.22	115.9901	39.56013
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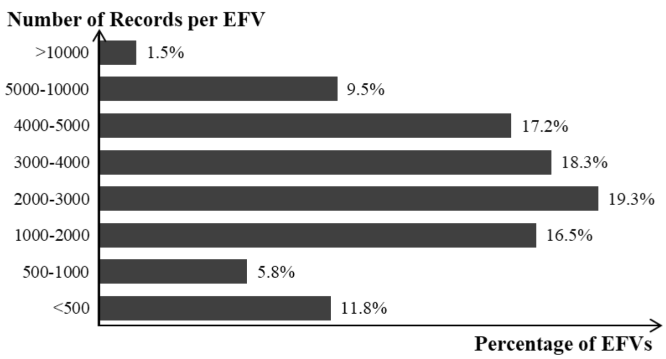


Fig. 2. Distribution of the Number of Records per EFV.

C. Trajectory Data Analytical Framework

An analytical framework (see Fig. 3) is proposed to process the GPS trajectory data on EFVs in order to extract trip, parking and charging patterns of EFVs, which will be further used to develop a bi-objective model of deploying battery stations (to be introduced in Section IV).

As shown by Fig. 3, firstly, we analyzed the data by matching the map, compressed the data to improve computational efficiency, and segmented the data (according to different fields and rules which were used to get different statistical patterns). Secondly, we identified trips and then cleaned the data in order to get valid records for subsequent analysis. In particular, we applied three rules regarding the "Key Fields", "Travel Distance for a Trip" and "Average Travel Speed for a Trip" in data cleaning. Finally, the key characteristics of the charging, trip, and parking patterns of actual EFVs were obtained for developing the bi-objective model.

D. Empirical Findings from Trajectory Data Analysis

To better define rules in the bi-objective model for deploying battery swap stations (to be introduced in Section IV) and also parameterize the model, we will extract the information needed

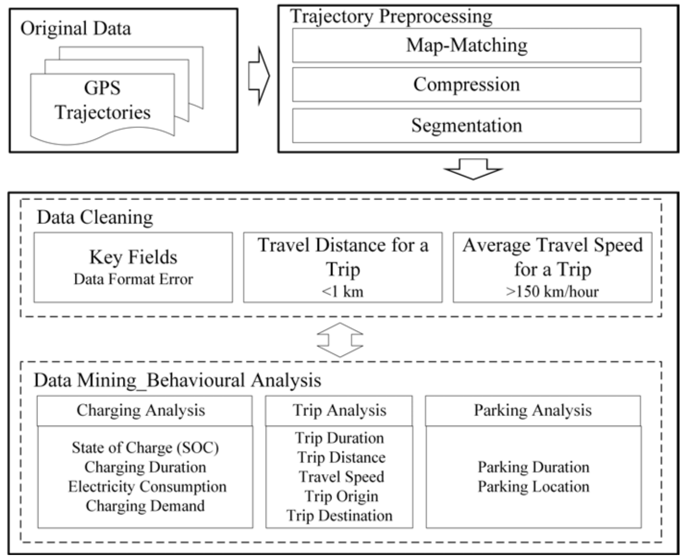


Fig. 3. Trajectory Data Analytical Framework (Source: Adapted from [47]).

from the trajectory dataset, including delivery hot spots, charging demand, charging speed, parking duration (see Appendix 2), and average travel speed of EFVs (see Appendix 3). This information needed is identified based on the structure of the bi-objective model: we prepare this information in order to use empirical findings as far as possible in modelling and parameterization, so as to help improve the model's realism and accuracy.

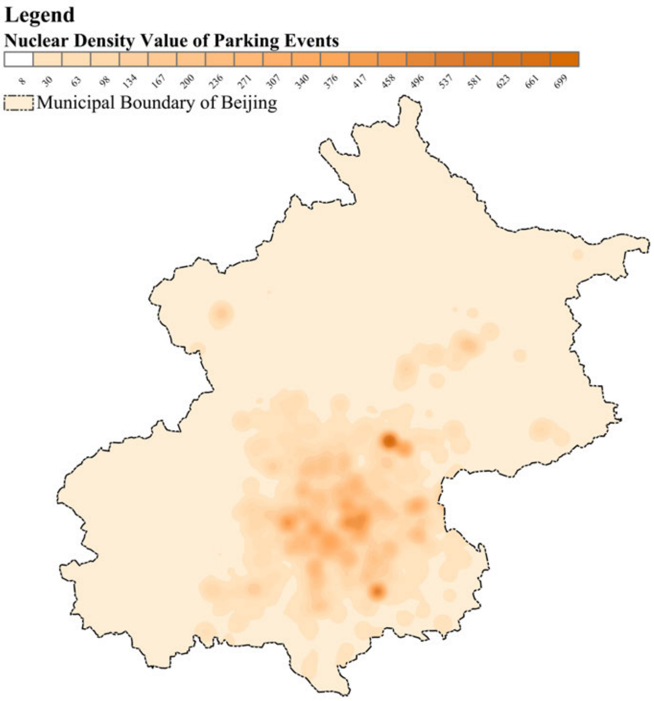
1) Delivery Hot Spots of EFVs

Delivery hot spots of EFVs were identified based on the spatial distribution of parking events of EFVs. These hot spots will be considered as candidate spots where battery swap stations may be deployed, so as to serve as many EFVs as possible. We used Moran's I to judge the rationality of identifying delivery hot spots, which indicates that it is feasible to merge adjacent grids into EFVs delivery hot spots. The nuclear density analysis method [49] was used to delineate the delivery hot spots of EFVs, which can directly reflect the distribution of discrete parking events in a continuous area. Here we used the nuclear density value of 145 as the boundary range (output pixel was 50; searching radius was 4000). Further, we used the transformation among the point elements, grid elements and area elements to get the delivery hot spots of EFVs (numbered with ID 1-30), as shown in Fig. 4. The area of each delivery hot spot is shown in Appendix 1.

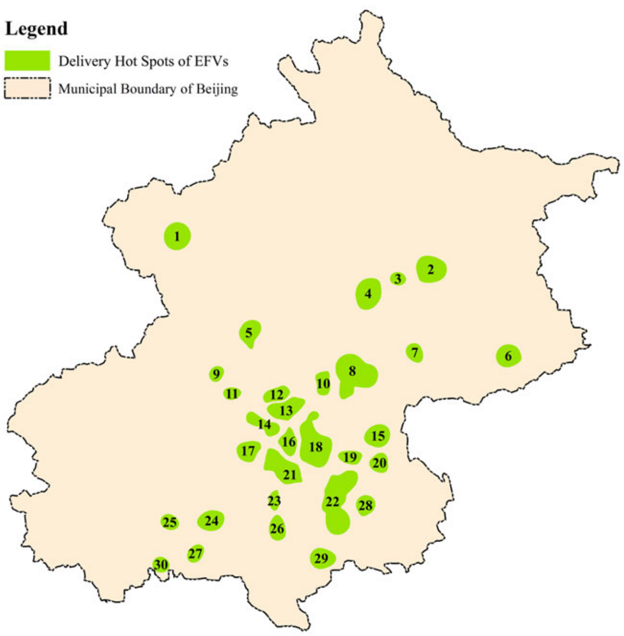
2) Charging Demand of EFVs

The deployment of battery swap stations is largely influenced by the charging demand of EFVs. We estimated the charging demand of EFVs in the delivery hot spots, based on the charging events of EFVs extracted from the trajectory data, as shown by Fig. 5. Effectively, those hot spots located in the city center tended to contain more charging events and thus higher charging demand.

The SOC of EFVs at the point when they get recharged is closely associated with the charging behavior of EFVs. The distribution of the SOC can be extracted from the GPS trajectory data as shown by Fig. 6. We plotted this distribution based on EFVs' charging events: specifically, we analyzed all charging events and figured out the SOCs when EFVs started



(a) The Nuclear Density of Parking Events



(b) The Identified Delivery Hot Spots

Fig. 4. The Delivery Hot Spots of EFVs in Beijing.

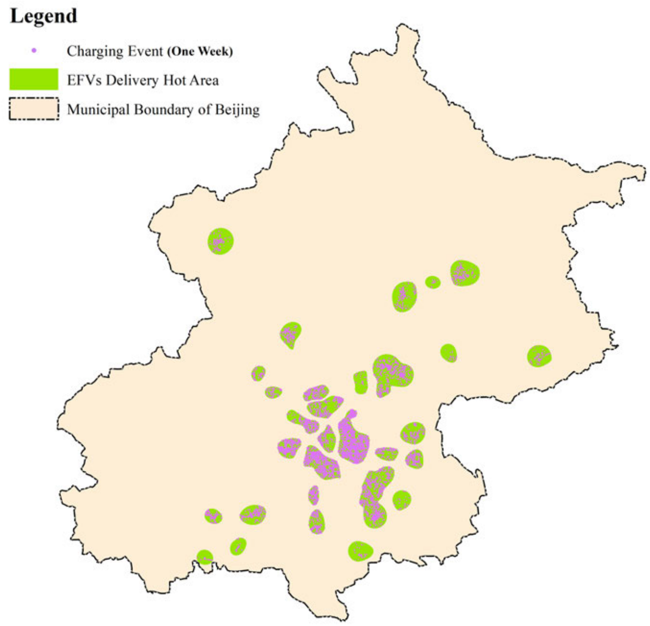


Fig. 5. Distribution of the Charging Events of EFVs in the Delivery Hot Spots.

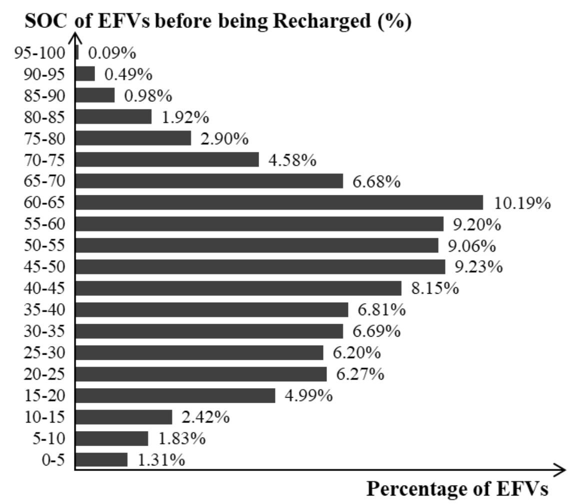
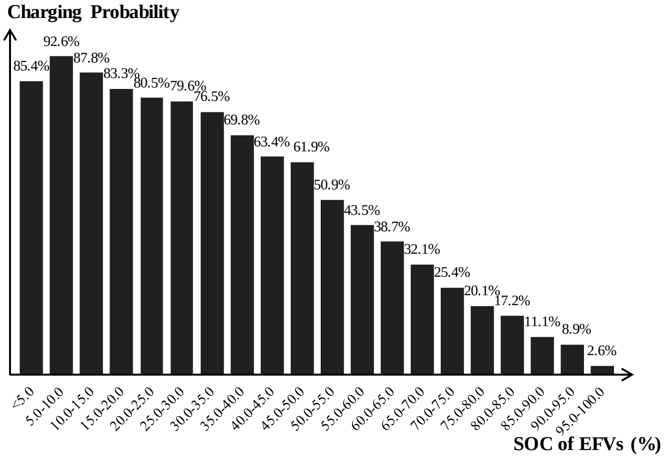


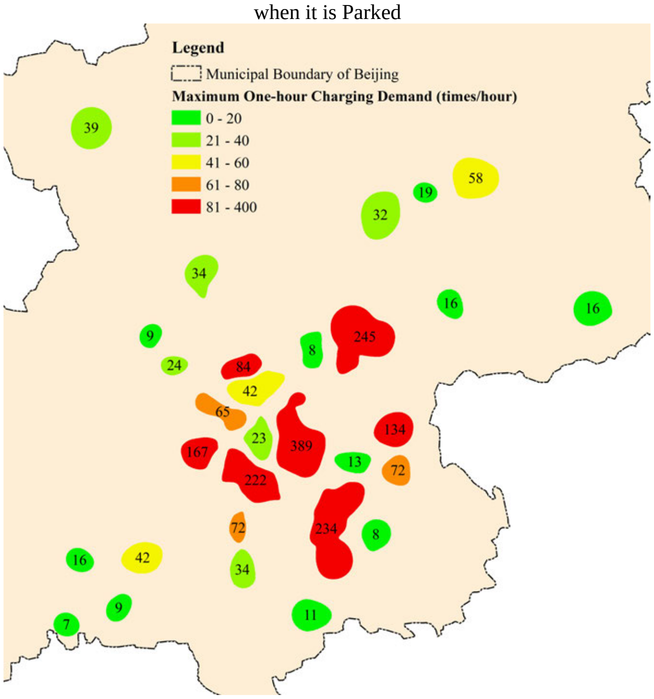
Fig. 6. Distribution of the SOCs before EFVs being recharged.

being charged. The figure shows the distribution of these SOCs. It can be found from Fig. 6 that the EFVs with a SOC ranging from 15% to 75% account for 76.8%. When the SOC of an EFV is high (e.g., a SOC above 75%), its charging probability, in general, is low, likely because it has sufficient charge; while EFVs tended to get recharged before their SOCs become too low (e.g., a SOC below 15%).

