Optimal Location of Electrical Vehicle Charging Stations With Both Self- and Valet-Charging Service

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***Abstract*— The inconvenience of charging is one of the major concern for potential electric vehicle (EV) users. In addition to building more charging facilities, electric vehicle charging assistance service has emerged for making EV charging more convenient to customers. In this paper, we consider an optimal EV charging station location problem with two types of customers. One is ordinary self-charging customers whereas the other is customers using a new service mode called valet-charging. We formulate the problem via bi-level location optimization model, where the lower level problem is a game model that characterizes customers' station choice behaviors. To solve the hard nonlinear mixed-integer optimization problem, we design an adaptive large neighbourhood search (ALNS) algorithm for the upper level problem and a construct-improve heuristic for the lower level problem. We conduct numerical experiments to justify the efficiency of our solution method. We also conduct a need-inspired case study to derive practical insights which will help EV charging assistant service providers make strategic decisions.**

***Note to Practitioners*—The convenience of charging service is one major concern for EVs. In China, NIO Inc., NETA AUTO, and FAW-Volkswagen have started to provide valet-charging service. Charging station location problem becomes complicated while taking this service into account. We believe our work develops an effective tool for charging station planners to analyze station locations as well as the impact of valet charging services.**

***Index Terms*— Electric vehicle, location-capacity problem, valet-charging, bi-level optimization, adaptive large neighbourhood search.**

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I. Introduction

THE main contributor to global warming is fossil fuel consumption and ensuing greenhouse gas emissions in human activities [1]. Increased attention is received to curb excessive consumption in the transportation sector. Electric vehicles (EVs) have been long recognized as a promising technology solution to reduce fossil fuel consumption. In the past decade, we witnessed the booming of EV industry worldwide. Figure 1 shows the scale increase of battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) stocks in the United States, Europe, and China from 2010 to 2020. The scale continues to grow rapidly, according to *Global EV Outlook 2021* [2]. Meanwhile, policies and regulations have been enacted in many countries worldwide to further accelerate technology adoption, commercial use, and consumer purchase of EVs. Norway, Finland, Germany, China, the United Kingdom, and France have announced a total ban on the sale of fossil fuel vehicles by 2025, 2030, 2030, 2035, 2035, and 2040, respectively [3], [4], [5], [6], [7]. Much of the evidence suggests strong intention of adopting EVs more widely in the near future, pending on the overcoming of several implementation barriers. One such barrier is inconvenience in charging EVs, which is especially a hindrance to private users.

Admittedly, for private EV use, it is not viable to many individual users installing their own charging piles due to economic and infrastructural reasons. However, public charging stations are often time not sufficient to these users. This contributes to the hesitation of EV purchase among potential buyers [8]. Knowing that city-wide construction of charging stations and public provision of accessory services can be lengthy and costly, the decision on where to locate charging piles among business or publicly accessible locations is an important strategic decision to EV manufacturers and city officials. This decision, subsequently, has significant socioeconomic implications, including city-wide EV adoption and transportation infrastructure upgrade.

Compared to the fueling operation of a gasoline-powered vehicle, it takes much longer to charge an EV [9], which results in less satisfied experience of EV use. Thus, it is critical to study how to deliver EV charging assistance service. Recently, valet-charging has emerged in China to make EV charging more accessible to individual users. Under this service mode, staff from a contracted service company are sent to help call-in customers charge their EVs. They would arrive at the appointment time, pick up the car, drive to the

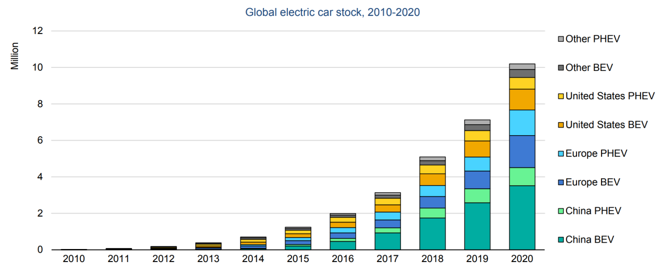

Fig. 1. Global EV stock.

charging station, then drive back after the charging and return the car to the customer. In this way, customers are free from the charging duty and their acceptance on EV use is likely improved.

In this paper, we study an optimal EV charging station location problem under a fixed percentage composition of two types of customers requesting EV charging. This strategic decision is of special interest to EV manufacturers and service providers. One type of customers is self-charging customers, who would bring their vehicles to a charging station and charge their vehicles themselves. These customers choose the charging station with the shortest total time of travel and waiting. For a charging station, the more customers come for charging service, the longer each of them would wait for the service, which in turn reduces the willingness of self-charging customers to choose that charging station. The other type of customers is valet-charging customers, who would have chosen the new service mode. Upon receiving a valet-charging request, service staff are dispatched to provide the charging service. We trade the valet-charging staff labor cost for the access convenience of self-charging customers.

We formulate this location optimization problem via a bi-level optimization model. We use the upper level problem to decide the location and number of charging piles of each charging station, as well as the dispatch decisions for valet-charging staffs. The upper level objective is to minimize the overall service cost, which comprises the costs of charging station construction, charging pile setting up, valet-charging staff labor, and access inconvenience of self-charging customers. We use the lower level problem to specify self-charging customers' station choice behaviors. For self-charging customers, their charging stations are solely dependent upon the convenience of self service. Hence, the lower level problem is a game among self-charging customers.

We design an adaptive large neighbourhood search (ALNS) algorithm to solve the upper level problem. We introduced an problem driven operator design method that mimics real-world situations. Meanwhile, we design a construct-improve heuristic to solve the lower level problem, and embed it into the upper level solution procedure for objective value evaluation of the charging station network design. We compare the proposed solution method with two web-based commercial solvers, namely BARON and scip, as well as a genetic algorithm. Our comparative results justify the tractability and efficiency of our approach.

