Integrated optimization of charging stations for electric taxis

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Abstract

Electric vehicles (EVs) are widely considered as environment-friendly transportation. However, the lack of charging stations (CSs) hinders the large adoption of EVs, especially these vehicles that travel cumulatively long-distance, such as electric taxis. To encourage the adoption of EVs, this article proposes an integrated charging station design model to optimize simultaneously the location of, charger type and capacity in CSs. An agent-based simulation model is proposed to address the difficulties raised in estimating charging demands and designed station performance considering the dynamics of the station-taxi system, the impact of station congestion, and taxi drivers' station choice behavior. The applicability of the proposed approach is demonstrated on a real case study in the metropolitan area of San Francisco, USA. The result shows that our proposed model could arrive at a charging station configuration that can mitigate significantly the congestion at station. Further study reveals the robustness of our approach to input data and the mechanism of budget impact on station performance. Furthermore, closest charging station choice assumption provides more robust result than shortest waiting time charging station choice in the integrated simulation-optimization charging station configuration design framework.

Keywords

Electric taxis, congestion, charging station, simulation-optimization, agent-based model

1 Introduction

With the continuous deterioration of environment and the depletion of fossil fuel (Xu *et al.,* 2018), transforming transportation to its sustainable counterpart fueled by clean energy attracts large attention. To date, electric vehicles (EVs) are foresighted as a promising substitution of conventional ones (Nykvist and Nilsson*,* 2015*,* Melton *et al.,* 2016). However, the short operation range of EVs and the lack of charging facility hinder its adoption (Needell *et al.,* 2016).

Nowadays, different types of charger have been invented to satisfy various charging demands (fast, slow, etc.). Nevertheless, the widely deployment of chargers and the penetration of EVs come to a classical chicken-egg dilemma. it is not economic to invest charging stations (CSs) when the market share of EVs is low, which is testified by the bankruptcy of Better Place (Noel and Sovacool*,* 2016). On the other hand, unless the facile availability of charger, private sector is unwilling to adopt EVs. Therefore, it is common practices that local authority (such as government) or EV-producing companies (such as Tesla) initiate the deployment of CSs. From the perspective of authority, electric taxis (ETs) are regarded as a suitable object (Jung *et al.,* 2014) to initiate transportation electrification project so as to encourage the adoption of EVs. For this reason, this article focus on designing CSs for ETs.

To design CSs, it is necessary to have the charging demands. However, this data is normally not available as CSs do not exist at the design phase. It has to be estimated. One approach is to estimate charging demands from conventional taxi operation tracking data. However, several factors, for example, the charging station configuration (location, type of charger and congestion condition), the station choice behavior of taxi drivers, and the dynamic and stochastic passenger requests that taxis are serving, will influence charging demands. Therefore, estimating charging demands is already very challenging. Let along designing CSs while estimating the demands considering these effects. Henceforth, to simplify the problem, we firstly ignore the uncertainty of passenger requests and confine our scope in designing charging station considering the impacts of system dynamics, and station congestion and taxi drivers' station choice behavior on estimating charging demands.

1.1 Literature review

Recent years have witnessed the fast increasing of scientific interest in charging station design. Models, ranging from classic location models (such as p-mean, p-median, etc), flow-refueling location model (FRLM) and its derivatives, to queuing theory based model, have been proposed and applied. Few review papers on charging station design problem are also available for reference (Meyer and Wang, 2018, Ko *et al.,* 2017a). To show the difference between our proposed model with the existing ones, the state-of-the-art of charging station design is discussed below.

The classic location-based models proposed in charging station design domain are trip-based model. As implied, these models estimate charging demands on a trip basis, like regarding the origin or the destination of a trip or the trip flow as a potential charging demand. The objective is to cover as many demands as possible with limited number of charging stations. For example, Ko and Shim (2016) apply p-median to locate battery exchange stations. Maximal set covering (Ko *et al.,* 2017b) and set covering (Wang and Lin, 2013) are applied to determine locations of charging stations. However, this class of model suffers from some fundamental shortcomings. First of all, the feasibility (arrive at charging station or destination without running of battery) of trips is ignored for long-distance trips while the dynamics is neglected in estimating charging demands for tours consist of short-distance trips since some of the trips does not need charge. More importantly, congestion at station at station is ignored. therefore, only location of charging station could be determined.

To resolve the trip infeasibility issue associated with aforementioned models, FRLM (Kuby and Lim, 2005) and its derivatives are proposed. This class of model tries to cover as many feasible trips instead of trips as possible. Since then, serveral extensions are proposed in the literature. For example, Kim and Kuby (2012) propose a deviation-flow-refueling location model (DFRLM) where the willingness of EV drivers to deviate to a CS is considered when computing the traffic flow captured by CSs. DFRLM model is further extended to avoid enumeration of paths for O-D pairs (YIldIz *et al.,* 2016), and to account for temporal and spatial distributions of trips (Li *et al.,* 2016). Another direction of extension is to incorporate randomness into the model, such as stochastic range of fully charged battery (Lee *et al.,* 2014), probabilistic initital range (Lee and Han, 2017). Moreover, Chung and Kwon (2015) extend the model to achieve multi-period station planning. As observed, usually, these models still focus on a single trip. Therefore, it is suitable to optimize the location of charging stations for inter-city transportation. However, the ignorance of dynamics in short-trip tour and of congestion at station still persist as the classical location models. Thus, this class of model might also suffers from the un-applicability to design CSs for ETs.

There are few models that incorporate congestion effect into the design of charging stations. Queuing theory is the tool that to which type of model usually refers. With the help of queuing theory, Zhang *et al.* (2018) derive the probability of charging without waiting at the station for both homogeneous and heterogeneous (type) electric vehicles. However, the charging demand arriving rate is assumed given. Hence, the influence of charging station location and taxi drivers' behavior to charging demands is not considered at all. In a same word, the dynamics in the transportation is overlooked. Jung *et al.* (2014) mitigate the shortcoming of assuming arriving rate through a simulation of shared vehicles operation to estimate the charging demands at stations. However, on one hand, the arriving rate of charging demand maybe not homogeneous; on the another hand, queuing theory is suitable to determine the number of charger in a station but limited in locating stations and determining the type of chargers. Moreover, the station optimization problem may be unfeasible because the condition may not hold that the service rate should be greater than arriving rate.