Specifically, the charging demand in each hot spot is described with the peak-hour charging demand extracted from trajectory data (see Fig. 7-(b)), which will be used in Objective 2 of the optimization model to be developed. In this dataset, the peak hour is from 8 to 9 AM. Here, the peak-hour charging demand is estimated with the relationship between the charging probability of an EFV and its SOC when it is parked. The relationship was quantified based on EFVs' parking events as follows: firstly, we grouped those parked EFVs into 20 categories according to their start SOCs; second, we counted those EFVs that got charged when they were parked and further calculated the percentage of these EFVs in the group to which they belong. The percentage of these EFVs can be viewed as the charging probability of EFVs in this group when they are parked. It can be found that for those parked EFVs, they were very likely to get recharged if their SOCs are low, possibly because of the so-called range anxiety. The highest peak-hour charging demand was 389 times/hour (see Fig. 7-(b)) in the delivery hot spot near the Beijing Central Business District (East Third Ring Road) in Beijing.



(a) The Relationship between Charging Probability of an EFV and its SOC when it is Parked



(b) The Peak-Hour Charging Demand (Unit: charging times/hour)

Fig. 7. Charging Demand of EFVs in Beijing.

IV. An Approach to Deploying Battery Swap Stations for EFVs

A. A Bi-Objective Model for Deploying Battery Swap Stations

A bi-objective model was developed to help freight companies to deploy battery swap stations for each of the EFV delivery hot spots, with the information extracted from the EFV trajectory data (see Section III D). The model has two objectives, about which freight companies tended to be more concerned:

Objective 1. Minimize the total cost of building battery swap stations;

Objective 2. Maximize the operational efficiency of EFVs.

On the one hand, freight companies are responsible for building battery swap stations, and thus generally hope to minimize the total cost (Objective 1), which is the sum of the costs of batteries, charging posts and station construction. On the other hand, freight companies generally hope that they could get access to as many stations as possible, and also, for each station, there could have as many charging posts and batteries as possible, to maximize the operational efficiency of EFVs (Objective 2). However, the numbers of batteries, charging posts and stations available are directly proportional to the total cost, and thus influence Objective 1. In other words, the two objectives conflict. In addition, the potential impacts of introducing EFVs on the power grid system could be an important factor in the deployment of battery swap stations. However, based on our estimation, the impacts tended to be relatively small: assuming that all freight vehicles in Beijing (about 480,000 vehicles in 2019) were electric, the average daily electricity demand of an EFV was about 28 kWh (as evident from our trajectory data on EFVs), and the annual electricity demand of charging would be about 281 million kWh, which accounts for 0.24% of total electricity consumption. Furthermore, it would be possible for operators to get those used batteries recharged at battery swap stations during the off-peak periods, which could help mitigate pressure on the power grid system.

Apart from the two objectives, the bi-objective model also has four constraints, as shown by Fig. 8. Specifically, in order to meet charging demand of EFVs, the total supply should be greater than the total charging demand of EFVs (see Constraint 1). In order to ensure service quality, the probability of getting battery swapped immediately should be greater than the EFV user's expected probability (see Constraint 2), which is connected to Objective 2. To ensure the steady-state of queuing at a battery swap station, the number of batteries finishing charging within a specific time slot should be greater than the number of EFVs arriving (see Constraint 3). To ensure the normal operation of EFVs, the electric range of an EFV should be greater than the distance between any two battery swap stations (see Constraint 4). It is hoped that Pareto Optimal solutions can be found with the consideration of the two objectives and four constraints.

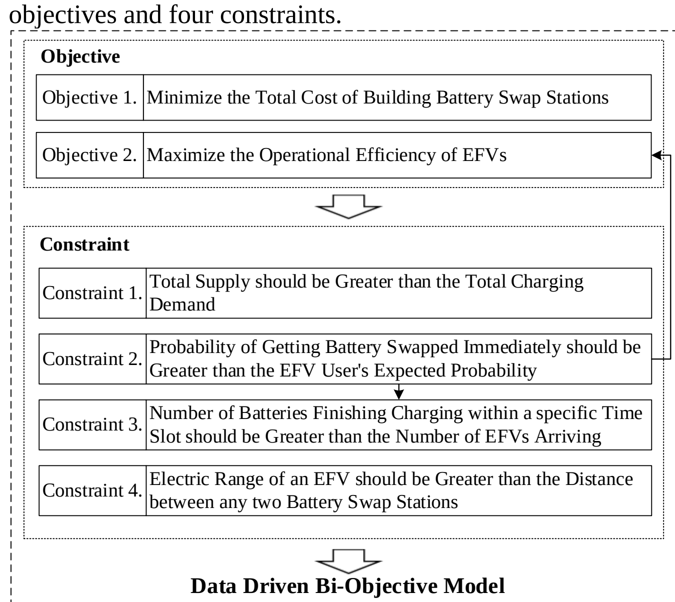


Fig. 8. The Connections between the Objectives and Constraints in the Bi-Objective Model.

Before introducing the bi-objective model, we summarized the model parameters in Table II.

TABLE II
PARAMETERS USED IN THE BI-OBJECTIVE MODEL

Symbol	Unit	Description	Source
z	N/A	ID for an EFV delivery hot spot	N/A
i	N/A	ID for an EFV	N/A
x	N/A	the index of a time slot, $x \in \{0,1,\cdots,23\}$. Note that we divide one day into 24 time slots with a bin of 1 hour	N/A
$Area^{(z)}$	km^2	the area of delivery hot spot z	Trajectory Data
a	dollar	the basic cost of a battery	Input by User (Source: Taobao, a famous Chinese e-commerce company)
c	dollar	the cost of a charging post	Input by User (Source: [47], [50] and Taobao, a famous Chinese e-commerce company)
b	dollar/kWh	the cost per unit energy capacity of a battery	Input by User (Source: Taobao, a famous Chinese e-commerce company)
s	dollar	the basic capital cost of a battery swap station	Input by User (Source: Taobao, a famous Chinese e-commerce company)
$q^{(z)}$	kWh	the average battery capacity of an EFV in the delivery hot spot z	Trajectory Data
$P_{EFV}^{(z)}$	kilowatt	the average battery output power of the EFVs in the delivery hot spot z	Trajectory Data
$P_{post,swap}$	kilowatt	the average charging power of the charging post at battery swap stations	Design Variables
$P_{post,charge}^{(z)}$	kilowatt	the average charging power of the charging posts at general charging stations in the delivery hot spot z	Trajectory Data
$v^{(z)}$	km/h	the average travel speed of an EFV in the delivery hot spot z	Trajectory Data
$\mu^{(z)}$	batteries/hour/post	the rate at which the battery is fully charged through a charging post at a battery swap station in the delivery hot spot z	N/A
r	hour	the time for replacing the used battery with a new one if available	Input by User (Source: NIO, a famous electric vehicle company)
$B^{(z)}$	station	the total number of battery swap stations in the delivery hot spot z	Design Variables
$N^{(z)}$	battery/station	the average number of batteries available at a station in the delivery hot spot z	Design Variables
$C^{(z)}$	post/station	the average number of charging posts at a station in the delivery hot spot z	Design Variables
γ	%	the minimum probability for an EFV to get battery swapped immediately	Design Variables
D_z^{ES}	times/day	charging demand of EFVs, namely the total number of charging times in delivery hot spot z	Trajectory Data
D_z^{swap}	times/day	the charging demand at a battery swap station in the delivery hot spot z, which is quantified with the total number of times EFVs get recharged at a battery swap station	Trajectory Data
D_z^{charge}	times/day	the charging demand at a general charging station in the delivery hot spot z, which is quantified with the total number of times EFVs get recharged at a general charging station	Trajectory Data
$P_{i,x}^{(z)}(swap)$	%	the probability for EFV i to get recharged at a battery swap station, which can be calculated with a function of $SOC^{(i,x)}$ and $Time_p{}^{(i,x)}$ in the delivery hot spot z	N/A
$SOC^{(i,x)}$	%	the Stage of Charge (SOC) of the EFV i at time x	Trajectory Data
$Time_p{}^{(i,x)}$	hour	the parking duration of the EFV i at time x	Trajectory Data
α, β, η	N/A	the parameters in the probability function for calculating $P_{i,x}^{(z)}(swap)$	Design Variables
$\overline{T_{ES}^{(z)}}$	hour/vehicle	the average charging duration at a battery swap station and general charging station in the delivery hot spot z	N/A
$\overline{T_{charge}^{(z)}}$	hour/vehicle	the average duration of getting recharged at a general charging station in the delivery hot spot z	N/A
$\overline{T_{swap}^{(z)}}$	hour/vehicle	the average duration of getting a battery swapped at a battery swap station in the delivery hot spot z, which considers both the swapping time and possible queuing time	N/A
$\lambda_S^{(z)}(x)$	times/hour	the battery swapping demand at the x time slot in the delivery hot spot z	N/A
$\lambda_C^{(z)}(x)$	times/hour	the general charging demand at the time slot x in the delivery hot spot z	N/A
$p_0^{(z)}$	%	the probability of the service state when there is no fully charged battery available at the battery swap station in the delivery hot spot z	N/A
nb	Number	the number of fully charged batteries at a battery swap station, $nb \in \{0,1,2,3,\cdots\}$	N/A
nv	Number	the number of EFVs queuing at a battery swap station, $nv \in \{0,1,2,3,\cdots\}$	N/A
(nb, nv)	N/A	the service state of a battery swap station	N/A
$P(nb, nv)$	%	the probability for the service state with nb fully charged batteries and nv EFVs queuing	N/A

1) Objective 1. Minimize the Total Cost of Building Battery Swap Stations

In this model, we consider three main costs involved, namely the cost of batteries, the cost of charging posts and the direct cost of building battery swap stations. For the former, it is associated with the number of batteries available at each station; for the middle, it is associated with the number of charging posts at each station; for the latter, it is associated with the number of stations to be built. It is worth noting that it is freight companies who are responsible for the building dedicated general charging posts and battery swap stations for EFVs (probably in collaboration with the government). We made this assumption because 1) EFVs generally have an almost fixed schedule (including both delivery tasks and charging events), and freight companies need to ensure that their EFVs can get recharged when needed, in order to maximize operational efficiency; and 2) battery swap stations could, in general, serve only a few types of electric vehicles (EVs), due to different battery standards across EVs. It is difficult to apply the same battery standard to all EVs, particularly for private EVs. However, battery swapping is more feasible for commercial EVs, such as EFVs, as freight companies could purchase EFVs with the same battery standard applied.

Here we further assume 1) a linear relationship between battery cost and energy capacity, and 2) each of the battery swap stations in a specific delivery hot spot has the same level of service with the same numbers of batteries and charging posts available (note that the charging posts here are used to get those used batteries charged). In general, the numbers of stations, charging posts and batteries for each delivery hot spot would be sufficient information for infrastructure planning: given these numbers, planners can further figure out the exact locations for each battery swap station (and also the numbers of charging posts and batteries needed), considering other influential factors, such as land use and power grid constraints.