The contributions of this research are as follows. First, we consider a novel sustainable transportation system infrastructure design problem for EV manufacturers and service providers, in which we consider EV charging can be delivered in two modes, self-charging and valet-charging. Specifically, we formulate a bi-level location optimization model and use a game model to capture self-charging customers' behaviors in the lower level problem in relation to the EV charging station locations and the charging assistance service delivery performance in general. Second, we propose an efficient solution method to generic bi-level location optimization model with equilibrium on customer location choice. Specifically, our approach comprises an ALNS algorithm with special operator design for the upper level problem, and a construct-improve heuristic for the lower level Nash equilibrium problem. Third, we test the optimal network design reliability for EV manufacturers and service providers who are interested in the sizeable catchment area of Yangpu District, Shanghai, China, and recommend to the decision-makers planning strategies on network construction in response to future demand changes.

The remainder of the paper is organized as follows. We review relevant literature in Section II. In Section III, we derive the bi-level location optimization problem. In Section IV, we present an ALNS for the upper level problem and a construct-improve heuristic for the lower level problem. In Section V, we compare our solution method to commercial solvers and a genetic algorithm. We also report our findings off simulation experiments and a real-world case study. We draw conclusions and outline future research directions in Section VII.

II. Literature Review

In this section, we review three categories of relevant literature. First, we review the literature on the novel service mode called valet-charging. Next, we will shift our focus to the literature concerning the challenges and issues on determining the locations of EV charging stations. Finally, we review the literature on the problem of optimal service facility location with congested queuing network.

Valet charging is a relatively new topic. To the best of our knowledge, there are only four academic studies concerning valet charging. Rao, Cao, and Klanner [10] first considered the valet-charging service in Singapore. They assume that service providers go to customers' location by their own e-bike, and drive customers' EV to the assigned charging station, before the next service request. The research question is how to decide the service sequence. It is modeled by a Sequential Ordering Problem and analyzed by a simulation tool. Lai and Li [11], [12] considered on-demand valet-charging service provided by a platform. When a request occurs, a staff will be dispatched to pick up the EV, driving to a station for charging, and return the EV. The city planner will decide the number of charging stations, while the platform will decide the price for valet-charging and wage for staff. A queuing network is formulated to capture the matching dynamic of staffs, customers and charging stations. Li et al. [13] considered a charging station location problem with both valet- and self-charging customers. In their model, both customers are allocated to underutilized charging stations. Their paper is most similar to ours. We also consider a charging station location problem with these two types of customers, but we incorporate the congestion of charging stations and the self-charging customers' station choice behavior.

Several literature reviews have already been conducted on the topic of charging station location problems. For further exploration, we recommend the following references: [14], [15], [16], [17], [18], [19]. The extensive research on the topic has various focuses. Liu et al. [20] proposed a fuzzy multi-criteria decision-making methodology to select charging station locations. Kazemi-Karegar [21] optimized the location with consideration of EV energy loss, grid energy loss, and urban road condition. The authors solved the problem using a genetic algorithm. Kong et al. [22] studied an optimal location problem that comprehensively considered users, service staff, traffic condition, and grid condition. The authors solved the problem with an iterative optimization algorithm. Limited research considers plug-in hybrid EVs. Karaşan [23] studied the optimal location problem of charging stations for plug-in hybrid EVs with different driving ranges. The model aims to maximize miles traveled on vehicle's electrical power and thereby minimize transportation costs under the existing electricity and gasoline cost structure. The authors proposed an arc-cover formulation and solved the problem with a Benders decomposition algorithm.

In this paper, we study an optimal location problem for plug-in EV charging stations, but we take the new service mode of valet-charging into consideration. Valet-charging customers interact with self-charging customers, making this system different from the traditional ones.

Next, we review the modeling of private EV owner's choice on the charging station in location analysis. When modeling the charging stations that private EV owners choose, much of the work assumed that the drivers choose a charging station with minimum travel distance or time. Only a few studies did not make this assumption, instead they built a behavior model to describe customers' station choices and incorporated the model into a location optimization model. For example, Tian et al. [24] first used a cloud model [25], [26] based on data features including expected value, entropy, and hyper entropy, to predict drivers' charging behavior. Then they formulated a location optimization model to minimize the operational cost of EV drivers. Considering that EV drivers may have several trip destinations and are more likely to make charging decisions based on the combination of these destinations, Pan et al. [27] proposed a process to determine EV charging options and built a coverage location model that aims to maximize EV drivers' existing activities, which implies the minimization of unreachable trips. Dong et al. [28] studied the optimal location of EV stations and discussed the impact of driving range increase of EVs on locating public charging facilities. They proposed an activity-based evaluation method to model each driver's driving and charging behaviors, and quantified the range anxiety related to limited-range vehicles. Yang [9] considered a utility-based user-choice behavior model in their location optimization model. In their model, user utility includes the charging distance and the number of chargers at the charging station, and users would choose charging station with the highest utility.

The other category of relevant literature is about EV location optimization problems with centralized customer allocation. Valet-charging customers' behavior is assumed to be under control of a service provider who can allocate charging demands to different stations in a centralized manner. As a result, location-allocation models were formulated. For example, Tan and Lin [29] formulated a stochastic location-allocation model, which allocates customer flows in the network. Worley, Klabjan, and Sweda [30] proposed a location-allocation model to determine EV routes while determining the location of charging stations, and conducted a case study on an express parcel delivery company. Zhang et al. [31] proposed a multi-objective bi-level model. The upper-level problem determines the location and capacity of charging stations to minimize the total cost and service tardiness. The lower-level problem addresses customer allocation to minimize the total travel time.