In light of the above literature review, among existing charging station design models, especially these for electric taxis, charging demand estimation is oversimplified. The impact of dynamics among trips inside a tour, of the congestion at stations, and of mutual interaction between taxi drivers and charging station on charging demand estimation have been seldom considered together when designing charging stations. Moreover, there is a lack of models that could optimize the charging station configuration simultaneously. Last but not least, the influence of taxi drivers' behavior and budget on the optimal charging station has been never investigated. Given these points, the contributions of this study are summarized as following

- Propose an agent-based charging station and taxi operation model to estimate charging demands considering the dynamic among the trips, congestion at stations as well as the interaction between taxi and charging station.
- Optimize the charging station configuration simultaneously and apply the proposed approach to a real case study in San Francisco.
- Through extensive simulation studies, this work also investigates influential factors on charging station configuration design. it is found out that closest charging station choice behavior assumption could help us to have a more robust station configuration. Moreover, the mechanism of budget on charging station has also been inspected.

The remaining of this article is organized in the following manner. Section 2 provides a statement and general model of charging station configuration design problem while Section 3 presents the detail of the proposed agent-based charging demands and station performance estimation model. Section 4 presents our case study and results analysis. The last section concludes the whole article.

2 Problem modeling

Hereinafter, the article focus on the charging station configuration design problem defined as below.

Find the optimal charging station configuration (location l, charger type t and number x) to maximize electric taxis' satisfaction while respecting the grid power transmission capacity $capg_l$, the space capacity $caps_l$ constraints at location l and the investment budget b constraint.

For additional remarks, the taxis' satisfaction is decomposed into two parts: charging experiences at stations and taxi drivers' revenue. As for the charging experience, the waiting time and charging time at a station are the most important indicators. Regarding electric taxis' revenue, it highly depends on passenger requests. In addition, since the scope of this article is to consider the dynamics in congested system, it is assumed that passenger requests are given and represented by pr_i ($i \in \{1, 2, 3, 4, \cdots, n\}$). Each passenger request has its own properties: beginning time T_i, origin O_i, destination D_i, duration of the trip d_i and route choice ru_i. In addition, all passenger requests are assigned to taxis in advance. Hence, the problem becomes designing charging stations to help the taxis to finish its trajectory as much as possible. Thus, taxi tracking data with passengers-on-board indication is the most suitable to our case study.

2.1 Mathematical modeling

According to our problem statement, the objective of our charging station configuration design problem is defined as the served passenger request duration minus the total charging duration (waiting time plus plug in charging time) of all taxis as formulated in Formula 1. The reason that we use passenger request duration rather than directly electric taxis' revenue lies in twofold. Revealed in real data, taxis' revenue is highly correlated (a correlation ratio of 0.9) to its operation duration when there are passengers. Moreover, the objective function could benefit from the uniform of unit if replacing taxis' revenue with their served passenger request duration. Then, the choice of weight ω in objective function is intuitive. Consequently, we model the charging station configuration design problem as represented by Formula 1 to 7.

$$\max_{\mathbf{x},\mathbf{y}} \quad \sum_i d_i y_i - \sum_j \omega \left(w_j + ch_j \right) \tag{1}$$

$$\text{s.t.} \quad \sum_l \sum_t c_t x_{lt} \leq b \tag{2}$$

$$\sum_t x_{lt} \leq caps_l \;\; \forall l \tag{3}$$

$$\sum_t r_t x_{lt} \leq capg_l \;\; \forall l \tag{4}$$

$$\mathbf{y} = f(\mathbf{x}, \mathbf{pr}) \tag{5}$$

$$\mathbf{w} = g(\mathbf{x}, \mathbf{pr}) \tag{6}$$

$$\mathbf{ch} = h(\mathbf{x}, \mathbf{pr}) \tag{7}$$

In this formulation, the independent decision variable $x_{lt} \in \{0, 1, \cdots, k\}$ represents the number of type t charger in location l. $x_{lt} = 0$ implies that type t charger is not installed in location l. $\sum_t x_{lt} = 0$ means location l is not chosen as a charging station. $\mathbf{x}$ is the aggregation of x_{it}. Constraint (2) to (4) confine the feasible space of $\mathbf{x}$, representing the budget, the space capacity and the power capacity constraints, respectively. The dependent decision variable $\mathbf{y}$ is a vector of dimension of n indicating whether the requests are served or not. If passenger request pr_i is served, $y_i = 1$; otherwise, $y_i = 0$. Whether a request is served depends on charging station configuration and the passenger requests as expressed by Formula 5. Formula 6 and 7 compute the waiting and the charging time of all charging demands. However, Formula 5 to 7 are hard to compute because of the dynamics of the congestion system.

- dynamic impact of charging: A taxi's current charging event will influence its future itinerary and charging demands. As a result, its service to passenger requests $\mathbf{y}$ will be influenced.
- dynamic impact of charging station congestion: In fact, current and future charging demands of one taxi will also influence the waiting and charging time of other taxis due to the limited number and type of charger (**congestion**) in a station. This influence will propagate to their future itinerary and their service to passengers' requests, charging event.

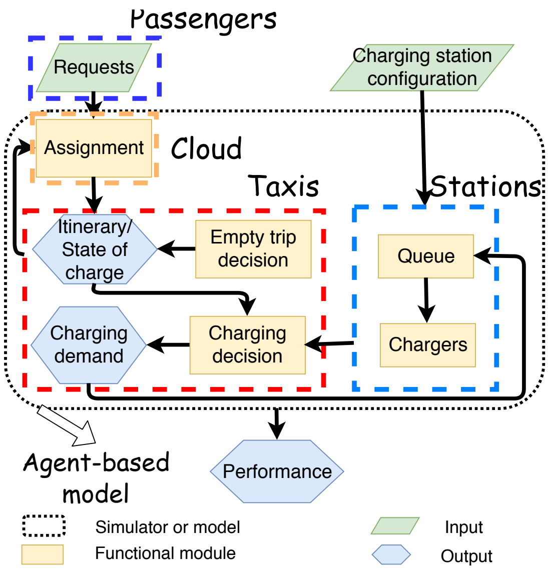


Figure 1: Agent-based charging station performance model

3 charging station performance estimation and optimization

To overcome the difficulties in calculating the waiting and charging time at stations as well as the service to passenger requests, an agent-based model is proposed. An agent is a representative of individual or collective entities such as organizations or groups that consist the system of interest. An agent-based model is a simulation model which attempts to represent or understand the system of interest though defining numbers of agents and the interactions among agents. To simulate the complex interactions among electric taxis and charging stations, this model is consisted of three types of agents: passenger, taxi, cloud, and charging station. The cloud agent is a special type of agent which determine the assignment of passenger requests to taxis. However, the number of agents depends on the number of individuals involved in the system.

3.1 Agent-based performance estimation model

3.1.1 Defining agents

The structure of the proposed agent-based model is presented in Figure 1. Before introducing the detail, we enumerate the properties and states of agents that are defined.