However, different delivery hot spots may have different numbers of stations, charging posts and batteries available. The cost of a battery is calculated by (1), which is defined as the sum of the basic cost of a battery and the cost associated with the battery capacity.

$$K\left(q^{(z)}\right) = a + b \cdot q^{(z)} \tag{1}$$

The total cost of the battery stations in a hot spot z includes the basic capital cost of all stations, the cost of all charging posts and the cost of all batteries in the delivery hot spots, as presented by (2).

$$COST^{(z)} = B^{(z)} \cdot \left(K\left(q^{(z)}\right) \cdot N^{(z)} + c \cdot C^{(z)} + s\right) \tag{2}$$

2) Objective 2. Maximize the Operational Efficiency of EFVs

Operational efficiency of EFVs is important to freight companies, as it could affect the companies' willingness to adopt EFVs. Shortening charging time is generally considered as an effective means to improve the operational efficiency of EFVs. Here, an EFV either swaps a battery at a battery swap station or gets recharged at a general charging station. Also, the battery swap stations to be deployed are uniformly distributed in each of the delivery hot spots. Therefore, for each hot spot, a fixed average travel time is used for those EFVs traveling to a battery swap station.

- Estimation of Charging Demand

For each delivery hot spot, the total charging demand is obtained from the trajectory data (see Section III D 2)). And the total demand is composed of the charging demands at both battery swap stations and those general charging stations with charging posts available, as shown by (3).

$$D_z^{ES} = D_z^{swap} + D_z^{charge} \tag{3}$$

Further, (3) can be rewritten by (4) considering the time slot.

$$D_z^{ES} = \sum_{x=0}^{23} \lambda_S^{(z)}(x) + \sum_{x=0}^{23} \lambda_C^{(z)}(x) = \sum_{x=0}^{23} \left(\lambda_S^{(z)}(x) + \lambda_C^{(z)}(x)\right) \tag{4}$$

As shown by (5), we here developed a probability function of parking duration ($Time_p^{(i,x)}$) and SOC ($SOC^{(i,x)}$) of an EFV to simulate whether it will get recharged through a general charging station or a battery swap station, based on empirical findings of SOC and parking duration (see Sections III D 2) and Appendix 2. The parameters α, β and η will be treated as design variables to be optimized through the Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II). This means we will search for an optimal solution to getting EFVs recharged through either general charging stations or battery swap stations.

$$\begin{aligned} &P_{i,x}^{(z)}(swap) = \alpha \cdot SOC^{(i,x)} + \beta \cdot Time_p^{(i,x)} + \eta \\ &P_{i,x}^{(z)}(swap) \in [0,1] \end{aligned} \tag{5}$$

Further, $\lambda_S^{(z)}(x)$ can be calculated by (6).

$$\lambda_S^{(z)}(x) = \sum_i P_{i,x}^{(z)}(swap) \tag{6}$$

- Average Charging Time

The average charging time is used to quantify the operational efficiency of EFVs, which is composed of two parts: the time of getting battery swapped at battery swap stations and the time of getting recharged at general charging stations, as presented by (7).

$$\overline{T_{ES}^{(z)}} = \frac{D_z^{charge} \cdot \overline{T_{charge}^{(z)}} + D_z^{swap} \cdot \overline{T_{swap}^{(z)}}}{D_z^{ES}} \tag{7}$$

a) Charging Time at General Charging Stations

We consider the possible queuing of EFVs due to charging posts being fully occupied when calculating charging time at a general charging station, as shown by (8). Specifically, a Monte Carlo method by [51] was adopted to simulate the queues. Here, the arrival distribution of EFVs at general charging stations ($\lambda_C^{(z)}(x)$) can be calculated by (4)-(6).

$$\overline{T_{charge}^{(z)}} = f\left(\lambda_C^{(z)}(x), \frac{P_{post,charge}^{(z)}}{q^{(z)}}\right) \tag{8}$$

b) Charging Time at Battery Swap Stations

The number of fully charged batteries available at a battery swap station varies over time. Here the probability ($p_0^{(z)}$) for the service state when there is no fully charged battery at a battery swap station will be calculated in Constraint 2. When an EFV arrives at a battery swap station, it may either get its battery swapped immediately or need to queue for a fully charged battery, as presented by (9).

$$\overline{T_{swap}^{(z)}} = \left(1-p_0^{(z)}\right)\cdot r + p_0^{(z)}\cdot\frac{1}{\mu^{(z)}} = r + \left(\frac{1}{\mu^{(z)}} - r\right)\cdot p_0^{(z)} \tag{9}$$

Where, $\mu^{(z)}$ can be calculated by $\mu^{(z)} = P_{post,swap}/q^{(z)}$.

3) Constraint 1. Total Supply should be Greater than the Total Charging Demand

The total service capacity of battery swap stations in a delivery hot spot should be greater than the total battery swapping demand, as presented by (10).

$$D_z^{swap} \le 24\cdot B^{(z)}\cdot\mu^{(z)} + N^{(z)}\cdot B^{(z)} \tag{10}$$

4) Constraint 2. Probability of Getting Battery Swapped Immediately should be Greater Than the EFV User's Expected Probability

When an EFV arrives at a battery swap station, its used on-board battery will be removed. Due to the limited number of batteries available at each station, the used batteries will be left at the station and needs to get charged for the other EFVs visiting this station later. We assume that those used batteries will get charged following the so-called first-in, first-out (FIFO) strategy, which is a classic task queue model.

For a specific time slot, the arrival probability of a battery is equal to the battery swapping demand of each battery swap station $\lambda_S^{(z)}(x)/B^{(z)}$ in the delivery hot spot z. "Battery Leaving" can be viewed as the end of getting a battery fully charged at a battery swap station. The leaving probability of a battery is associated with both $\mu^{(z)}$ and the number of batteries being currently charged.

When an EFV arrives at a station for battery swapping, it will get a fully charged battery immediately if available; otherwise, the EFV needs to queue at the station until a fully charged battery becomes available.

Next, we will describe the service state of a battery swap station within three scenarios considering the availability of fully charged batteries and EFVs queuing.

- Scenario 1: All Batteries fully Charged & No EFVs Queuing

When the service state is $\left(N^{(z)},0\right)$ (see Fig. 9), this means that there are $N^{(z)}$ fully charged batteries and no EFVs queuing at the battery swap station. The state can only transform from $\left(N^{(z)},0\right)$ to $\left(N^{(z)}-1,0\right)$ when an EFV arrives.

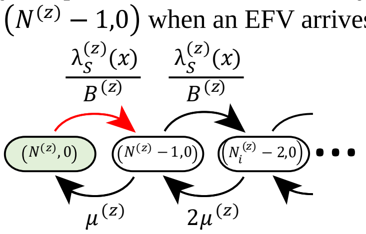


Fig. 9. The Service State Transformation of a Battery Swap Station in Scenario 1.

- Scenario 2: Some Batteries Fully Charged & No EFVs Queuing

When the service state is $(nb,0)$ (see Fig. 10), this means that no EFV is queuing at the battery swap station. The state can transform from $(nb,0)$ to $(nb+1,0)$ (there are $\left(N^{(z)}-nb\right)$ batteries leaving with a rate of $\mu^{(z)}$) or $(nb-1,0)$ (there will be a battery leaving when an EFV arrives).

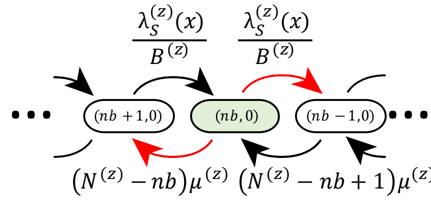


Fig. 10. The Service State Transformation of a Battery Swap Station in Scenario 2.

- Scenario 3: No Batteries fully Charged & EFVs Queuing

When the service state is $(0,nv)$ (see Fig. 11), this means that there is no fully charged battery at the battery swap station. The state can transform from $(0,nv)$ to $(0,nv-1)$ (there are $N^{(z)}$ batteries leaving at a rate $\mu^{(z)}$; an EFV leaves when a battery finishes charging) or $(0,nv+1)$ (an EFV starts queuing after its arrival).

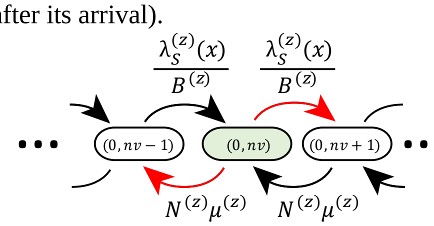


Fig. 11. The Service State Transformation of a Battery Swap Station in Scenario 3.

To sum up, the probability for the service state transformation is associated with the parameters $\lambda_S^{(z)}(x)/B^{(z)}$,$\mu^{(z)}$, $N^{(z)}$, and (nb,nv). The difference equation for the transformation between different states in a steady state is presented by (11).

$$\begin{cases} P\left(N^{(z)},0\right)\cdot\lambda_S^{(z)}(x)/B^{(z)} = P\left(N^{(z)}-1,0\right)\cdot\mu^{(z)} \\ P(nb,0)\cdot\left(\lambda_S^{(z)}(x)/B^{(z)} + \left(N^{(z)}-nb\right)\cdot\mu^{(z)}\right) = \\ P(nb+1,0)\cdot\lambda_S^{(z)}(x)/B^{(z)} + P(nb-1,0)\cdot\left(\left(N^{(z)}-nb+1\right)\cdot\mu^{(z)}\right), nb>0, nv=0 \\ P(0,nv)\cdot\left(\lambda_S^{(z)}(x)/B^{(z)} + N^{(z)}\cdot\mu^{(z)}\right) = \\ P(0,nv-1)\cdot\lambda_S^{(z)}(x)/B^{(z)} + P(0,nv+1)\cdot N^{(z)}\cdot\mu^{(z)}, nv>0, nb=0 \end{cases} \tag{11}$$

Here we would get the exact equation for $P(nb,nv)$, and further, get the probability of getting battery swapped immediately (i.e., $p_0^{(z)}$).

According to (11), $P(nb,nv)$ is associated with $P\left(N^{(z)},0\right)$, as presented by (12).

$$P(nb,nv) = f\left(P\left(N^{(z)},0\right)\right), \forall nb,nv\in\{0,1,2,\cdots\} \tag{12}$$

The sum of the probabilities of all the service states is equal to 1, as presented by (13).

$$\sum P(nb,nv) = 1 \tag{13}$$

According to (12) and (13), the derivation of parameter $p_0^{(z)}$ is shown by (14).

$$\left.\begin{aligned} P(nb,nv) &= f\left(P\left(N^{(z)},0\right)\right) \\ \sum P(nb,nv) &= 1 \end{aligned}\right\} \to P\left(N^{(z)},0\right) \to P(nb,nv) \to p_0^{(z)} \tag{14}$$

Where, $P\left(N^{(z)},0\right)$ denotes the probability for the service state with $N^{(z)}$ fully charged batteries and no EFV queuing at the battery swap station, and can be calculated by (15).

$$P\left(N^{(z)},0\right)=\left(\sum_{k=0}^{N^{(z)}}\frac{1}{k!}\left(\frac{\lambda_S^{(z)}(x)}{\mu^{(z)}\cdot B^{(z)}}\right)^k+\frac{\left(\frac{\lambda_S^{(z)}(x)}{\mu^{(z)}\cdot B^{(z)}}\right)^{N^{(z)}+1}}{N^{(z)}!\left(N^{(z)}-\frac{\lambda_S^{(z)}(x)}{\mu^{(z)}\cdot B^{(z)}}\right)}\right)^{-1} \tag{15}$$

Where, $P(nb, nv)$ denotes the probability for the service state with nb fully charged batteries and nv EFVs queuing at the battery swap station, and can be calculated by (16).