In this paper, we are the first to consider two distinct types of customers. In addition to self-charging customers (mostly studied in the literature), we consider valet-charging customers in a charging station location optimization model. We model their station choice behaviors quite differently from the existing literature. We use equilibrium constraints to model the spatial distribution of customer demands, which captures the interplay between the two customer types. Finally, we review optimal service station location problems that assume an underlying congested queuing network. The distinct feature here is to incorporate queuing performance measures in the resultant optimization models. It is challenging to solve such optimization models due to the nonlinearity of queuing system performances (e.g., waiting time) with respect to the decision variables in the optimization model. And such nonlinearity may increase and the optimization becomes more intractability as assumptions for convenient analysis of queuing networks are dropped for practical relevance. Another difficulty lies in the complexity of user's choice behavior. We do not see any EV charging station location optimization with simultaneous incorporation of centralized user allocation and individualized user choice. The following review will not be limited to EV charging station location problems.

In our problem, as part of the total demand, valet-charging customers will be allocated to different charging stations. The allocation problem is often solved together with the location problem. Amiri [32] built an integer programming model to determine where to build facilities and how to allocate customers to each facility, aiming to minimize construction cost and operation cost. The problem is then solved by heuristic procedures based on Lagrange relaxation. Aboolian et al. [33] extended the above model by further considering the capacity of each facility. The authors proposed a new algorithm, which first determines the customer allocation and then determines the location and capacity of each facility. Elhedhli [34] presented a location-allocation model and proposed a linearization-based method to solve the problem.

Another type of demand considered in our problem, self-service customers, choose charging stations by themselves. User choice behavior is often described by equations. For example, choosing the charging station with the shortest time or distance can be formulated as linear equations. Wang et al. [35] established an optimization model to minimize construction cost and operation cost. The model assumes that customers go to the nearest facility. The operation cost includes customers' travel time and expected waiting time. The waiting time was calculated with the M/M/1 formula. A greedy-dropping heuristic is designed to solve this model. Aboolian et al. [36] went further to use the M/M/k formula to calculate the waiting time which is much more computationally expensive. The authors presented an exact solution and several heuristic methods such as simulation annealing. Computing complex user choice behavior at a Nash equilibrium is a challenging task by itself. Cavadas et al. [37] considered the impact of charging station location on demand in their location optimization model. They assumed that the charging probability of EVs each time they stop in a day is proportional to the time of the stop. Since an EV may stop at more than one location a day, the location of the charging demand may be affected by the station location. The authors formulated the problem as a MIP model.

We formulate our problem via a bi-level optimization model. The first bi-level mathematical optimization model was proposed by Bracken and McGill [38], and was used to study a Stachelberg game with two decision makers. The so-called leader in the game minimizes his objective function subject to conditions composed (in part) by optimal decisions of the so-called follower [39]. In recent years, lower-level problems describing follower decisions are no longer limited to a optimization problem. Li and Liao [40] considered a bi-level model of optimal deployment of shared autonomous vehicles (SAVs). The upper level problem determines the hub locations and initial SAV distribution, while the lower level captures travelers' activity-travel scheduling behavior by an extended dynamic user equilibrium model. Jung et al. [41] proposed a bi-level charging station location model for electric taxi. The upper level problem is a multiple server allocation problem and the lower level problem is a dispatch simulation. Ma and Xie [42] developed a bi-level model that tackles the charging operation problem for shared EVs. The upper level problem is to decide the location of fast-charging stations, while the lower level problem incorporates simulation-based methods to calculate dynamic EV assignments.

In this paper, we consider a location-allocation problem in the upper level problem for station location and capacity, as well as valet-charging customers' allocation. In the lower level problem, we model the self-charging customers' station choice behaviors as a game.

III. A Bi-Level Location Model

In this section, we first present a model for estimating charging demands. Then we introduce our bi-level location optimization model with two types of customers, where the leader is a company which can be an EV manufacturer or a service operator and the follower is self-charging customers. The upper level is a location-allocation problem for the company to decide where to locate charging stations and how to dispatch valet-charging staffs. The lower level is a game among self-charging customers, each of whom wants the shortest total process time, including travelling, charging and possible waiting.

A. Upper Level Problem

The upper level problem considers the company's decision. It consists of two components. The first component is the location decision, i.e., where to build each charging station and with how much capacity (number of piles). The second one is the allocation decision, i.e., which station valet-charging staff will be dispatched to for each demand node. The objective of the upper level problem is to minimize the construction and operating costs.

Let I be the set of demand nodes. Each demand node is associated with some catchment area of EV users. These catchment areas are disjoint. Note that we can divide the city transportation network into a grid, and estimate the demand of each grid cell by its internal commercial and residential areas. This demand estimation method is recommended by NIO. Since charging station location is a long-term plan, we emphasized customers' long-term behavior and disregarded the short-term fluctuations in demand. In practice, the values of total demand rate can be derived by calculating the average charging demand over a specific time span. We assume that the demand arrival at each node follows a Poisson distribution, with parameter λ_i^1 for valet-charging customers and λ_i^0 for self-charging customers. We assume that customer choices between self- and valet-charging are exogenous based on the following considerations: First, some customers receive monthly free charging sessions either through bundled services or as a complimentary offering from the company. These customers will definitely choose valet charging. For other customers, due to the relatively high one-time cost of valet charging, in the early stages when their consumption habits have not yet changed, only customers for whom time inconvenience is a hard constraint (e.g., users who are too busy to charge their EVs) would choose valet charging. Thus, We set a fixed proportional division between self- and valet-charging demands. We admit such specification can be a significant simplification of the problem. However, it is worth noting that without this specification, the modeling becomes much more inconvenient and the problem becomes hard to solve. In Section V-B3, we analyze the impact of varying this proportion. In Section VI, we discuss how to model and analyze the scenario where the choice between self- and valet-charging is regarded endogenous. We also point out the potential challenges in solving the alternative problem.