1. Properties:
   - Passenger i has a property vector $[T_i, O_i, D_i, Ts_i, Ta_i]$. Each of them represents the passenger request's happening time, request origin and destination, trip starting time and ending time of request i, respectively.
   - Taxi j has its properties shown as $[Cap_j, Cr_j, Sp_j, Ic_j, Uc_j]$, which means the battery capacity, the energy consumption rate per km, the driving speed, service initial charge and unit charge (per km) of taxi j .
   - Charging station k has a property vector of $[Ps_k, Cas_k, Sp_k, Ec_k]$ which represents the position, a vector of charger number, the speed vector of chargers and the service price vector of station k. Here, $Cas_k = (Cas_{1k}, \cdots, Cas_{Mk})$, $Sp_k = (Sp_{1k}, \cdots, Sp_{Mk})$ and $Ec_k = (Ec_{1k}, \cdots, Ec_{Mk})$ as M types of charger are installed at station k
2. States:
   - Passenger i has states $[y_i]$. y_i represents if the passenger request i served ((Yes = 1, otherwise = 0)),
   - The states of taxi j are expressed as $[t_j, P_j, SoC_j, Cus_j, Ch_j, R_j]$. These variables represent the time step, the position, the state of charge, whether a passenger is on board (Yes = 1, otherwise = 0), whether the taxi is in charging (Yes = 1, otherwise = 0) and profit of taxi j.
   - Charging station k has a state vector$[t_k, Oc_k, Wl_k]$, each representing the time step of the station, the occupied number of charger for all the types and the waiting list of taxis at the time step. Because there are M types of charger, $Oc_k = (Oc_{1k}, \cdots, Oc_{Mk})$

3.1.2 Action of agents

Each type of agent in the model is composed of different modules. As a summary, passenger agent includes a "Request simulator", the cloud agent has an "Assignment" module, the taxi agent includes "Empty trip decision" and "Charging decision" module, and the charging station agent includes an "Operation" module. As mentioned before, to simplify the problem, we assume that passenger requests are the same as indicated in tracking data and passenger requests are assigned to the taxi as they were served in the data. In addition, for the empty trip decision of taxis, we also assume that the taxi will follow the same route as it chose in the tracking data. Therefore, passenger agent, cloud agent, and empty trip decision module of taxis agent are not necessary. However, the whole simulation framework is presented for the integrity of the agent-based model.

Under the above assumption, taxi j will start from its first trip 1 to repeat its tracked trajectory until it starts to charge. At the beginning of each trip tr, the state of the taxi will be updated as

Eq. (8) to (11). If the trip has passenger i, the state of request i will be recorded according to Eq. (12). where a_{jtr} is the distance of trip tr.

$$Cus_j = 1 \tag{8}$$

$$t_j = Ta_i \tag{9}$$

$$P_j = D_i \tag{10}$$

$$SoC_j = SoC_j - a_{jtr} * Cr_j/Cap_j \tag{11}$$

$$y_i = 1 \tag{12}$$

The "Charging decision" module takes taxi's state and charging stations' state as input. Then, the module can make a charging decision including to charge or not, if charge, when and where to charge for how long. This model adopts a rule-based charging decision strategy which is stated as **a taxi begins to charge at the closest station to full when its state of charge is lower than a threshold α if the taxi has no passenger, or lower than a threshold β if the taxi is occupied**. Once taxi j decides to charge at station k to which it needs to travel b km, its state variables change according to Eq. (13) to (16)

$$t_j = t_j + b/Sp_j \tag{13}$$

$$P_j = Ps_k \tag{14}$$

$$SoC_j = SoC_j - b * Cr_j/Cap_j \tag{15}$$

$$Ch_j = 1 \tag{16}$$

At the same time, the chosen charging station will receive a charging demand. every time a new charging demand is arriving, it will go to the "Queue" module first. if there is no waiting vehicle in the queue, the taxi will query the "Chargers" module to see if there are unoccupied chargers. If no, it will stay in the queue, then Wl_k appends j and time stamp t_j of taxi j will keep updating. If there is an fastest available charger of type m, the state of the taxi will update following Eq. (17) to (19) while charging station k will update its occupied charger as Eq. (20).

$$t_j = t_j + (1 - SoC_j) * Cap_j/Sp_{mk} \tag{17}$$

$$R_j = R_j - Ec_{mk} * (1 - SoC_j) * Cap_(j) \tag{18}$$

$$SoC_j = 1 \tag{19}$$

$$O_{mk} = O_{mk} + 1 \tag{20}$$

Finally, the "Chargers" module inside charging station agent handle the finish of charging demands and charge new taxis. When a taxi j finishes charging at station k at time t, it is removed immediately. Accordingly, the taxi's states will update according to Eq. (21) and Eq. (22) while the charging station states will update following Eq. (23). Then the front taxi j' in the waiting queue (if any) will take the free charger. Wl pops out the front number. Taxi j' will update its states the same as Eq. (17) to (19). If there is no queue, the charger will be set as free and charging station k will decrease an occupied charger as Eq. (24).

$$t_j = t \tag{21}$$

$$Ch_j = 0 \tag{22}$$

$$t_k = t \tag{23}$$

$$O_{mk} = O_{mk} - 1 \tag{24}$$

These modules, combining with each other, form our agent-based charging station performance model. After a simulation, we can know which passenger requests are served ($\mathbf{y}$). Additional charging station performance indicators can be also calculated, such as the congestion level in a station according to the history of Wl, the profit of one taxi R_j, etc. With these performance indicators, we can optimize the charging station configuration accordingly.

3.2 Charging station configuration design

Given the above agent-based model which could give us the fitness of one charging station configuration, we can optimize the charging station configuration accordingly. In this work, simulated annealing (Kirkpatrick *et al.,* 1983, Eglese, 1990, Ingber, 1993) is adopted as the algorithm to optimize the charging station configuration because of its successful application to similar problems (Chiang and Kouvelis, 1994, Ghamami *et al.,* 2016, Yu *et al.,* 2017).

Assume that we have n potential charging stations and m types of chargers, then a $m \times n$ dimension matrix is used to represent decision variables, with each column represents a charging station and each element represents the number of the corresponding type of charger. An illustration is given by the "Original configuration" matrix in Fig. 2. Based on this representation of decision variables, the neighborhoods of a solution are illustrated by the remaining matrix in Fig. 2. It includes increasing charger number, decreasing charger number, swapping the number of two different types of charger in the same station, and swapping configurations of two stations. Every time that a new neighbor is obtained, except for decreasing charger number and swapping configurations of two stations, budget constraint will be checked for each neighborhood generated until a valid neighborhood is found.