$$P(nb,nv)=\begin{cases}P\left(N^{(z)},0\right)\cdot\frac{1}{\left(N^{(z)}-nb\right)!}\cdot\left(\frac{\lambda_S^{(z)}(x)}{\mu^{(z)}\cdot B^{(z)}}\right)^{\left(N^{(z)}-nb\right)}, nb>0, nv=0;\\ P\left(N^{(z)},0\right)\cdot\frac{\lambda_S^{(z)}(x)^{N^{(z)}}}{N^{(z)}!\cdot\mu^{(z)N^{(z)}}\cdot B^{(z)}}\cdot\left(\frac{\lambda_S^{(z)}(x)}{N^{(z)}\cdot\mu^{(z)}\cdot B^{(z)}}\right)^{nv}, nb=0, nv>0.\end{cases} \tag{16}$$

According to (16), $p_0^{(z)}$ can be calculated by (17).

$$\begin{aligned}p_0^{(z)}&=\sum_{m=0}^{\infty}P(0,m)\\&=\frac{N^{(z)}\cdot\left(\frac{\lambda_S^{(z)}(x)}{\mu^{(z)}\cdot B^{(z)}}\right)^{N^{(z)}}}{N^{(z)}!\left(N^{(z)}-\frac{\lambda_S^{(z)}(x)}{\mu^{(z)}\cdot B^{(z)}}\right)\cdot\left(\sum_{k=0}^{N^{(z)}}\frac{1}{k!}\left(\frac{\lambda_S^{(z)}(x)}{\mu^{(z)}\cdot B^{(z)}}\right)^k\right)+\left(\frac{\lambda_S^{(z)}(x)}{\mu^{(z)}\cdot B^{(z)}}\right)^{N^{(z)}+1}}\end{aligned} \tag{17}$$

Here, we consider the worst situation: the greater the $p_0^{(z)}$ is, the longer time an EFV needs to queue. The maximum of $\lambda_S^{(z)}(x)$ is chosen, $\lambda_{S,max}^{(z)}=\max\left(\lambda_S^{(z)}(x)\right)$, as $p_0^{(z)}$ becomes the greatest when $\lambda_S^{(z)}(x)$ is the greatest. The probability for no fully charged batteries at a battery swap station should satisfy (18).

$$p_0^{(z)}=\frac{N^{(z)}\cdot\left(\frac{\lambda_{S,max}^{(z)}}{\mu^{(z)}\cdot B^{(z)}}\right)^{N^{(z)}}}{N^{(z)}!\left(N^{(z)}-\frac{\lambda_{S,max}^{(z)}}{\mu^{(z)}\cdot B^{(z)}}\right)\cdot\left(\sum_{k=0}^{N^{(z)}}\frac{1}{k!}\left(\frac{\lambda_{S,max}^{(z)}}{\mu^{(z)}\cdot B^{(z)}}\right)^k\right)+\left(\frac{\lambda_{S,max}^{(z)}}{\mu^{(z)}\cdot B^{(z)}}\right)^{N^{(z)}+1}}\le 1-\gamma \tag{18}$$

The purpose of deploying battery swap stations is to provide a fast-charging service. To ensure a high possibility of getting battery swapped immediately, we used a parameter γ to describe the probability.

According to (18), $p_0^{(z)}$ decreases monotonically with respect to $N^{(z)}$. Therefore, there should be a minimum number of batteries that satisfies the probability γ for an EFV to get the battery swapped immediately. Since whether an EFV can get its battery swapped immediately upon its arrival could heavily influence the users' decisions on choosing a battery swap station to recharge, the probability γ can be viewed as the users' expected probability.

5) Constraint 3. Number of Batteries Finishing Charging within a Specific Time Slot should be Greater than the Number of EFVs Arriving

When there is no battery fully charged and EFVs are queuing (see Scenario 3 in Constraint 2), in order to ensure the steady-state of queuing at battery swap stations in the delivery hot spot z, the arrival probability of a battery $\lambda_{S,max}^{(z)}/B^{(z)}$ should be smaller than the rate $N^{(z)}\cdot\mu^{(z)}$ of transformation from $\left(N^{(z)},0\right)$ to $(0, nv-1)$, as presented by (19). In other words, the number of batteries finishing charging within a specific time slot should be greater than the number of EFVs arriving.

$$\frac{\lambda_{S,max}^{(z)}}{N^{(z)}\cdot\mu^{(z)}\cdot B^{(z)}}<1 \tag{19}$$

6) Constraint 4. Electric Range of an EFV should be Greater than the Distance between any two Battery Swap Stations

In order to avoid running out of electricity during the journeys of EFVs, the maximum distance that an EFV can travel with a fully charged battery should be greater than the distance between any two battery swap stations in the delivery hot spot z, as presented by (20).

$$\frac{q^{(z)}\cdot v^{(z)}}{P_{EFV}^{(z)}}\ge\frac{Area^{(z)}}{B^{(z)}} \tag{20}$$

7) The Bi-Objective Model

In summary, the bi-objective model, which incorporates the two objectives and four constraints above, can be presented by (21).

$$\begin{cases}\min COST^{(z)}=B^{(z)}\cdot\left(\left(a+b\cdot q^{(z)}\right)\cdot N^{(z)}+c\cdot C^{(z)}+s\right)\\ \min\overline{T_{ES}^{(z)}}=f\left(\lambda_C^{(z)}(x),\frac{P_{post,charge}^{(z)}}{q^{(z)}}\right)+\\ \frac{\sum_x\sum_i\left(\alpha\cdot SOC^{(i,x)}+\beta\cdot Time_p^{(i,x)}+\eta\right)}{D_z^{ES}}\cdot\left(r+\left(\frac{1}{\mu^{(z)}}-r\right)\cdot p_0^{(z)}-f\left(\lambda_C^{(z)}(x),\frac{P_{post,charge}^{(z)}}{q^{(z)}}\right)\right)\\ S.T.\begin{cases}p_0^{(z)}=\frac{N^{(z)}\cdot\left(\frac{\lambda_{S,\max}^{(z)}}{\mu^{(z)}\cdot B^{(z)}}\right)^{N^{(z)}}}{N^{(z)}!\left(N^{(z)}-\frac{\lambda_{S,\max}^{(z)}}{\mu^{(z)}\cdot B^{(z)}}\right)\cdot\left(\sum_{k=0}^{N^{(z)}}\frac{1}{k!}\cdot\left(\frac{\lambda_{S,\max}^{(z)}}{\mu^{(z)}\cdot B^{(z)}}\right)^k\right)+\left(\frac{\lambda_{S,\max}^{(z)}}{\mu^{(z)}\cdot B^{(z)}}\right)^{N^{(z)}+1}}\\ \mu^{(z)}=\frac{P_{post,swap}}{q^{(z)}}\\ \frac{q^{(z)}\cdot v^{(z)}}{P_{EFV}^{(z)}}\ge\frac{Area^{(z)}}{B^{(z)}}\\ \sum_x\sum_i\left(\alpha\cdot SOC^{(i,x)}+\beta\cdot Time_p^{(i,x)}+\eta\right)\le 24\cdot B^{(z)}\cdot\mu^{(z)}+B^{(z)}\cdot N^{(z)}\\ \frac{\lambda_{S,\max}^{(z)}}{N^{(z)}\cdot\mu^{(z)}\cdot B^{(z)}}<1\\ p_0^{(z)}<1-\gamma\\ \alpha\cdot SOC^{(i,x)}+\beta\cdot Time_p^{(i,x)}+\eta\in[0,1]\\ \forall N^{(z)},C^{(z)},B^{(z)}\in\{0,1,2,3,\ldots\}\\ \forall x\in\{0,1,2,3,\ldots,23\}\end{cases}\end{cases} \tag{21}$$

B. Solving the Bi-objective Model with an Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II)

We will use an Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II) to search for the Pareto Optimal solutions, as it has a fast computation speed [52], [53] and has been widely used to solve multi-objective optimization problems, such as deploying the interactive buildings-vehicles energy sharing network [54], expanding the fast-charging stations for EVs [55] and deploying the general charging stations for EVs [56]. A detailed introduction to NSGA-II can be found in the references cited above.

Specifically, the bi-objective model has many model parameters involved (see Table II for a full list). We parameterized the model in the following three ways:

(1) Ten model parameters are set with the information from trajectory data, including $Area^{(z)}$(see Appendix 1), $q^{(z)}$(see Section III D 2)), $P_{EFV}^{(z)}$(see Section III D 2)), $P_{post,charge}^{(z)}$(see Section III D 2)), $v^{(z)}$(see Appendix 3), D_z^{ES} (see Section III D 2)), D_z^{swap} (see Section IV A 2)), D_z^{charge} (see Section IV A 2)), $SOC^{(i,x)}$(see Section III D 2)), ${Time_p}^{(i,x)}$(see Appendix 2).

(2) The parameters, a, c, b, s, r, are situation-specific and may vary across study areas. For example, s is the basic capital cost of a battery swap station and may vary according to the economic development. In the test case (see Section V), s is set to 4,500 US dollars per station according to the work by the Ministry of Transport of the People's Republic of China [50] and Guo *et al*, [47].

(3) We search solutions for the eight design variables through an Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II), i.e., the total number of battery swap stations ($B^{(z)}$), the average numbers of batteries ($N^{(z)}$) and the average number of charging posts ($C^{(z)}$) available at a station, the average charging power of the charging post at battery swap stations ($P_{post,swap}$), the minimum probability for an EFV to get battery swapped immediately (γ), and the parameters in the probability function for calculating $P_{i,x}^{(z)}(swap)$ including α, β, η. These eight are key parameters for deploying battery swap stations and could directly influence the freight companies' 'choices'. However, it would be rather difficult to observe these variables, and also they are correlated and could be affected by the EFV attributes. For example, charging power of the charging posts could affect the battery swap demand of EFVs. Moreover, the numbers of batteries, charging posts and stations are interrelated, and could affect the supply capacity of battery swap stations. Therefore, a genetic algorithm is used to search for solutions to these eight design variables.

V. Testing the Bi-Objective Model in Beijing

The bi-objective model and NSGA-II algorithm (see Section IV) were tested using Beijing as a study area with the information extracted from the GPS trajectory data on EFVs (see Section III D).

A. Model Results

1) Parameterizing the Model and Algorithm

The key model parameters were set as follows:

- The basic cost of a battery (a) was set to 1,500 US dollars.
- The cost per unit energy capacity of a battery (b) was set to 700 US dollars per battery.
- The basic capital cost of a battery swap station (s) was set to 2,000 US dollars per station.
- In this test case, we considered both slow and fast chargers at battery swap stations. Two general options for the power of charging post at a battery swap station ($P_{post,swap}$) are provided, namely the fast charging post ($P_{post,swap}^{fast}$) and the slow charging post ($P_{post,swap}^{slow}$), which were 60 kilowatts and 7 kilowatts, respectively. These are two typical post types in Beijing. Thus, the average charging power of the charging posts at the battery swap station ($P_{post,swap}$) can be derived with $P_{post,swap}^{fast}$ and $P_{post,swap}^{slow}$, as shown by (22).

$$P_{post,swap} = \frac{P_{post,swap}^{fast} \cdot C_{fast}^{(z)} + P_{post,swap}^{slow} \cdot C_{slow}^{(z)}}{C_{fast}^{(z)} + C_{slow}^{(z)}} \tag{22}$$

Where, $C_{fast}^{(z)}$ and $C_{slow}^{(z)}$ are the average numbers of fast and slow charging posts at a station in the delivery hot spot z, respectively. The costs of the fast (c^{fast}) and slow (c^{slow}) charging post were set to 4,500 and 300 US dollars in the Beijing scenario, respectively, according to the Ministry of Transport of the People's Republic of China [50] and Guo *et al*, [47], as well as the available charging posts in Taobao, a famous Chinese e-commerce company.