We assume that there is a finite set of candidate station locations, denoted by J. We aim to select a subset of nodes from J to build EV charging stations and determine the capacity at each station.

We define three sets of decision variables. Let $x_j \in \{0, 1\}$ be the location decision, and $x_j = 1$ implies that a charging station will be established at candidate location j. Let $s_j \in \mathbb{N}$ be the capacity decision, which specifies the number of charging piles at station j. Let $y_{ij} \in [0,1]$ represent the fraction of valet-charging customers assigned from demand node i to station j. For exposition simplicity, we introduce intermediate variables to the model. Let p_{ij} be the fraction of self-charging customers from demand node i getting charging service at station j. Thus, the expected demand arrival rate at station j is $a_j = \sum_{i \in I}(\lambda_i^1 y_{ij} + \lambda_i^0 p_{ij})$. Our upper level location-allocation problem is presented as:

$$\text{(P1)} \quad \min_{\mathbf{x},\mathbf{s},\mathbf{y}} \sum_{j\in J}(c_j x_j + c_s s_j) + c_1 t_c \sum_{i\in I}\sum_{j\in J} (t'_{ij} + \bar{W}(a_j, s_j))\lambda_i^1 y_{ij} + c_0 t_c \sum_{i\in I}\sum_{j\in J}(t'_{ij} + \bar{W}(a_j, s_j))\lambda_i^0 p_{ij} \tag{1}$$

$$s.t. \quad s_j \le M x_j, \quad j \in J \tag{2}$$

$$\sum_{j\in J} y_{ij} = 1, \quad i \in I \tag{3}$$

$$t'_{ij} \ge t_{ij} + M(1 - x_j), \quad i \in I, j \in J \tag{4}$$

$$x_j \in \{0,1\}, \ s_j \in \mathbb{N}, \quad j \in J \tag{5}$$

$$y_{ij} \ge 0, \quad i \in I, j \in J \tag{6}$$

The first term of equation (1) represents the construction cost, comprising a fixed cost and several variable costs. Denoted by c_j is the fixed cost of building a charging station, and denoted by c_s is the variable cost of installing a charging pile at a station. The second and third terms represent operation costs. The second term represents valet-charging staff labor cost where c_1 is the unit-time coefficient. The third term represents the access inconvenience of self-charging customers, with unit-time penalty cost c_0. Denoted by $\bar{W}(a_j, s_j)$ is the expected time a customer at the station for charging and possible waiting. $\bar{W}(a_j, s_j)$ is a monotonically increasing with respect to a_j and monotonically decreasing with respect to s_j. It can be computed with the corresponding queuing-theoretic formula. We denote t_c to be the entire duration of effective operation, which is used to balance the fixed cost and operating cost.

Each inequality (2) restricts charging piles to be installed and operating at a candidate location only after a charging station is built there; M being a sufficiently large constant. Equations (3) ensures all valet-charging demands to be satisfied. The travel time from node i to station j via the shortest path is denoted by t_{ij}. Each inequality (4) ensures the travel time to be set with a sufficiently large value if going to a candidate location with no charging station established, thus preventing demand from going to those locations.

Note that the upper level problem includes variables p_{ij}'s, which represent self-charging customers' station choice behaviors. The lower level problem is used to determine the values of p_{ij}'s after the company's decision.

B. Lower Level Problem

The lower level problem incorporates the station choice of each self-charging customer. We assume that all self-charging customers are homogeneous and rational. These assumptions are commonly employed to describe customer choice behavior, e.g. Fisk [43]. We consider self-charging customers' station choice as a game. Each customer is a participant in this game aiming to minimize his total processing time of travelling, charging and possible waiting. Each participant could only choose one station for charging, which is his action in this game. When no participant could shorten his total processing time by only changing his own strategy, we call that the game has reached a *Nash equilibrium*.

Our lower level Nash equilibrium problem is presented as:

$$\text{(P2)} \quad \sum_{j\in J} p_{ij} = 1, \quad i \in I \tag{7}$$

$$a_j / s_j \mu = \sum_{i\in I}(\lambda_i^1 y_{ij} + \lambda_i^0 p_{ij})/s_j\mu \le 1 - \varepsilon, \quad j \in J \tag{8}$$

$$t'_{ij} + \bar{W}(a_j, s_j)\begin{cases} = T_i^*, & \text{if } p_{ij} > 0 \\ \ge T_i^*, & \text{if } p_{ij} = 0 \end{cases} \quad i \in J \tag{9}$$

$$p_{ij} \ge 0, \quad i \in I, j \in J \tag{10}$$

Equation (7) ensures all self-charging demands to be satisfied. Inequality (8) ensures that the long-run utilization rate of each charging station is comfortably below 1 with $\varepsilon \in [0,1)$ being a model coefficient preset by the decision maker. Equation (9) is the equilibrium equation for each $i \in I$ and $j \in J$, which is used to specify the charging station location choice behavior of self-charging customers at demand node i. The left side of the equation represents the expected total time T_i that customers from node i take in order to charge their EVs at station j. It is composed of two parts: (i) the travel time from node i to station j through the shortest path, denoted by t'_{ij}; and (ii) the expected time a customer at the station for charging and possible waiting. The right side of the equation is T_i^*, which represents the minimum expected total time that a self-charging customer at node i could take for the charging service. **Lemma 1** explains why T_i^* is the minimum expected total time.