Original configuration

$$\begin{pmatrix} a_1 & \cdots & a_i & \cdots & a_n \\ b_1 & \cdots & b_i & \cdots & b_n \\ c_1 & \cdots & c_i & \cdots & c_n \end{pmatrix}$$

increase/decrease pile number

$$\begin{pmatrix} a_1 & \cdots & a_i \pm x_i & \cdots & a_n \\ b_1 & \cdots & b_i \pm y_i & \cdots & b_n \\ c_1 & \cdots & c_i \pm z_i & \cdots & c_n \end{pmatrix}$$

swap rate inside a station

$$\begin{pmatrix} a_1 & \cdots & a_i & \cdots & a_n \\ b_1 & \cdots & c_i & \cdots & b_n \\ c_1 & \cdots & b_i & \cdots & c_n \end{pmatrix}$$

swap pile number between stations

$$\begin{pmatrix} \cdots & a_j & \cdots & a_i & \cdots \\ \cdots & b_j & \cdots & b_i & \cdots \\ \cdots & c_i & \cdots & c_j & \cdots \end{pmatrix}$$

Figure 2: A representation of decision variable and its neighbors

4 Case study and results

The physical setting of this case study is first introduced. Then, various station performance indicators are proposed to quantify the soundness of our proposed design approach. Through a comparison with a benchmark, results show that our proposed algorithm could save the waiting time significantly for the electric taxis, and therefore, increase their revenue and passengers' satisfaction considerably.

4.1 General setting

Thanks to the open-source taxi tracking data collected in San Francisco in 2008 (Piorkowski *et al.,* 2009), the metropolitan area (San Francisco -Oakland- San Jose) are chosen as the place for our case study. The data consists the trajectories of 537 taxis for 23 continuous days. For the favor of robustness test of our proposed charging station design approach, the data is divided on daily basis, each of which is labeled according to its tracking date. The first day is labeled as day 1. For the results presented in this document, tracking data from day 2, day 6 and day 14 are used as inputs. Due to the temporal gap between two measuring points is too large to estimate the actual route chosen, the geographical distance is adopted as the distance between two measuring points. This simplification can be compensated through a proper choice of electric taxi range, which is assumed 120 km for all taxis.

Besides, proper locations for charging station needs to be find out. Because the studied place is highly populated and utilized, existing parking spots or gas stations are more suitable to equip with chargers. Provided by (GEOFABRIK, 2018), more than 1520 parking or gas spots

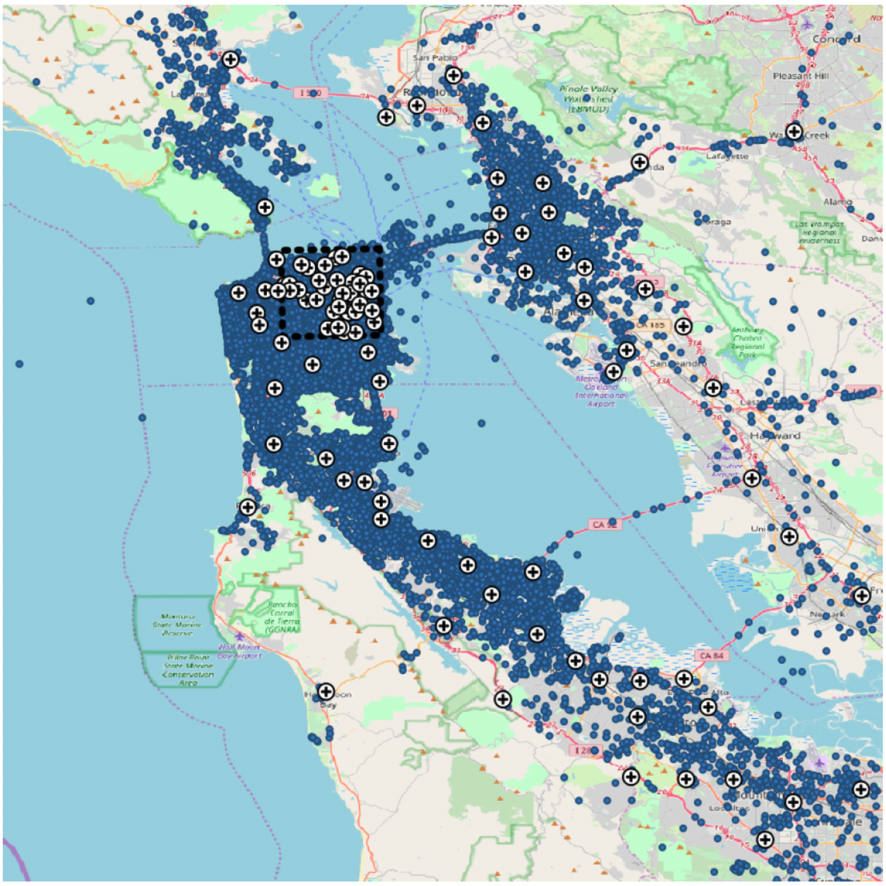
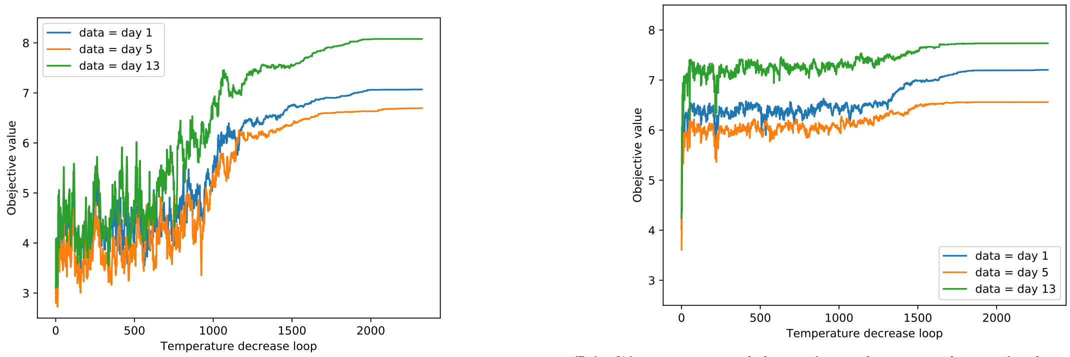


Figure 3: The potential 100 locations of charging station, represented by the circles with cross

are obtained in the study area. Out of these places, most are situated in the periphery of San Francisco and San Jose, and therefore, removed to save the distance to a charging station. For these places which are close to each, the average position is assigned as a potential location. Adding two spots in the airport, we arrive at 100 potential locations as shown in Figure 3. For demonstration purpose, we assume that there are three types of chargers available to choose from. Their charging speeds are $20kW$, $60kW$, and $120kW$, which represent current fast charging technologies. Prices of corresponding chargers are 1, 4, 11 after unification.

$$p_r = p_g * g_c/(e_c/r) * rf \tag{25}$$

For estimating the revenue of electric taxis, the taxi fare executed in San Francisco is adopted. It includes 3.5 \$ as starting fee, and 1.71 \$ per kilometer (km) afterwards. Extra charge for long distance and other special tariffs are not considered in our revenue calculation. The energy cost is considered exclusively as the operation cost of a taxi in a day. The service price of the charger is estimated from formula (25). p_r is the service fare of a charger with charging rate r; p_g is the



(a) Closest charging station choice behavior

(b) Shortest waiting duration station choice behavior

Figure 4: Charging station configuration optimization simulated annealing performance history

price of gasoline which is taken as 0.94 \$/liter; g_c and e_c are the average amount of gasoline consumed by a private combustion vehicle and electricity by a electric vehicle to run for 100 km. Their values are set as 7 liter and $20kWh$, respectively. A reduction factor (rf) varying with the charging rate (r) is applied to the formula to lower down the operation bill of an electric taxis so as to encourage its adoption. rf is adopted as 0.5, 0.6, 0.75 for 20 kW, 60 kW, 120 kW chargers, respectively. As for the operation cost of a charging station, it only pays an electricity bill which is assumed as 0.1 \$ per kWh.