- The cost of the fast charging post (c^{fast}) and the slow charging post (c^{slow}) were set to 4,500 and 300 US dollars respectively, according to the Ministry of Transport of the People's Republic of China [50], Guo *et al*, [47] and Taobao, a famous Chinese e-commerce company.
- The time needed to swap one battery at a battery swap station (r) was set to 0.1 hour according to NIO, a famous electric vehicle company.
- Constraint 4 (see Equation (20)) was removed in this test case, as the delivery hot spots were small in the Beijing Scenario (see Table AI in Appendix 1). In other words, Constraint 4 would not influence the optimization results in this test.

For the NSGA-II algorithm, the following parameters need to be set properly: crossover probability ($P(crossover)$), mutation probability ($P(mutation)$), population size (N), and the number of generations (G). Through trial and error, we finally set $P(crossover) = 0.9$, $P(mutation) = 0.1$, $N = 50$, $G = 150$.

2) Model Outputs

Given the identified thirty delivery hot spots in Beijing, as well as the associated information, such as charging demand and average travel speed (see Section III D), we got Pareto Optimal solutions for each delivery hot spot by solving the bi-objective model using the NSGA-II algorithm. All the solutions are optimal, but freight companies might choose the one with a specific cost and operational efficiency of EFVs, which can better meet their own needs, for example, considering the total budget and also land use.

We used the delivery hot spot with ID 18 as an example to show how the model works. All the Pareto Optimal solutions are shown by the points in Fig. 12, suggesting that the total cost (or Objective 1) has an inverse proportion to operational efficiency (or Objective 2). We further take a closer look at the three special points: 1) the Min-Min case, in which both the total cost and operational efficiency are minimum; 2) the Mid-Mid case, in which the total cost and operational efficiency stay at the middle; 3) the Max-Max case, in which the total cost and operational efficiency are maximum. Table III shows the objective values and the three key indicators in the three cases, suggesting that the deployment of battery swap stations can at least reduce average charging time by 61.19% in the Min-Min case, compared to the Reference Scenario, which is defined with the general existing charging facilities and charging demands of EFVs extracted from the trajectory data. Moreover, the battery swap stations can at least accommodate 76.32% of the total charging demand, as evident from the Min-Min case. Given there is no constraint on the budget, the average charging time can decrease by 96.56% in the Max-Max case. However, the total cost in the Max-Max case would be 36% higher than the Min-Min case. Moreover, the charging demand at battery swap stations is 92.15% of the total charging demand in the Max-Max case.

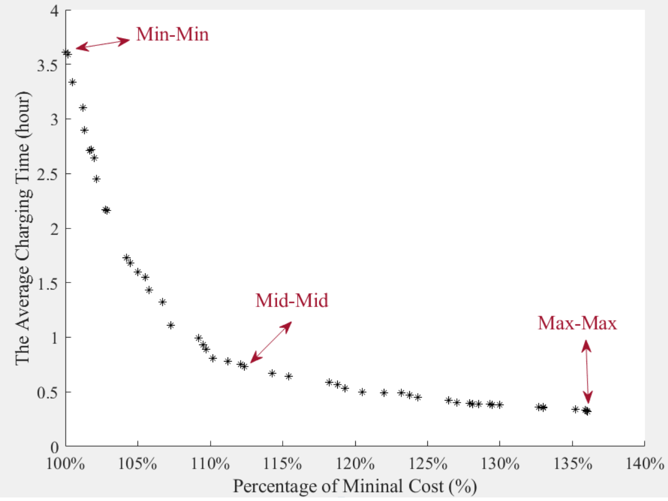


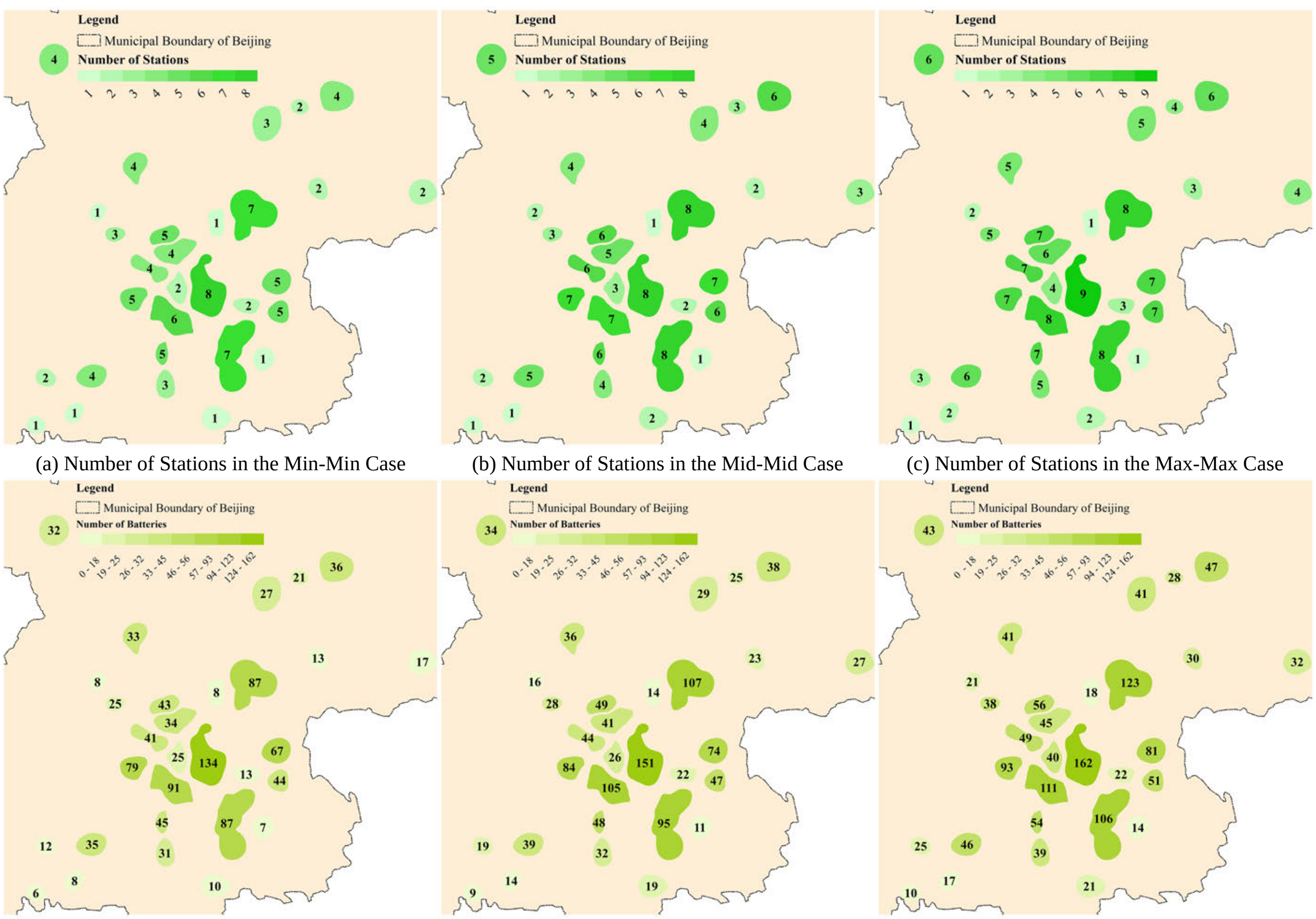
Fig. 12. All Pareto Optimal Solutions for the Delivery Hot Spot with ID 18.

We further investigated the spatial differences between the three special cases in the numbers of battery swap stations, batteries and fast/slow charging posts in each delivery hot spot, as shown by Fig. 13. Such spatial patterns would be useful for the freight companies (e.g., freight companies and urban planners) who want to know the numbers of battery swap stations, batteries and charging posts in each delivery hot spot. On one hand, they can compare the spatial differences between different cases, which is useful for their decision-making (for example, on choosing a proper case for the study area); On the other hand, they can further figure out the exact location of the battery swap stations for each delivery hot spot, considering other influential factors, such as land use and power grid constraints. Effectively, there is no significant difference between the three cases in terms of spatial patterns. Specifically, those top delivery hot spots with higher numbers of battery swap stations and batteries remain almost the same across the cases.

TABLE III
THERE SPECIAL PARETO OPTIMAL SOLUTIONS FOR THE DELIVERY HOT SPOT WITH ID 18

Solution	Objective 1*	Objective 2	$B^{(z)}$	$N^{(z)}$	$C_{fast}^{(z)}$	$C_{slow}^{(z)}$	γ	α	β	η
Min-Min	100%	3.61	8	134	21	23	0.38	1.42×10^{-2}	0.32	0.13
Mid-Mid	112%	0.73	8	151	18	17	0.53	1.36×10^{-2}	0.33	0.21
Max-Max	136%	0.32	9	162	26	21	0.76	2.56×10^{-2}	0.53	0.42

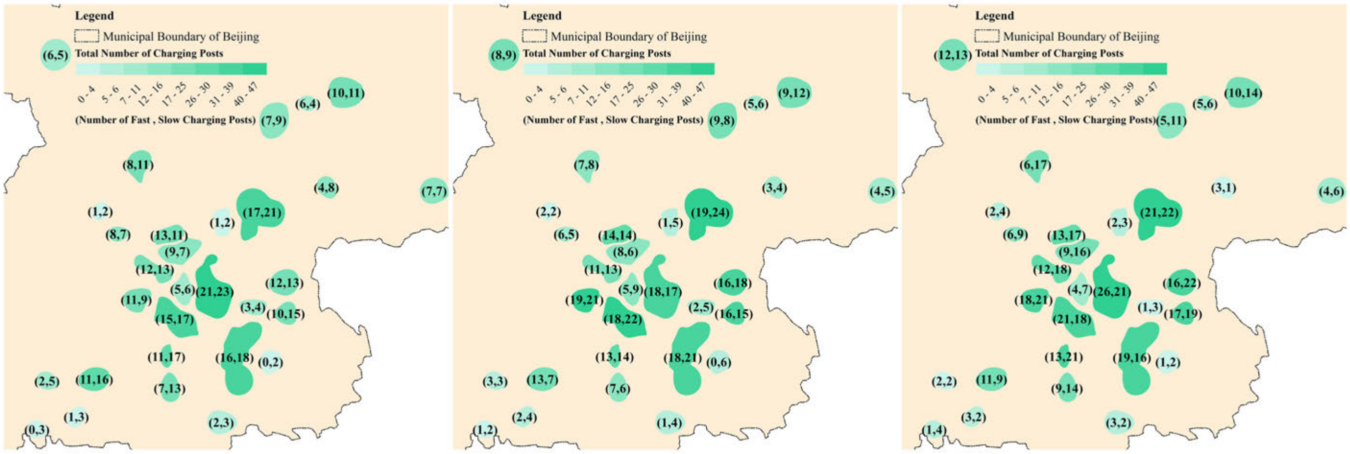
*We used the value of objective 1 (i.e., 62,219,200 US dollars) from the Min-Min case as a reference, and converted the values from the Mid-Mid and Max-Max cases into percentages.



(a) Number of Stations in the Min-Min Case (b) Number of Stations in the Mid-Mid Case (c) Number of Stations in the Max-Max Case

(d) Number of Batteries in the Min-Min Case (e) Number of Batteries in the Mid-Mid Case (f) Number of Batteries in the Max-Max Case

Fig. 13. The Numbers of Battery Swap Stations, Batteries and Charging Posts in each Delivery Hot Spot.



(g) Total Number of Charging Posts at Swap Stations in the Min-Min Case
(h) Total Number of Charging Posts at Swap Stations in the Mid-Mid Case
(i) Total Number of Charging Posts at Swap Stations in the Max-Max Case

Fig. 13 (continued). The Numbers of Battery Swap Stations, Batteries and Charging Posts in each Delivery Hot Spot.

To further explore the potential influence of the added battery swap stations on trajectories of EFVs, we find that 76%, 81%, and 83% of EFVs only need a short detour distance (specifically, with a distance of 1 km or shorter) in the Min-Min, Mid-Mid, and Max-Max cases respectively. This indicates that the added battery swap stations would have limited influence on trajectories of EFVs.

3) Model Comparison

In order to evaluate the performance of our model, we compared it against two typical facility location models, namely P-median model [57] and flow-refueling location model (FRLM) [58], which have been widely used to deploy various facilities, including charging facilities [59].