Lemma 1: For any feasible solution of (P1), we have $T_i^* = \min_j\{t'_{ij} + \bar{W}(a_j, s_j)\}$, for all $i \in I$.

The proof for **Lemma 1** is given in Appendix A.

A bi-level optimization problem has an optimal solution when the lower level problem has a unique solution. (P2) is a pure strategy game with discrete decision spaces for each participant. In **Lemma 2**, we show that (P2) has a Nash equilibrium.

Lemma 2: The Nash equilibrium of (P2) exists.

The proof for **Lemma 2** is given in Appendix B.

According to Zhang et al. [44], a unique equilibrium almost always exists in (P2), except for few extremely symmetric cases. Hence, an optimal solution of the bi-level optimization problem almost always exists. The above bi-level optimization model can be rewritten as:

$$\text{(P3)} \quad \min_{\mathbf{x},\mathbf{s},\mathbf{y}} \sum_{j\in J}(c_j x_j + c_s s_j) + c_1 t_c \sum_{i\in I}\sum_{j\in J}$$

$$\left(t'_{ij} + \bar{W}(a_j, s_j)\right)\lambda_i^1 y_{ij} + c_0 t_c \sum_{i \in I}\sum_{j \in J}\left(t'_{ij} + \bar{W}(a_j, s_j)\right)\lambda_i^0 p_{ij}$$
$$s.t. \quad (2) \sim (6), (7) \sim (10)$$

It is easy to see that (P3) contains binary, general integer, and continuous decision variables. The objective function (1) is non-convex, and due to the network congestion, $\bar{W}(\cdot, \cdot)$ is highly nonlinear with respect to s_j, x_j, and y_{ij}, even by assuming the simplest M/M/1 queue at each established facility. The above implies that (P3) is a non-convex MINLP, which is difficult to solve in general. Further, equation (9) brings great difficulty to solving this problem.

IV. An ALNS Based Solution Method

With preliminary experiments, we found that state-of-the-art off-the-shelf solvers, such as BARON and scip, could not solve the problem to exact optimality even for small sizes (e.g., 4 demand nodes and 3 candidate facilities). When the instance size further increased slightly, the above solvers even could not yield a feasible solution under reasonable time or memory limitation (See Section V-A).

Moreover, it is difficult to apply decomposition methods, such as Generalized Benders Decomposition [45], for industry-sized instances because of the non-convexity in the objective function and equation (9). We resort to heuristics.

We design an construct-improve heuristic to solve the lower level problem when the upper level decision is fixed. We embedded this heuristic to a customized ALNS algorithm, which is designed to solve the upper level problem.

A. An ALNS Algortihm for Upper Level Problem

ALNS is a heuristic first proposed by Ropke and Pisinger [46]. This heuristic is widely used these years due to its good performance on VRP problems. We adapt its framework in our location optimization problem. The algorithm involves two main ideas: (1) define a neighbourhood of a feasible solution by the destroy-repair operator; (2) dynamically adjust the probability of selecting each destroy-repair operator (adaptive weight adjustment). We present the ALNS heuristic in Algorithm

A feasible solution can be easily reached by assuming that each candidate node has a charging station with maximum capacity, and valet-charging staff at each demand node are dispatched to charging stations evenly. Note that computing the objective value with a feasible solution $sol = (\mathbf{x}, \mathbf{s}, \mathbf{y})$ requires solving the lower level problem first. We present the solution method for the lower level problem in the next section. We elect to use a naive acceptance and stopping criterion as follows. We accept any inferior solution with a fixed probability prb. The algorithm terminates after G iterations.

Before introducing the destroy-repair operators, we first introduce a representation of the solution in the algorithm. In the algorithm, we use $\mathbf{y}' = \left\{y'_{ij}\right\}$ ($y'_{ij} \in [0, 1]$, $\forall i \in I, j \in J$) to represent the solution in place of $\mathbf{y} = \left\{y_{ij}\right\}$ in the model. Let $y_{ij} = \frac{x_j y'_{ij}}{\sum_{j \in J} x_j y'_{ij}}$, $\forall i \in I, j \in J$. Thus, Equation (3) is always satisfied. We assume $s \in [s_{min}, s_{max}]$.

Algorithm 1 ALNS

Input: A feasible solution $sol \in$ {solution}.
Output: Best found solution sol_{best}.

```
sol_best ← sol;
while stop-criterion not met do
    sol' ← sol;
    randomly choose a destroy-repair operator with probability weight w;
    Destroy(sol'), Repair(sol');
    if Obj(sol') ≥ Obj(sol) then
        sol ← sol';
    else
        sol ← sol' with probability prb;
    end if
    if Obj(sol') < Obj(sol_best) then
        sol_best ← sol';
    end if
    Update operator weight w;
end while
return sol_best;
```

We design five problem-driven destroy-repair operators by mimicking read-world situations, instead of employing standard random destroy-repair operators. We introduce their physical meanings and corresponding realization methods next.

1) **Re-construction.** Randomly choose a candidate node j. Build a charging station of random size at that point with probability prb_1, which means $x_j = 1$ and $s_j =$ rand($[s_{min}, s_{max}]$). Otherwise, do not build a charging station at that point, which means $x_j = 0$ and $s_j = 0$.
2) **Capacity expansion.** Randomly choose a candidate node j where $x_j = 1$. Let $s_j =$ rand($[s_j, \frac{s_j + s_{max}}{2}]$). This means expanding the capacity of the station.
3) **Capacity reduction.** Randomly choose a candidate node j where $x_j = 1$. Let $s_j =$ rand($[\frac{s_j + s_{min}}{2}, s_j)$. This means reducing the capacity of the station.
4) **More staff come.** Randomly choose a candidate node j where $x_j = 1$. For each demand node i, let $y'_{ij} =$ rand($[y'_{ij}, \frac{y'_{ij}+1}{2}]$). This means more staff come to the station from each demand node.
5) **Less staff come.** Randomly choose a candidate node j where $x_j = 1$. For each demand node i, let $y'_{ij} =$ rand($[\frac{y'_{ij}}{2}, y'_{ij}]$). This means less staff come to the station from each demand node.