The initial temperature for simulated annealing is 1000. It decrease by a ratio of 0.986 after every five simulations until it reaches 1 or smaller. After, the temperature decreases slower by a ratio of 0.995. When the temperature decreases to 0.0001, the optimization process ends.

4.2 Optimization results

4.2.1 Simulated annealing optimization history

The simulated annealing optimization histories under different input data and station choice behaviors are presented in Figure 4. In the same diagram, the difference among the objective evolving curves comes from the variations in the input data. In different day, the passenger requests are different, including the request number, timing, origin and destination (OD). These differences in request lead to the variation of time that taxis are occupied by passengers as well as the the charging duration through a complex process. With a comparison with macroscopic summary of the daily taxis operation status which is presented in Figure 5, we found that the objective is positively correlated with the taxis total revenue and request number.

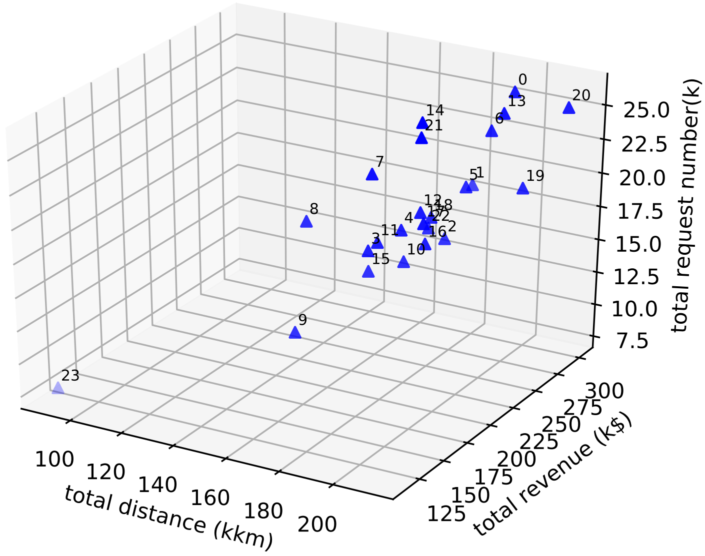


Figure 5: Macroscopic summary of taxis operation status in the measured days

Besides, comparing diagram 4(a) with diagram 4(b), we found that the objective value is more diverse when taxis choose to charge at closest charging station rather than shortest waiting duration station. This indicates that the closest charging station choice behavior makes the system more sensitive to station configuration difference. This phenomenon might be raised by the ignorance of congestion at stations when taxis make the station choice. As a result, in some cases, taxis are heavily congested in some stations instead of serving passenger requests. In the case of shortest-waiting-time station choice, the waiting time is always minimized. Even, in the worst case, the charging time will be around 1 hour. In effect, the time that taxis spend on providing service does not change so significantly, which is revealed in the objective value. Thus, considering the congestion in the station design might be very important as it can be imaged that taxi drivers prefer to choose the closest station to charge.

4.2.2 Charging station performances

Besides the objective, more intuitive indicators are proposed to quantify the performance of the designed charging stations. From the perspective of charging experience, waiting duration and charging duration at stations are proposed. In addition, taxi drivers care also their revenue. Thus, electric taxis' revenue ratio, which is defined as the revenue of electric taxis to the revenue of conventional taxis, is also computed. To quantify the satisfaction of passengers, served passenger requests ratio, that is the percentage of passenger requests that are served out of the whole requests, is proposed. Table 1 gives the performance of the optimal charging stations corresponding the above six simulated annealing optimization curves quantified by the proposed indicators.

Table 1: Performance of charging stations with respect to different indicators

	Waiting time (h)	Charging time (h)	Revenue ratio (%)	Served request ratio (%)
D1C1	0.87	1.20	84.53	87.35
D5C1	0.41	1.05	87.31	89.82
D13C1	0.63	1.25	85.94	87.96
D1C2	0.08	0.97	87.60	90.59
D5C2	0.10	0.95	87.94	90.57
D13C2	0.05	1.02	88.76	90.99

From the table, it is observed that the waiting time at charging station differs quite significantly under different charging station choice behavior. If taxis choose the closest charging station, they might wait for 30 minutes to 50 minutes at stations in one day, while they barely wait if they choose the station with shortest waiting time. Except for this, the optimal charging stations, obtained from different station choice behavior and input data, perform similarly under corresponding behavior assumptions. Each taxi needs to charge about 1 hour in a day to support its operation, and could earn 85% to 90% of conventional taxis' revenue through serving around 90% of passenger requests. As suggested by these results, the designed charging stations make taxis electrification feasible.

4.3 Sensitivity analysis

Results obtained previously are based on some deterministic assumptions, such as fixed passenger requests, and closest taxi station choice behavior. In reality, the system, including passenger, taxis (drivers), charging station, is highly stochastic. Empirical data, as presented by Figure 5, shows that passenger requests vary on a daily basis. Under this circumstance, trajectory and charging demands of taxis differ as well. In effect, the performance of charging stations might change. Moreover, the charging station choice behavior of taxi drivers might be not the same as what we assume or even not uniform among taxi drivers. For these reasons, sensitivity analysis is carried out to study robustness of the optimal charging stations to stochastic passenger requests and other influential parameters such as taxi drivers' station choice behavior and investment budget. The results show that the optimal charging station performance is sensitive to stochastic passenger requests and taxi drivers' station choice behavior assumption. However, different input tracking data influences marginally on the station performance in the long run.