In order to compare the three models, we used the average charging time as an indicator to see how adding battery swap stations could shift general charging demand and reduce charging time. Specifically, we kept the main setting (including the total cost, the number of general charging posts, and the number of battery swap stations) the same for these three models, and then compare the average charging times obtained. Taking delivery hot spot with ID 18 as an example (see Table IV), we used the same setting (i.e., key model parameters) to compare the performance of the three models in the three special cases, i.e., Min-Min, Mid-Mid and Max-Max.

It can be found that in the delivery hot spot 18, the average charging times from the P- median model were 5.32, 1.48 and 0.92 hours, and from FRLM model were 4.87, 1.96 and 0.94 hours, which were longer than those (i.e., 3.61, 0.73 and 0.32 hours) from the bi-objective model in this paper. This suggests that our model can find a better solution to deploying battery swap stations and outperforms the P- median model and the FRLM.

B. Sensitivity Analysis

We further examined the performance of the model through sensitivity analysis, in order to quantify the influences of three key parameters on model outcomes, again using the delivery hot spot with ID 18 as an example.

- Test 1: b is the cost per unit energy capacity of a battery, which can directly influence the total cost and is likely to decrease as the battery technologies are improved over time. In the baseline Beijing scenario, we set b to 700 US dollars per unit energy capacity of a battery, according to the battery cost of those EFVs which are available in the Beijing vehicle market in 2019 (when the trajectory data was collected).
- Test 2: s is the basic capital cost of a battery swap station, which is difficult to estimate, due to no swap station available for EFVs. In the baseline Beijing scenario, we set s to 2,000 US dollars per station, according to the cost of a general charging station in Beijing.
- Test 3: the number of EFVs (denoted as NUM_{EFV}) in the baseline scenario was 17,716, accounting for 99.8% of the EFV fleet. We will further examine how the EFV fleet size, NUM_{EFV}, may influence the deployment of battery swap stations.

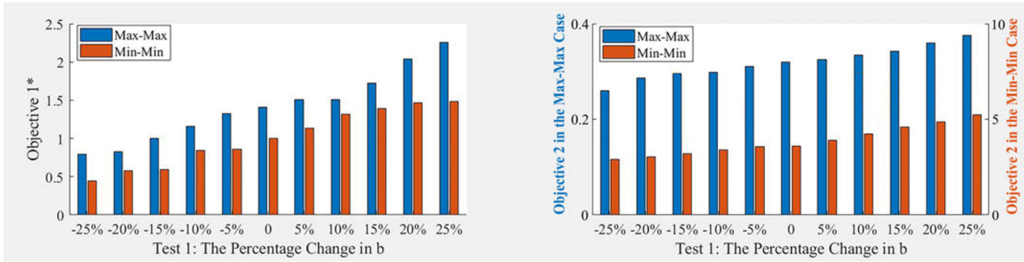
In the sensitivity analysis, we varied b, s, and NUM_{EFV} between $-25\%\sim+25\%$ with an interval of 5% in both the Max-Max and Min-Min cases, respectively.

In order to understand how the three parameters would influence model outcomes, we compared the objectives (see Fig. 14), and the number of stations, batteries and charging posts (see Fig. 15) against those from the original Max-Max and Min-Min cases introduced in Section V A 2).

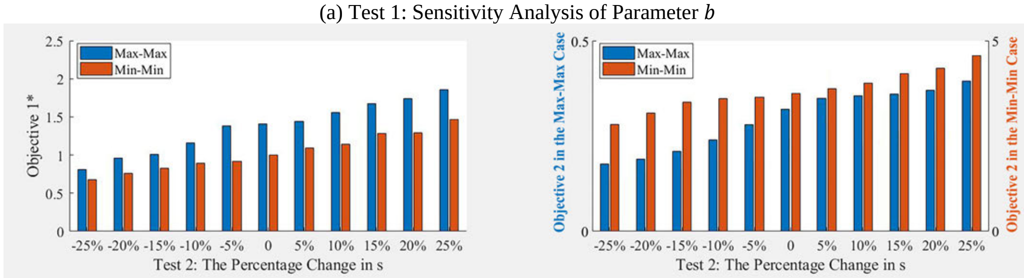
TABLE IV
THE AVERAGE CHARGING TIME BASED ON THE TWO METHODS WITH ID 18

Solution	Key Model Parameters										The Average Charging Time (hour)		
	Total Cost*	$C_{fast}^{(z)}$	$C_{slow}^{(z)}$	c^{fast}	c^{slow}	$P_{post,swap}^{fast}$	$P_{post,swap}^{slow}$	a	b	s	The Model in this Paper	P- median Model	FRLM
Min-Min	100%	21	23								3.61	5.32	4.87
Mid-Mid	112%	18	17	4,500	300	60	7	1,500	700	2,000	0.73	1.48	1.96
Max-Max	136%	26	21								0.32	0.92	0.94

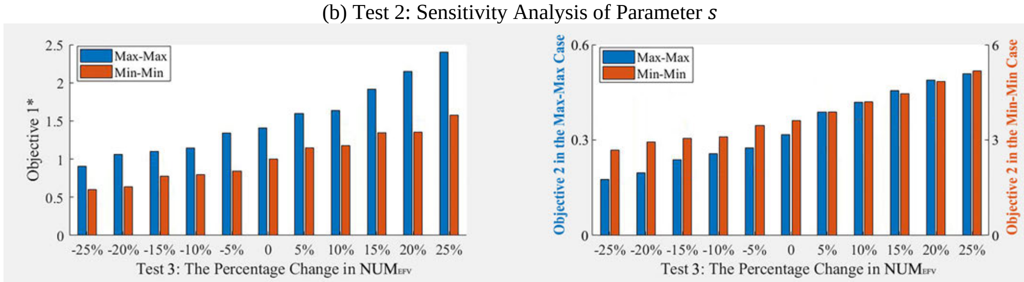
* We used the total cost (i.e., 62,219,200 US dollars) from the Min-Min case as a reference (i.e., 100%).



(a) Test 1: Sensitivity Analysis of Parameter b



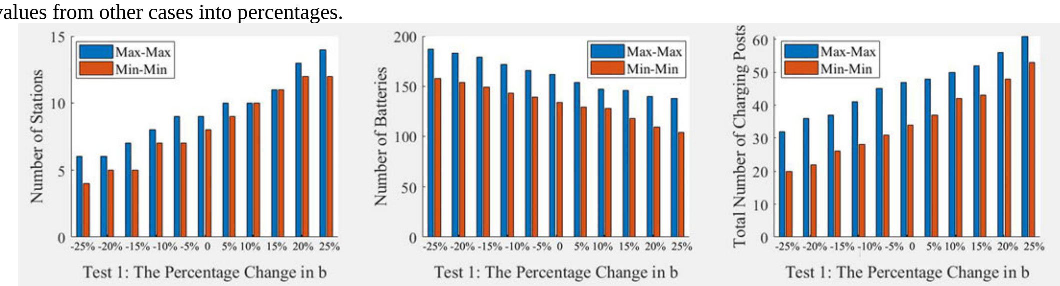
(b) Test 2: Sensitivity Analysis of Parameter s



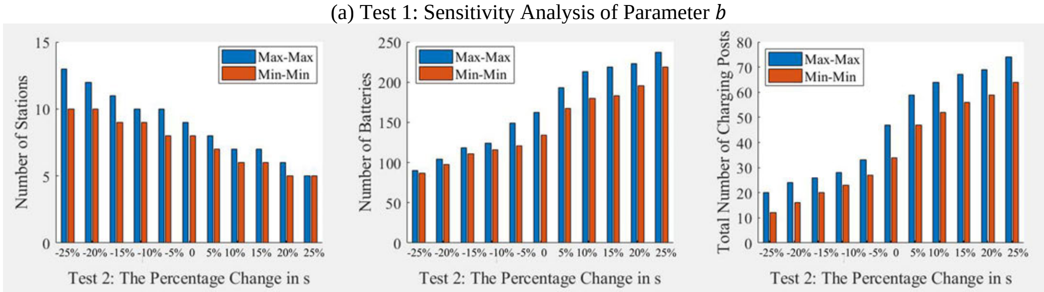
(c) Test 3: Sensitivity Analysis of Parameter NUM_{EFV}

Fig. 14. The Sensitivity Analysis Results - Influences on the two Objective Values.

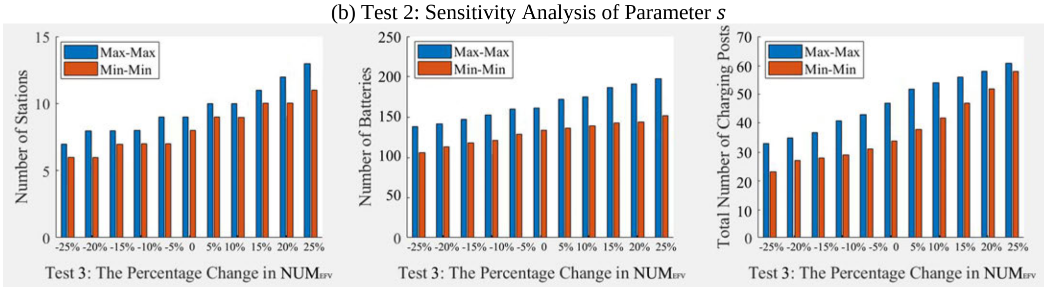
*Note: In the subfigures for Objective 1, we used the value of Objective 1 (i.e., 62,219,200 US dollars) from the original Min-Min case as a reference, and converted the values from other cases into percentages.



(a) Test 1: Sensitivity Analysis of Parameter b



(b) Test 2: Sensitivity Analysis of Parameter s



(c) Test 3: Sensitivity Analysis of Parameter NUM_{EFV}

Fig. 15. The Sensitivity Analysis Results – The Influences on the Numbers of Battery Swap Stations, Batteries and Charging Posts Needed.

In Test 1, Test 2, and Test 3, an increase in b (i.e., the battery cost), s (i.e., the station cost), and NUM_{EFV} (i.e., the number of EFVs) would all give rise to an increase in the total cost (i.e., the value of Objective 1) in both the Max-Max and Min-Min cases, and an increase in the average charging duration (i.e., the value of Objective 2), as shown by Fig. 14-(a), Fig. 14-(b), and Fig. 14-(c), respectively. For example, in terms of Test 1, when b is increased by 25% from 0% to 25%, the total costs in the Max-Max and Min-Min cases increase by 60.02% and 48.00%, respectively, and the average charging duration increases by 17.40% and 44.04%. In terms of Test 2, when s is increased by 25 % from 0% to 25%, the total costs in the Max-Max and Min-Min cases increase by 31.19% and 47.00%, respectively, and the average charging duration increases by 23.44% and 27.42%. In terms of Test 3, when NUM_{EFV} is increased by 25 % from 0% to 25%, the total costs in the Max-Max and Min-Min cases increase by 70.88% and 57.25%, respectively, and the average charging duration increases by 59.38% and 41.83%.

For another three indicators, namely the numbers of battery swap stations, batteries and charging posts, they can be influenced by the changes in b, s, and NUM_{EFV} (i.e., in Test 1, Test 2, and Test 3 respectively), as shown by Fig. 15-(a), Fig. 15-(b), and Fig. 15-(c). In general, a lower battery cost would result in a larger number of batteries needed, but a smaller number of stations and charging posts needed, as the total charging demand in each delivery hot spot is fixed. Similarly, a higher station cost may result in a smaller number of stations needed, but a larger number of batteries and charging posts are needed. This indicates that for each delivery hot spot, the numbers of battery swap stations, batteries and charging posts are interlinked. However, the numbers of stations, batteries and charging posts do not change monotonically when the battery cost is changed. In addition, more stations, batteries, and posts are needed to meet the increased charging demand due to the growth number of EFVs.