We use a *roulette wheel selection principle* to select an operator from the above five. Denote by w_k is the wight of operator k, $k \in \{1, 2, \ldots, 5\}$. Let

$$P(\text{“Operator } l \text{ is selected”}) = \frac{w_l}{\sum_{k=1}^{5} w_k}, \quad \forall l \in \{1, 2, \ldots, 5\}.$$

Algorithm 2 Improving Heuristic

Input: A non-equilibrium state $\mathbf{p}' = \left(p'_{ij}\right)$,modified travel time t'_{ij}, arrival rate a_j, number of charging piles s_j, number of iterations N_1.
Output: Final equilibrium state $\mathbf{p} = \left(p_{ij}\right)$.

```
k ← 0;
for k ≤ N_1 do
    for i ∈ I, j ∈ J do
        T̄_ij ← t'_ij + W̄(a_j, s_j);
    end for
    for i ∈ I do
        j^- ← arg min_j T̄_ij;
        j^+ ← arg max_{j, p_ij ≠ 0} T̄_ij;
        p_ij+ ← p_ij+ − Δp;
        p_ij- ← p_ij- + Δp;
    end for
    k ← k + 1;
end for
return p;
```

Let $w_1 = w_2 = \cdots = w_5$ initially. Then at each iteration, we update each w_k as:

$$w_{k,d+1} = \begin{cases} w_{k,d}, & \text{if } \theta_d = 0 \\ (1-r)w_{k,d} + r\dfrac{\pi_{k,d}}{\theta_{k,d}}, & \text{if } \theta_d \neq 0 \end{cases}, \quad \forall k \in \{1, 2, \cdots, 5\},$$

where $\pi_{k,d}$ is the score of operator k at the d-th iteration, and $\theta_{k,d}$ is the number of times we have attempted to use operator k at the d-th iteration. Denoted by r ($r \in [0, 1]$) is the reaction factor, which quantifies how quickly the weight adjustment reacts.

B. A Construct-Improve Heuristic for Lower Level Problem

In this subsection, we describe how to solve the lower level problem with a construct-improve heuristic. Once the lower level problem is solved, the objective function value can be evaluated accordingly.

We first provide the intuition behind the heuristic. If a solution $\mathbf{p}' = \left(p'_{ij}\right)$ satisfies (7), (8) and (10), we call it a non-equilibrium state. We can obtain a solution to the lower level problem by improving $\mathbf{p}'$ while keeping other constraints satisfied. If the network were not at its equilibrium, some self-service customers would have the intent to change their station choices, i.e., from a station with longer service time to a station with shorter service time. If no one could benefit from changing his/her station, the network would have reached its equilibrium. Given any non-equilibrium state, the following *improving heuristic* (Algorithm 2) offers a computational procedure to find an equilibrium state. At each iteration, the final solution accuracy is relative to Δp. Decreasing Δp makes the result more accurate, but the corresponding N_1 needs to be set larger. Properly setting the values for the N_1 and Δp pair can be easily achieved by several rounds of preliminary experimentation.

Algorithm 3 Construction Heuristic

Input: modified travel time t'_{ij}, arrival rate a_j, number of charging piles s_j, number of iterations N_2.
Output: A non-equilibrium state $\mathbf{p}' = \left(p'_{ij}\right)$.

```
k ← 0;
p' ← 0;
Δp ← 1/N_2;
for k ≤ N_2 do
    for i ∈ I, j ∈ J do
        T̄_ij ← t'_ij + W̄(a_j, s_j);
    end for
    for i ∈ I do
        j* ← arg min_j T̄_ij;
        p_ij* ← p_ij* + Δp;
    end for
    k ← k + 1;
end for
return p';
```

Furthermore, we design a *construction heuristic* to construct a feasible non-equilibrium state (see Algorithm 3). Note that randomly generated $\mathbf{p}' = \left(p'_{ij}\right)$ may not satisfy equation (8), thus not necessarily a feasible state.

V. Numerical Experiments

In this section, we first compare our ALNS algorithm with a genetic algorithm (GA) and two state-of-the-art off-the-shelf solvers to verify the computational efficiency of our algorithm. We then conduct a case study based on Yangpu District, Shanghai. We further perform sensitivity analysis on several model parameters and conduct strategic planning for several future demand scenarios.

ALNS and GA are coded in C++, and all the instances are solved with ALNS and GA on a PC with 3.6 GHz CPU and 16 GB RAM. The same instances are solved with the two solvers on the NEOS server (neos-guide.org). NEOS (Network-Enabled Optimization System) server is a free Internet-based service for solving numerical optimization problems.