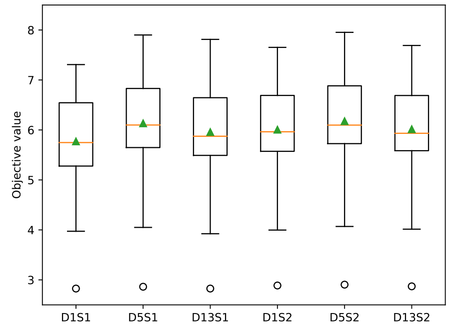
4.3.1 Performance sensitivity to stochastic system

The uncertainties that we consider in this study includes passenger requests and taxi drivers' station choice behavior. The passenger requests uncertainty is represented by the 23-days tracking data as, suggested by Figure 5, each day has different passenger requests. Besides the closest charging station choice behavior, shortest waiting duration station choice behavior is also assumed and tested.

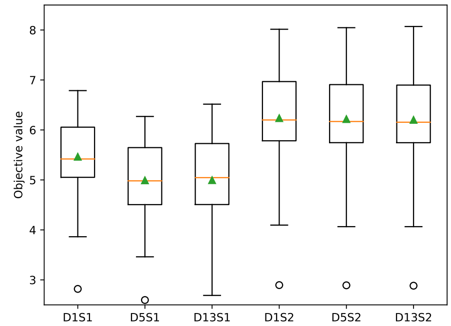
A simulation of charging stations and taxis operation for each day is performed and corresponding charging station performance indicators are obtained. The results are presented using box plot as shown in Figure 6. In this figure, one box is obtained from 23 data points of the same performance index, with each point represents a simulation result of one specific day. The larger the range a single box covers, the less robust the optimal charging station is. In one diagram, we have six boxes, representing the results of three optimal charging station configurations optimized using different input data (day 1, day 5, day 13) under two different station-choice behaviors (choose the closest station or shortest-waiting-time station). For example, D_1S_1 represents the optimal configurations that is obtained using the first day tracking data (D_1) while taxi drivers' station choice in the simulation is to choose the closest station (S_1).

From the figure, the variation of the charging station performance under different passenger requests does ont have a uniform pattern. The objective value of all configurations under different passenger request differ significantly. The reason behind is the difference in passenger requests of distinct days. Suggested by our objective function, the objective value highly depends on the passenger requests duration. As indicated in Figure 5, passenger requests vary significantly across days. Thus, the objective value differs considerably. When looking at other performance indicators, the difference is less diverse. However, for example, the revenue ratio or the served passenger request ratio could differ up to 10% when taxi drivers choose the closest station to charge. This motivates the design of charging stations that are more robust to the stochastic passenger requests.

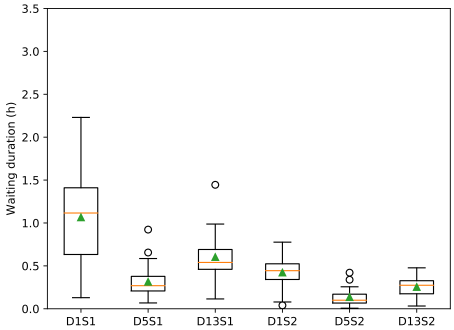
Additionally, through comparing within the boxes labeled D_iS_1 of the left column diagrams or labeled D_iS_2 of the right column diagrams, configurations optimized using data from different days give similar results. The difference in waiting duration from day 1 in Figure 6(c) is caused



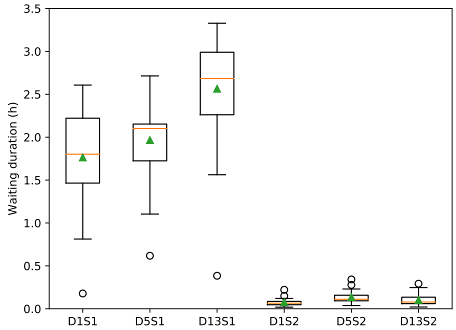
(a) Objective under station choice 1



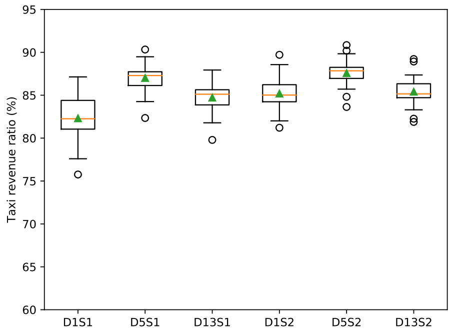
(b) Objective under station choice 2



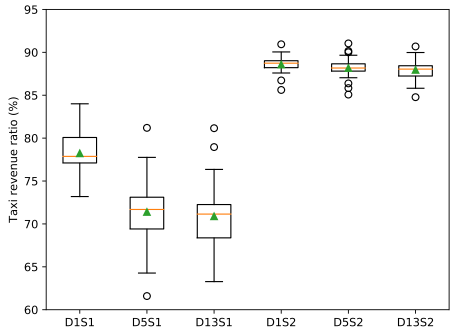
(c) Waiting time under station choice 1



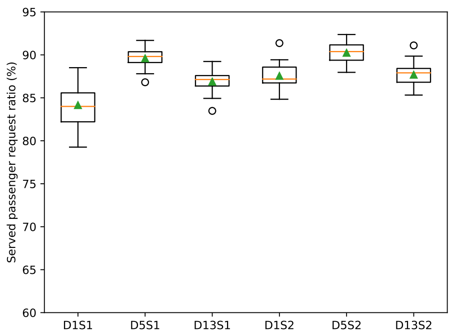
(d) Waiting time under station choice 2



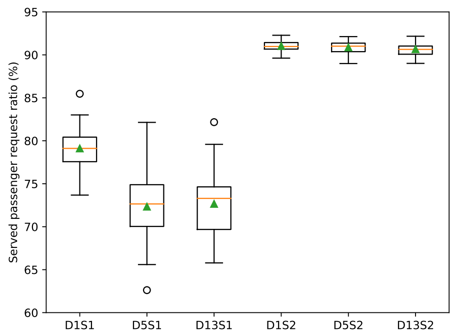
(e) Charging time under station choice 1



(f) Charging time under station choice 2



(g) Charging time under station choice 1



(h) Charging time under station choice 2

Figure 6: Charging station performance sensitivity analysis with respect to taxi operation environment, and station choice

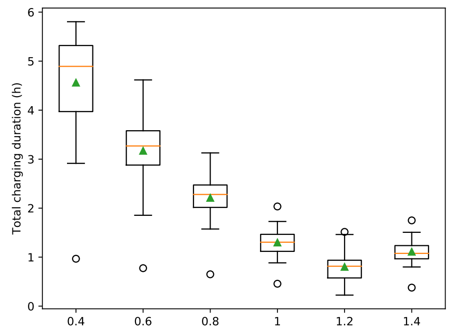
by some unknown reasons. However, this difference does not cause significant changes in the revenue ratio of taxi drivers or served passenger request ratio. Thus, the proposed charging station design model is robust to taxi tracking input data.