VI. Conclusions

This paper proposed a bi-objective model to deploy battery swap stations for Electric Freight Vehicles (EFVs), using GPS trajectory data on actual EFVs in Beijing. The trip, parking and charging patterns extracted from the trajectory data were used to better define the rules in the model, in order to make the model more realistic and accurate. The model was tested in Beijing. Sensitivity analysis was also conducted to quantify the influence of two key model parameters on the outputs of interest.

The empirical findings from the trajectory data suggest that the high charging demand of EFVs is mainly concentrated in the central of Beijing, and the maximum peak-hour charging demand was 389 times/hour in the delivery hot spot near the Beijing Central Business District (East Third Ring Road) in Beijing. Around 79.5% of charging duration was shorter than 20 minutes, which is probably because they had a busy timetable. This indicates that fast charging infrastructure, such as battery swap stations, would be helpful for these EFVs which tend to have insufficient time to get their EFVs fully charged.

The model test suggested that the bi-objective model and NSGA-II can be used to provide useful suggestions for freight companies, who could choose a suitable solution from the Pareto Optimal solutions according to their own needs, for example, considering the total budget available and land use constraints. From the model results, it can be found that the average charging time could reduce by up to 96.56% through the deployment of battery swap stations, compared to a reference scenario with existing general charging posts and charging demand of EFVs. To test the performance of the bi-objective model, we compared it against two classical facility location optimization models, namely P-median model and flow-refueling location model (FRLM). The results suggested that our model could get much shorter charging duration, on average, with the same setting (e.g., total cost) applied. In addition, the parameter sensitivity analysis indicated that the parameters of battery, infrastructure and number of EFVs could heavily influence the total cost and average charging time.

In future work, we will further improve the bi-objective model and overcome the limitations. First, the approach can be extended to incorporate a location model, which can help to determine the exact location of battery swap stations for each delivery hot spot. However, this would need more disaggregate input data, such as land use data. Second, the bi-objective model aims to minimize the total cost and maximize the operational efficiency. There is a dynamic relationship between the cost and efficiency: freight companies may wish to invest more money in deployment of battery swap stations due to the profit gained through the increased efficiency. This dynamic relationship could be further explored by updating the existing bi-objective model to a dynamic one. Third, the model could be adjusted to couple battery swap stations with renewable energy (e.g., solar and wind energy) systems. In the resulting integrated system, on-board batteries can get charged through a renewable energy system and will then be transported to the battery swap stations. In other words, no charging facilities would be needed at stations.

Appendix

A. Appendix 1 The Area of each Delivery Hot Spot in Beijing

The area of each delivery hot spot in Beijing is shown as Table AI, suggesting that the area tended to be small, compared to the electric range of an EFV. Therefore, Constraint 4 (i.e., the electric range of an EFV should be greater than the distance between any two battery swap stations, $\frac{q^{(z)} \cdot v^{(z)}}{P_{EFV}^{(z)}} \geq \frac{Area^{(z)}}{B^{(z)}}$) was removed when the bi-objective model was tested in the Beijing scenarios.

B. Appendix 2 Parking Duration of EFVs

Apart from SOC, parking duration is also associated with general charging or battery swapping demand, as it reflects an EFV's delivery timetable and the time available for recharging. Thus, it would directly influence which charging modes (i.e., general charging or battery swapping) an EFV will choose, considering its SOC. The extracted distribution of parking duration of EFVs in Beijing is shown in Fig. AI. Around 79.5% of charging duration was shorter than 20 minutes, indicating that most of the parking events lasted for a short time, and the EFVs tended to have a busy timetable. As a result, they appeared to get insufficient time to get fully charged through

TABLE AI
THE AREA OF EACH DELIVERY HOT SPOT IN BEIJING

ID of Delivery Hot Spot	1	2	3	4	5	6	7	8	9	10
Area (km^2)	49.84	56.46	14.10	55.44	35.11	38.36	21.76	105.74	15.09	25.09
ID of Delivery Hot Spot	11	12	13	14	15	16	17	18	19	20
Area (km^2)	14.72	26.62	47.22	33.18	39.25	29.58	32.56	97.84	22.09	24.79
ID of Delivery Hot Spot	21	22	23	24	25	26	27	28	29	30
Area (km^2)	67.73	121.43	14.50	37.16	19.11	28.02	19.53	26.13	35.61	17.80

general charging posts when they have a low SOC. To meet the demand of getting EFVs recharged in a short time, battery swap stations could be a good alternative. Therefore, the SOC and parking duration of each charging event in each of the delivery hot spots are used to estimate the probability of using a battery swap station for recharging. Specifically, a battery swapping probability function of SOC and parking duration (see Equation (5)) is developed for the bi-objective model.

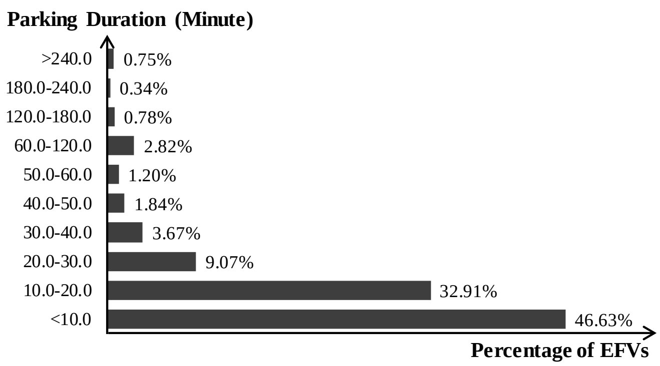
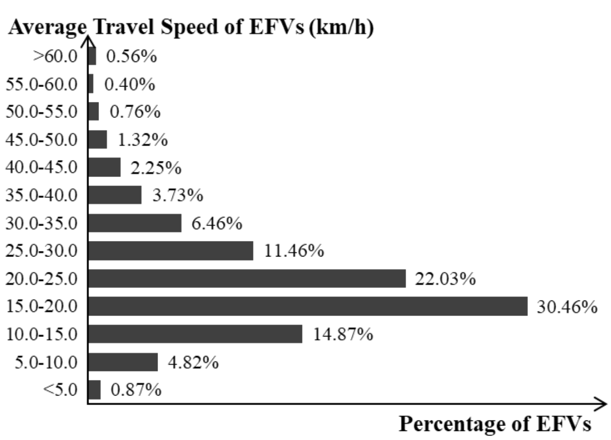


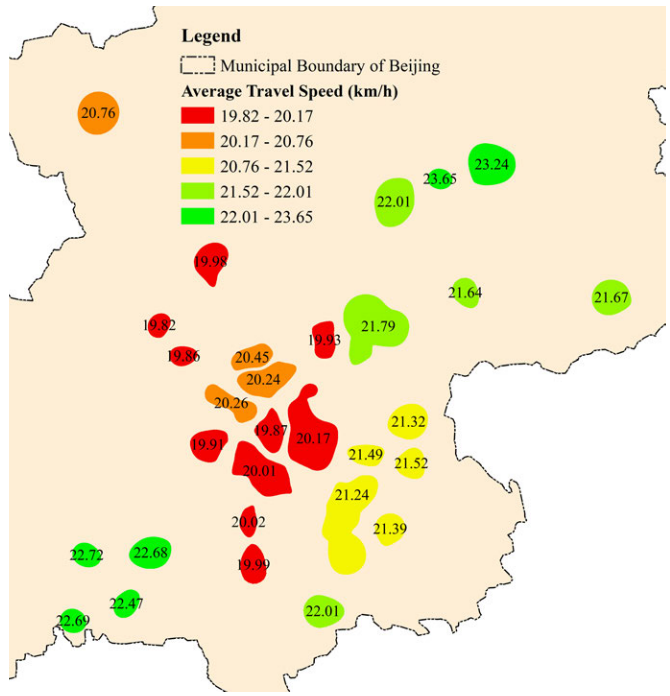
Fig. AI. Distribution of Parking Duration of EFVs in Beijing.

C. *Appendix 3 Average Travel Speed of EFVs*

Travel speed is associated with the accessibility of battery swap stations. Therefore, we estimated the average travel speed of EFVs for each hot spot, which is used in the bi-objective model to calculate the constraint (see Constraint 4) that the electric range of an EFV should be greater than the distance between any two battery swap stations, as shown by Fig. AII-(a). Fig. AII-(b) aggregates the travel speed at the city level, indicating that most of the trips had a travel speed ranging from 10 to 35 km/h, accounting for 85.3%.



(a) Statistical Distribution of Average Travel Speed of EFVs



(b) Average Travel Speed of EFVs for each hot spot
Fig. AII. Distribution of Average Travel Speed of EFVs in Beijing.

REFERENCES

[1] S. Pelletier, O. Jabali, and G. Laporte, "50th Anniversary Invited Article—Goods Distribution with Electric Vehicles: Review and Research Perspectives," *Transportation Science*, vol. 50, no. 1, 2016, doi: 10.1287/trsc.2015.0646.

[2] C. Zhuge, C. Shao, and X. Li, "A comparative study of en route refuelling behaviours of conventional and electric vehicles in Beijing, China," *Sustainability (Switzerland)*, vol. 11, no. 14, 2019, doi: 10.3390/su11143869.

[3] H. Talebian, O. E. Herrera, M. Tran, and W. Mérida, "Electrification of road freight transport: Policy implications in British Columbia," *Energy Policy*, vol. 115, 2018, doi: 10.1016/j.enpol.2018.01.004.

[4] IEA, "Global EV Outlook 2019," Aug. 5, 2019. [Online]. Available: www.iea.org/publications/reports/globalevoutlook2019/

[5] C. Zhuge and C. Shao, "Agent-Based Modelling of Locating Public Transport Facilities for Conventional and Electric Vehicles," *Networks and Spatial Economics*, vol. 18, no. 4, 2018, doi: 10.1007/s11067-018-9412-3.

[6] S. Hardman *et al.*, "A review of consumer preferences of and interactions with electric vehicle charging infrastructure," *Transportation Research Part D: Transport*

and Environment, vol. 62, 2018, doi: 10.1016/j.trd.2018.04.002.

[7] I. Rahman, P. M. Vasant, B. S. M. Singh, M. Abdullah-Al-Wadud, and N. Adnan, "Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle charging infrastructures," *Renewable and Sustainable Energy Reviews*, vol. 58. 2016. doi: 10.1016/j.rser.2015.12.353.

[8] R. S. Widrick, S. G. Nurre, and M. J. Robbins, "Optimal policies for the management of an electric vehicle battery swap station," *Transportation Science*, vol. 52, no. 1, 2018, doi: 10.1287/trsc.2016.0676.

[9] F. Schneider, U. W. Thonemann, and D. Klabjan, "Optimization of battery charging and purchasing at electric vehicle battery swap stations," *Transportation Science*, vol. 52, no. 5, 2018, doi: 10.1287/trsc.2017.0781.

[10] CALSTART. "Technologies, challenges and opportunities: I-710 zero-emission freight corridor vehicle systems (Revised Version Final V1)," Jun. 12, 2015. [Online]. Available: http://media.metro.net/projects_studies/I710/images/TSWG_2011_06_Zero_Emission_Trucks_CALSTART.pdf

[11] B. Sun, X. Sun, D. H. K. Tsang, and W. Whitt, "Optimal battery purchasing and charging strategy at electric vehicle battery swap stations," *European Journal of Operational Research*, vol. 279, no. 2, 2019, doi: 10.1016/j.ejor.2019.06.019.

[12] M. A. Masmoudi, M. Hosny, E. Demir, K. N. Genikomsakis, and N. Cheikhrouhou, "The dial-a-ride problem with electric vehicles and battery swapping stations," *Transportation Research Part E: Logistics and Transportation Review*, vol. 118, 2018, doi: 10.1016/j.tre.2018.08.005.

[13] E. Çabukoglu, G. Georges, L. Küng, G. Pareschi, and K. Boulouchos, "Battery electric propulsion: an option for heavy-duty vehicles? Results from a Swiss case-study," *Transportation Research Part C: Emerging Technologies*, vol. 88, 2018, doi: 10.1016/j.trc.2018.01.013.