A. Solution Performance Comparison

We compare ALNS with the three benchmark solution methods to verify the efficiency of ALNS. We rewrite equation (9) as the following equivalent form

$$t'_{ij} + \bar{W}(a_j,\ s_j) - T_i^* \geq 0, \quad \forall i \in I, j \in J, \tag{11}$$

$$p_{ij}\left(t'_{ij} + \bar{W}\left(a_j,\ s_j\right) - T_i^*\right) = 0 \quad \forall i \in I, j \in J, \tag{12}$$

where the expected waiting time, $\bar{W}\left(a_j,\ s_j\right)$, is further expressed by the sum of queuing time and service time, i.e.,

$$\bar{W}\left(a_j,\ s_j\right) = W_{queue}\left(a_j,\ s_j\right) + W_{service}. \tag{13}$$

To make the optimization model compatible to the solvers, we elect to use the M/M/1 queue formula to approximate queue time $W_{queue}\left(a_j, s_j\right)$ at station j. The service rate of

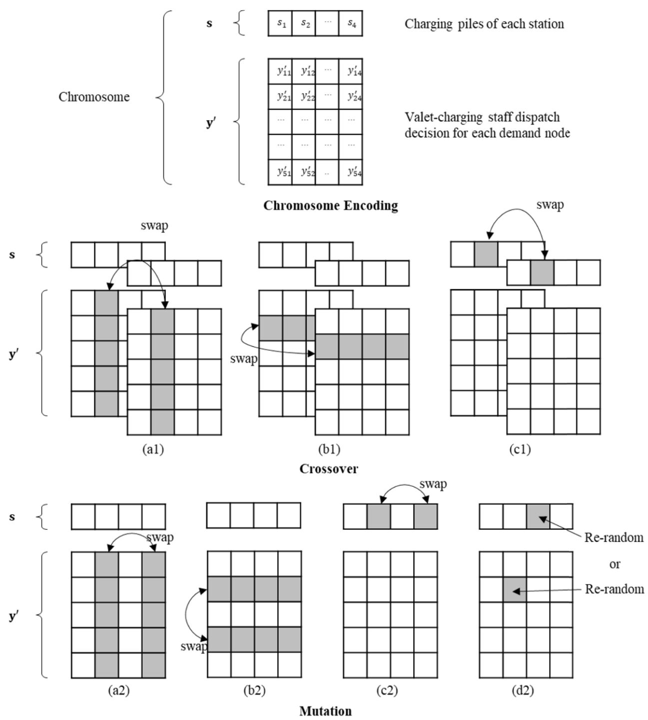

Fig. 2. Chromosome encoding and genetic operators in GA.

a single charging pile is μ, and the service rate of a charging station with s_j charging piles is regarded as $s_j\mu$. That is,

$$W_{queue}(a_j,\ s_j) \approx \frac{a_j/s_j\mu}{s_j\mu - a_j}. \tag{14}$$

The service time $W_{service}$ of a single EV is μ^{-1}, which is independent of the station. Hence, we have

$$\bar{W}(a_j,\ s_j) = W_{queue}(a_j,\ s_j) + W_{service} \approx \frac{a_j/s_j\mu}{s_j\mu - a_j} + \frac{1}{\mu}. \tag{15}$$

We also design a genetic algorithm (GA) to serve as a benchmark method. Genetic algorithms have great flexibility to solve optimization problem with complex constraints. Figure 2 provides an illustration of chromosome encoding, as well as crossover and mutation operations. Like the ALNS algorithm above, we use unnormalized $\mathbf{y}'$ instead of $\mathbf{y}$ to ensure that equation (3) is satisfied. For each $j \in J$, x_j can be determined by s_j, i.e., if $s_j > 0$, $x_j = 1$, otherwise $x_j = 0$. Therefore, we only need to encode $\mathbf{s}$ and $\mathbf{y}'$ into the chromosome. We design three crossover operators and four mutation operators. We use elitism strategy to retain better chromosomes.

We run the solution methods on ten test instance classes of different problem scales. Each instance class contains 10 instances. Demand nodes and candidate facility locations are uniformly distributed on the map with both length and width being $6\sqrt{|I|}$. The demand is proportional to $|I|$. We consider two measures: the time taken to solve the instance and the relative gap on the objective between different solution methods. We calculate the average result over the ten instances in each class. Because even start-of-the-art solvers may not always be able to find a feasible solution, we also record the number of instances with no feasible solution (NFS) for each class and exclude them when calculating the averages.

Due to the default settings of the solvers, BARON always stops at around 8 minutes 30 seconds and scip always stops at around 10 hours. Upon termination, both output their incumbent solution if it is found. For GA, we set the size of the population to be 80 and the maximum number of generations to be 2000. For ALNS, We set the maximum number of iterations to 10000. Under this setting, the GA and ALNS solution times are positively correlated to the instance size. With a small size, the instances only require tens of seconds for GA and several seconds for ALNS to solve.

ALNS will almost find better results every time. Even it takes more time to solve, the solution found by GA is somewhat worse than that of ALNS. The solver's performance will be more worse. The performance of Scip is very unstable. There are often situations where no solution can be found. The solution of BARON is more comparable to that of ALNS if the instance is small. But as the instance size increases, BARON's performance becomes less stable, needlessly to say it continues to be much slower than ALNS. There are situations where no solution can be found via BARON. In conclusion, the ALNS solution is of reasonable efficiency, effectiveness, and stability.

B. Case Study

1) A Case of Yangpu District, Shanghai: Yangpu District is northeast of the central city of Shanghai, and on the northwest bank of the lower reaches of Huangpu River. The total area of Yangpu District is 60.61 square kilometers, and it has a total permanent resident population of 1.31 million by the end of 2020. NIO Inc. is a global EV manufacturer. It was established in November 2014 and successfully listed on the New York Stock Exchange in September 2018. Based on the feedback from NIO Inc., we divide Yangpu District into 1km $\times$ 1km grids, and consider each grid as a demand node for a total of 53 demand nodes. We use the cell-based demand distribution estimated by NIO Inc. We designate the center of the cell to be the location of each demand node. In Figure 3, circles of different sizes are used to represent demand nodes with different demand levels. A larger circle implies more demand. There are also 18 candidate EV charging station locations, marked with vehicle icons.