Finally, comparing the boxes labeled D_iS_1 ($i = \{1, 5, 13\}$) with the boxes labeled D_iS_2 in the same diagram, we could see how the optimal charging stations could perform under different station choice behavior. From diagrams on the left of Figure 6, we observe that charging stations optimized under closest charging station choice behavior perform similarly under shortest waiting time station choice behavior. The opposite case, nonetheless, does not hold as the diagrams on the right column indicates. The optimal charging stations acquired under shortest waiting time station choices performs much worse when the station choice behavior changes to the closest charging station. The waiting duration of each taxis will increases from almost zero to two to three hours (Figure 6(d); the revenue ratio of taxi drivers decreases from 90% to 70% (Figure 6(f)); and the served passenger request ratio decreases from more 90% to 70% (Figure 6(h)). Given these points, we conclude that, without compromising its performance, it may be a better idea to assume closest charging station choice behavior to taxi drivers rather than shortest waiting time station choice behavior when optimizing charging station configurations.

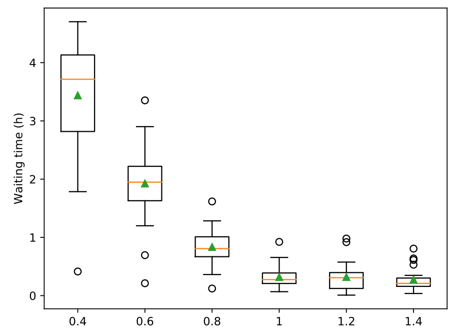
4.3.2 Impact of Budget

Since the budget in the above is assumed as a fixed constraint, it would be interest to understand how the charging station would perform with the change of budget. In this context, we alter the investment budget by multiplying the normal investment with a budget factor and optimize the charging station accordingly. Then, the performance of the charging station is simulated using the 23-day tracking data. The corresponding results are shown in Figure 7.

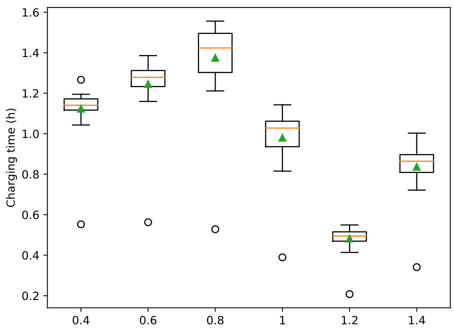
The x axis of the diagrams represents the budget factors adopted while the y axis represents the performance indicators. From Figure 7(a), with the increase of budget, the average time that a taxi spends in charging stations in a day decreases from 4.6 hours to 1.1 hours. At the mean time, the average waiting duration decreases from 3.5 hours to 0.4 hours as shown in Figure 7(b). Looking at Figure 7(c), it seems counter-intuitive as the charging time increase at the beginning. This is caused by the increasing number of charge. The decreasing waiting time increases the operation time of taxis, which increases their operation distance. As a result, taxis need to charge more to support the increasing range. However, when the budget increases to a certain level, the increasing charging rate offsets the marginal charging number. Therefore, the charging time decreases. In a short summary, when the investment is smaller than a threshold (which is around 80% of pre-defined budget), the main contribution of increasing budget is to



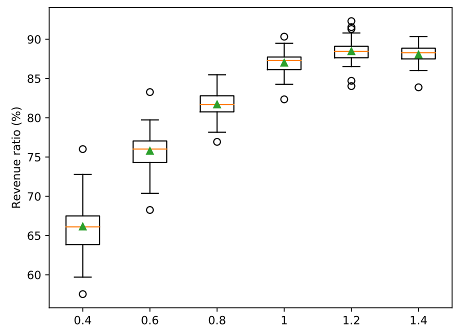
(a) Average total charging duration



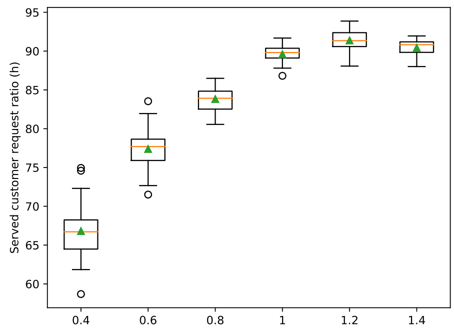
(b) Average waiting time



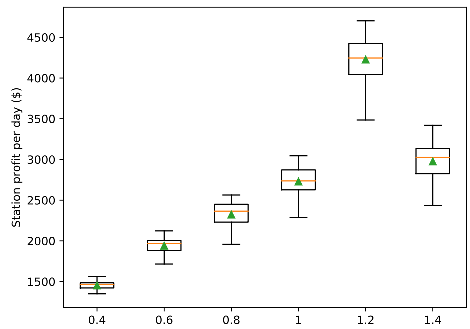
(c) Average charging time



(d) Taxi revenue ratio



(e) Served passenger request ratio



(f) Charging station profit

Figure 7: Charging station performance with respect to investment budget

decrease waiting duration at charging station rather than accelerate the charging of a taxi. After this threshold, the effect becomes the opposite.

Thanks to the decreased waiting time, taxis could spare more time to serve passenger requests, which increases taxis' revenue and served passengers request ratio as shown in Figure 7(d) and Figure 7(e). Numerically, the taxi revenue ratio increases from 65% to 88% which represents a revenue increase of more 100 $. At the same time, served passenger request ratio increases from

66% to 90%. To the taxi drivers and the passengers, the marginal contribution of increasing investment becomes smaller and smaller.

Figure 7(f) shows the profits of charging stations with respect to the increase of budget. As indicated, the profit of charging station increase almost linearly when the budget is smaller than our pre-defined value. When the budget continues increasing, the revenue of charging station increases even larger. This phenomenon can be explained from the point of increasing consumption and price. With the increase of budget, the optimal charging stations are equipped with more fast chargers whose service is higher. Moreover, as discussed above, increasing budget also encourages more charging demands. These two reasons finally lead to the increasing profit. Since the extraordinary complexity and non-linearity of the system studied, these increase does not happen linearly. So, there might be points where either of these changes happen step-wisely, the profit will also follow the same trend. Finding the points where these profit jumps happen is very important to the investment decision in the private sector.

5 Conclusion

An agent-based simulation-optimization disaggregated charging station design model is proposed for electric taxis considering the system dynamics, station congestion, and taxi drivers' station choice behavior. Through the model, a comprehensive charging station configuration, including charging station location, charger type and number in the station can be optimized. The results show that, even under strict passenger assignment, the designed charging station can help the taxi drivers to earn more than 90% of conventional taxi drivers and to serve more than 90% of passenger requests. This result suggests the feasibility of encouraging electric taxis through careful design of charging station.