[14] T. T. Taefi *et al*., "Comparative Analysis of European Examples of Freight Electric Vehicles Schemes—A Systematic Case Study Approach with Examples from Denmark, Germany, the Netherlands, Sweden and the UK," in *Lecture Notes in Logistics*, 2016. doi: 10.1007/978-3-319-23512-7_48.

[15] M. Altenburg, N. Anand, S. Balm, and W. Ploos van Amstel, "Electric freight vehicles in city logistics : Insights into decision-making process of frontrunner companies .," *European Battery, Hybrid and Fuel Cell Electric Vehicle Congress*, no. March, 2017.

[16] S. M. Mirhedayatian and S. Yan, "A framework to evaluate policy options for supporting electric vehicles in urban freight transport," *Transportation Research Part D: Transport and Environment*, vol. 58, 2018, doi: 10.1016/j.trd.2017.11.007.

[17] M. Schiffer and G. Walther, "Strategic planning of electric logistics fleet networks: A robust location-routing approach," *Omega (United Kingdom)*, vol. 80, 2018, doi: 10.1016/j.omega.2017.09.003.

[18] R. Hoed, S. Bal, B. Kin, *et al*. "Charging infrastructure for electric vehicles in city logistics in Amsterdam," Nov. 2019. [Online]. Available: https://www.researchgate.net/publication/337242871_Charging_infrastructure_for_electric_vehicles_in_city_logistics_in_Amsterdam

[19] F. Guo, J. Yang, and J. Lu, "The battery charging station location problem: Impact of users' range anxiety and distance convenience," *Transportation Research Part E: Logistics and Transportation Review*, vol. 114, 2018, doi: 10.1016/j.tre.2018.03.014.

[20] J. Yan, M. Menghwar, E. Asghar, M. Kumar Panjwani, and Y. Liu, "Real-time energy management for a smart-community microgrid with battery swapping and renewables," *Applied Energy*, vol. 238, 2019, doi: 10.1016/j.apenergy.2018.12.078.

[21] M. A. Quddus, M. Kabli, and M. Marufuzzaman, "Modeling electric vehicle charging station expansion with an integration of renewable energy and Vehicle-to-Grid sources," *Transportation Research Part E: Logistics and Transportation Review*, vol. 128, 2019, doi: 10.1016/j.tre.2019.06.006.

[22] A. Almuhtady, S. Lee, E. Romeijn, M. Wynblatt, and J. Ni, "A degradation-informed battery-swapping policy for fleets of electric or hybrid-electric vehicles," *Transportation Science*, vol. 48, no. 4, 2014, doi: 10.1287/trsc.2013.0494.

[23] K. An, W. Jing, and I. Kim, "Battery-swapping facility planning for electric buses with local charging systems," *International Journal of Sustainable Transportation*, vol. 14, no. 7, 2020, doi: 10.1080/15568318.2019.1573939.

[24] H. R. Sayarshad, V. Mahmoodian, and H. O. Gao, "Non-myopic dynamic routing of electric taxis with battery swapping stations," *Sustainable Cities and Society*, vol. 57, 2020, doi: 10.1016/j.scs.2020.102113.

[25] X. Zhang, L. Peng, Y. Cao, S. Liu, H. Zhou, and K. Huang, "Towards holistic charging management for urban electric taxi via a hybrid deployment of battery charging and swap stations," *Renewable Energy*, vol. 155, 2020, doi: 10.1016/j.renene.2020.03.093.

[26] F.-H. Huang, "Understanding user acceptance of battery swapping service of sustainable transport: An empirical study of a battery swap station for electric scooters, Taiwan," International journal of sustainable transportation, vol. 14, no. 4, pp. 294–307, 2020, doi: 10.1080/15568318.2018.1547464.

[27] Y. Liang, X. Zhang, J. Xie, and W. Liu, "An optimal operation model and ordered charging/discharging strategy for battery swapping stations," *Sustainability (Switzerland)*, vol. 9, no. 5, 2017, doi: 10.3390/su9050700.

[28] Y. Zheng, Z. Y. Dong, Y. Xu, K. Meng, J. H. Zhao, and J. Qiu, "Electric Vehicle Battery Charging/Swap Stations in Distribution Systems: Comparison Study and Optimal Planning," IEEE transactions on power systems, vol. 29, no. 1, pp. 221–229, 2014, doi: 10.1109/TPWRS.2013.2278852.

[29] M. R. Sarker, H. Pandzic, and M. A. Ortega-Vazquez, "Optimal Operation and Services Scheduling for an Electric Vehicle Battery Swapping Station," IEEE transactions on power systems, vol. 30, no. 2, pp. 901–910, 2015, doi: 10.1109/TPWRS.2014.2331560.

[30] F. Adegbohun, A. von Jouanne, and K. Y. Lee, "Autonomous battery swapping system and methodologies

of electric vehicles," Energies (Basel), vol. 12, no. 4, p. 667, 2019, doi: 10.3390/en12040667.

[31] Yang, J., & Sun, H. (2015). Battery swap station location-routing problem with capacitated electric vehicles. *Computers & Operations Research*, 55, 217-232.

[32] J. Hof, M. Schneider, and D. Goeke, "Solving the battery swap station location-routing problem with capacitated electric vehicles using an AVNS algorithm for vehicle-routing problems with intermediate stops," *Transportation Research Part B: Methodological*, vol. 97, 2017, doi: 10.1016/j.trb.2016.11.009.

[33] J. Yang, F. Guo, and M. Zhang, "Optimal planning of swapping/charging station network with customer satisfaction," *Transportation Research Part E: Logistics and Transportation Review*, vol. 103, 2017, doi: 10.1016/j.tre.2017.04.012.

[34] C. Chen, J. Ma, Y. Susilo, Y. Liu, and M. Wang, "The promises of big data and small data for travel behavior (aka human mobility) analysis," *Transportation Research Part C: Emerging Technologies*, vol. 68. 2016. doi: 10.1016/j.trc.2016.04.005.

[35] D. Milne and D. Watling, "Big data and understanding change in the context of planning transport systems," *Journal of Transport Geography*, vol. 76, 2019, doi: 10.1016/j.jtrangeo.2017.11.004.

[36] X. Yang, Z. Sun, C. Author, and J. Wojtowicz, "Urban Freight Performance Evaluation Using GPS Data," *Transportation Research Board 93rd Annual Meeting. January 12-16, Washington, D.C.*, 2014.

[37] J. Huang, L. Wang, C. Tian, F. Zhang, and C. Xu, "Mining freight truck's trip patterns from GPS data," 2014. doi: 10.1109/ITSC.2014.6957996.

[38] D. Tian, X. Shan, Z. Sheng, Y. Wang, W. Tang, and J. Wang, "Break-taking behaviour pattern of longdistance freight vehicles based on GPS trajectory data," *IET Intelligent Transport Systems*, vol. 11, no. 6, 2017, doi: 10.1049/iet-its.2016.0195.

[39] X. Yang, Z. Sun, X. J. Ban, and J. Holguín-Veras, "Urban Freight Delivery Stop Identification with GPS Data," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2411, no. 1, 2014, doi: 10.3141/2411-07.

[40] S. Hadavi, S. Verlinde, W. Verbeke, C. MacHaris, and T. Guns, "Monitoring Urban-Freight Transport Based on GPS Trajectories of Heavy-Goods Vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 10, 2019, doi: 10.1109/TITS.2018.2880949.

[41] F. Yanhong and S. Xiaofa, "Research on Freight Truck Operation Characteristics Based on GPS Data," *Procedia - Social and Behavioral Sciences*, vol. 96, 2013, doi: 10.1016/j.sbspro.2013.08.261.

[42] A. Kinjarapu, "Analysis of Truck Travel behaviour using passive GPS data–Case study of Calgary Region," M.S. thesis, University of Alberta, Edmonton, Canada, 2018.

[43] E. Taniguchi, R. G. Thompson, and T. Yamada, "New Opportunities and Challenges for City Logistics," in *Transportation Research Procedia*, 2016, vol. 12. doi: 10.1016/j.trpro.2016.02.004.

[44] A. A. Juan, C. A. Mendez, J. Faulin, J. de Armas, and S. E. Grasman, "Electric vehicles in logistics and transportation: A survey on emerging environmental, strategic, and operational challenges," *Energies*, vol. 9, no. 2, 2016, doi: 10.3390/en9020086.

[45] G. Wang, A. Gunasekaran, E. W. T. Ngai, and T. Papadopoulos, "Big data analytics in logistics and supply chain management: Certain investigations for research and applications," *International Journal of Production Economics*, vol. 176. 2016. doi: 10.1016/j.ijpe.2016.03.014.

[46] Bureau, B. S. "Beijing statistical yearbook 2020," Beijing, China. Feb. 25, 2020. [Online]. Available: http://nj.tjj.beijing.gov.cn/nj/main/2020-tjnj/zk/indexch.htm

[47] J. F. Guo, X. Li, G. C. Wang, H. M. Wen, and Y. Liu. "Beijing transport annual report," Beijing, China. 2020. [Online]. Available: http://www.bjtrc.org.cn/List/index/cid/7.html

[48] J. D. Mazimpaka and S. Timpf, "Trajectory data mining: A review of methods and applications," *Journal of Spatial Information Science*, vol. 13, no. 2016, 2016, doi: 10.5311/josis.2016.13.263.

[49] C. J. Batty, E. Friedman, H. J. Gils, and H. Rebel, "Experimental Methods for Studying Nuclear Density Distributions," in *Advances in Nuclear Physics*, 1989. doi: 10.1007/978-1-4613-9907-0_1.

[50] Ministry of Transport of the People's Republic of China. "Opinions on Accelerating the Promotion and Application of Electric Vehicles in the Transportation Industry," Mar. 2015. [Online]. Available: http://www.china-nengyuan.com/news/74571.html

[51] P. Brémaud, Markov chains : Gibbs fields, Monte Carlo simulation, and queues. New York ; Hong Kong: Springer, 1999.

[52] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, 2002, doi: 10.1109/4235.996017.

[53] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, "A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 1917, 2000, doi: 10.1007/3-540-45356-3_83.

[54] Y. Zhou, S. Cao, R. Kosonen, and M. Hamdy, "Multi-objective optimisation of an interactive buildings-vehicles energy sharing network with high energy flexibility using the Pareto archive NSGA-II algorithm," *Energy Conversion and Management*, vol. 218, 2020, doi: 10.1016/j.enconman.2020.113017.

[55] G. Battapothula, C. Yammani, and S. Maheswarapu, "Multi-objective simultaneous optimal planning of electrical vehicle fast charging stations and DGs in distribution system," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 4, 2019, doi: 10.1007/s40565-018-0493-2.

[56] J. Zhang *et al*., "Multi-objective planning of charging stations considering vehicle arrival hot map," in *2017 IEEE Conference on Energy Internet and Energy System Integration, EI2 2017 - Proceedings*, 2017, vol. 2018-January. doi: 10.1109/EI2.2017.8245374.

[57] T. D. Chen, K. M. Kockelman, and M. Khan, "Locating Electric Vehicle Charging Stations Parking-Based Assignment Method for Seattle, Washington," Transportation research record, vol. 2385, no. 2385, pp. 28–36, 2013, doi: 10.3141/2385-04.

[58] M. Kuby and S. Lim, "The flow-refueling location problem for alternative-fuel vehicles," *Socio-Economic Planning Sciences*, vol. 39, no. 2, 2005, doi: 10.1016/j.seps.2004.03.001.

[59] J. Ko, T.-H. T. Gim, and R. Guensler, "Locating refuelling stations for alternative fuel vehicles: a review on models and applications," *Transport reviews*, vol. 37, no. 5, pp. 551–570, 2017, doi: 10.1080/01441647.2016.1273274.

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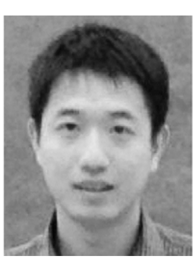

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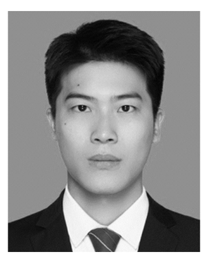

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