Sensitivity analysis also indicates that our proposed model is robust to the input taxi tracking data, which benefits the free choice of optimization input data. Moreover, charging station optimized under closest charging station choice behavior assumption is robust (the performance level is maintained) to shortest waiting duration station choice behavior but the reverse does not hold. Hence, it is preferable to adopt the closest charging station choice behavior when applying our proposed model. From the sensitivity analysis with respect to investment, it is revealed that it is mainly the waiting time that limit the performance of charging stations when the investment is limited. After certain investment level, it is the charging speed that confines the station performance. No matter what the investment is, the operation benefit of charging station increases. At some critical values, the benefits could increase step-wisely. It is of great investment interest to find these jump points either at the service-level or the profit curves.

Foremost, as observed, the resulted charging stations services providing to electric taxis varies quite significantly with the stochastic passenger requests. One future extension of this model is to incorporate the stochastic aspect of the system. Moreover, a more sound consideration of the operation of charging stations and taxis and integration of other sectors (such as the energy sector, environment sector) could help us to understand more realistically the benefits and potentials of careful charging station configuration design.

6 References

Chiang, W. C. and P. Kouvelis (1994) Simulated annealing and tabu search approaches to unidirectional flowpath design for Automated Guided Vehicle Systems, *Annals of Operations Research*, **50** (1) 115–142, ISSN 02545330.

Chung, S. H. and C. Kwon (2015) Multi-period planning for electric car charging station locations: A case of Korean expressways, *European Journal of Operational Research*, **242** (2) 677–687, ISSN 03772217.

Eglese, R. W. (1990) Simulated annealing: A tool for operational research, *European Journal of Operational Research*, **46** (3) 271–281, ISSN 03772217.

GEOFABRIK (2018) No Title, `https://download.geofabrik.de/north-america/us/california.html`.

Ghamami, M., A. Zockaie and Y. M. Nie (2016) A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel, *Transportation Research Part C: Emerging Technologies*, **68**, 389–402, ISSN 0968090X.

Ingber, L. (1993) Simulated annealing: Practice versus theory, *Mathematical and Computer Modelling*, **18** (11) 29–57, ISSN 08957177.

Jung, J., J. Y. Chow, R. Jayakrishnan and J. Y. Park (2014) Stochastic dynamic itinerary interception refueling location problem with queue delay for electric taxi charging stations, *Transportation Research Part C: Emerging Technologies*, **40**, 123–142, ISSN 0968090X.

Kim, J. G. and M. Kuby (2012) The deviation-flow refueling location model for optimizing a network of refueling stations, *International Journal of Hydrogen Energy*, **37** (6) 5406–5420, ISSN 03603199.

Kirkpatrick, S., C. . D. Gelatt and M. . P. Vecchi (1983) Optimization by Simulated Annealing, *Science*, **220** (4598) 671–680.

Ko, J., T.-H. T. Gim and R. Guensler (2017a) Locating refuelling stations for alternative fuel vehicles: a review on models and applications, *Transport Reviews*, **37** (5) 551–570, sep 2017, ISSN 0144-1647.

Ko, J., D. Kim, D. Nam and T. Lee (2017b) Determining locations of charging stations for electric taxis using taxi operation data, *Transportation Planning and Technology*, **40** (4) 420–433, ISSN 10290354.

Ko, J. and J. S. Shim (2016) Locating battery exchange stations for electric taxis: A case study of Seoul, South Korea, *International Journal of Sustainable Transportation*, **10** (2) 139–146, ISSN 15568334.

Kuby, M. and S. Lim (2005) The flow-refueling location problem for alternative-fuel vehicles, *Socio-Economic Planning Sciences*, **39** (2) 125–145, ISSN 00380121.

Lee, C. and J. Han (2017) Benders-and-Price approach for electric vehicle charging station location problem under probabilistic travel range, *Transportation Research Part B: Methodological*, **106**, 130–152, ISSN 01912615.

Lee, Y.-G., H.-S. Kim, S.-Y. Kho and C. Lee (2014) User Equilibrium-Based Location Model of Rapid Charging Stations for Electric Vehicles with Batteries That Have Different States of Charge, *Transportation Research Record: Journal of the Transportation Research Board*, **2454**, 97–106, ISSN 0361-1981.

Li, S., Y. Huang and S. J. Mason (2016) A multi-period optimization model for the deployment of public electric vehicle charging stations on network, *Transportation Research Part C: Emerging Technologies*, **65**, 128–143, ISSN 0968090X.

Melton, N., J. Axsen and D. Sperling (2016) Moving beyond alternative fuel hype to decarbonize transportation, *Nature Energy*, **1** (3) 16013, ISSN 2058-7546.

Meyer, D. and J. Wang (2018) Integrating Ultra-Fast Charging Stations within the Power Grids of Smart Cities: A Review, 1–8, ISSN 2515-2947.

Needell, Z. A., J. McNerney, M. T. Chang and J. E. Trancik (2016) Potential for widespread electrification of personal vehicle travel in the United States, *Nature Energy*, **1** (9), ISSN 20587546.

Noel, L. and B. K. Sovacool (2016) Why Did Better Place Fail?: Range anxiety, interpretive flexibility, and electric vehicle promotion in Denmark and Israel, *Energy Policy*, **94**, 377–386, ISSN 03014215.

Nykvist, B. and M. Nilsson (2015) Rapidly falling costs of battery packs for electric vehicles, *Nature Climate Change*, **5** (4) 329–332, ISSN 17586798.

Piorkowski, M., N. Sarafijanovic-Djukic and M. Grossglauser (2009) Taxi trajectory tacking data in San Francisco, `https://crawdad.org/epfl/mobility/20090224/`.

Wang, Y. W. and C. C. Lin (2013) Locating multiple types of recharging stations for battery-powered electric vehicle transport, *Transportation Research Part E: Logistics and Transportation Review*, **58**, 76–87, ISSN 13665545.

Xu, Y., S. Çolak, E. C. Kara, S. J. Moura and M. C. González (2018) Planning for electric vehicle needs by coupling charging profiles with urban mobility, *Nature Energy*, **3** (6) 484–493, ISSN 20587546.

YIldIz, B., O. Arslan and O. E. Karasan (2016) A branch and price approach for routing and refueling station location model, *European Journal of Operational Research*, **248** (3) 815–826, ISSN 03772217.

Yu, V. F., A. A. Redi, Y. A. Hidayat and O. J. Wibowo (2017) A simulated annealing heuristic for the hybrid vehicle routing problem, *Applied Soft Computing Journal*, **53**, 119–132, ISSN 15684946.

Zhang, H., S. J. Moura, Z. Hu, W. Qi and Y. Song (2018) A Second-Order Cone Programming Model for Planning PEV Fast-Charging Stations, *IEEE Transactions on Power Systems*, **33** (3) 2763–2777, may 2018, ISSN 0885-8950.