We used the route planning service of AutoNavi Map (https://www.amap.com/) to obtain realistic travel time t_{ij} in our case study, which account for real-time road congestion information. Admitting the travel time differs by the time of the day and day of the week, we have taken the estimates at different times. The average of these extracted travel times was considered a good estimate for the strategic location decision optimization. More specifically, since we consider a long-term equilibrium of customer choices, we did not model the road congestion as a distribution over time, but rather used the mean value as the representative parameter value.

We set the service rate of a single charging pile to be $\mu = 1/50$ EV per minute. We set the total charging demand to be 7 EVs per minute and the ratio of self-charging customers to valet-charging customers is 7:3. We assume their operation cost coefficients c_0 and c_1 to be 27 CNY/h

TABLE I
COMPARISON OF ALNS, GA AND SOLVERS

$\lvert I\rvert \times \lvert J\rvert$	ALNS		GA		BARON			Scip		
	Gap(%)	CPU(s)	Gap(%)	CPU(s)	Gap(%)	# of NFS	CPU(s)	Gap(%)	# of NFS	CPU(s)
4×3	<1	<1	2	17	23	0	515	26*	3	36012*
6×3	<1	1	4	25	22	0	507	30*	2	36013*
6×4	<1	1	5	29	35	0	515	34*	5	36012*
8×4	0	2	7	36	31	0	510	32*	7	36012*
8×5	0	2	10	44	46*	1	521*	55*	2	36014*
8×6	<1	2	6	47	56*	1	506*	59	0	36012
10×5	0	2	13	51	44	0	520	55*	1	36013*
10×6	0	3	16	59	72*	2	514*	63	0	36014
10×7	<1	3	11	68	82*	3	509*	68	0	36013
10×8	0	3	18	75	99*	7	512*	76	0	36012

$\lvert I\rvert$ = Numbers of demand nodes; $\lvert J\rvert$ = Numbers of candidate nodes
Gap(%), Gap from best found solution.
# of NFS, The number of times no feasible solution was found in 10 cases.
*, Mean of cases with feasible solutions founded.

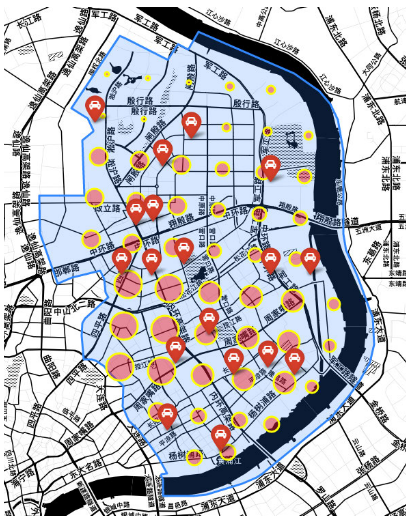

Fig. 3. Demand nodes and candidate nodes.

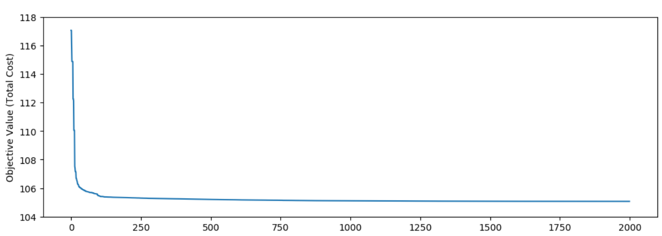

Fig. 4. Convergence curve of ALNS algorithm.

and 36 CNY/h, respectively, and set the decision epoch to be 1 year. We assume that all charging activities occur between 8 am to 8 pm every day, and 365 days a year, so there is an average of $365 \times 12 \times 60 = 262,800$ minutes over the entire decision epoch. We further assume that the construction cost of a charging station is 240,000 CNY, and each charging pile requires an additional variable cost of 96,000 CNY.

For the parameter selection of the construct-improve heuristic, we set N_1 to be 100 and N_2 to be 300. This can fit our data size and improve solution efficiency with a reasonable level of solution accuracy.

Figure 4 shows the convergence curve of ANLS algorithm on this case. Table II reports a breakdown of the ALNS

TABLE II
SOLUTION OF THE CASE

Number of charging stations built $\sum x_j$		7	Stations
Number of charging piles built $\sum s_j$		408	Piles
Cost	Construction cost	40.85	10^6 CNY
	Operation cost of self-service customers	40.62	10^6 CNY
	Operation cost of valet-charging customers	23.37	10^6 CNY
	Total cost	104.84	10^6 CNY
Self-charging customers	Travel time (avg)	14.1	min
	Waiting time (avg)	56.5	min
	Total time (avg)	70.6	min
Valet-charging customers	Travel time (avg)	14.3	min
	Waiting time (avg)	56.6	min
	Total time (avg)	70.9	min
Stations	Utilization rate ρ (avg)	83.8%	-
	Waiting time W (avg)	57.4	min

solution. According to this solution, 7 charging stations and a total of 408 charging piles would be built. As a result, valet-charging customers would have longer average travel time and average total time for charging their EVs. The utilization rate of the charging stations would be more than 85%, and the sum of average long-run waiting and charging times would be close to one hour.

2) Benefits of the Valet-Charging Business model: When the revenue generated by valet-charging surpasses the associated costs, a higher proportion of valet-charging can bring increased income to the company. In this section, we discuss the impact of valet-charging on customers' benefits and station utilization. To provide a clearer contrast of the effects resulting from valet-charging, we maintain the fixed construction plan obtained before and the total charging demand, but we vary the proportion of valet-charging customers, denoted as k.

The results are presented in Table III. We observe that as the proportion of valet-charging customers increases, the average travel time for all customers also increases. However, both the waiting time and total process time decrease. This implies that valet-charging services enable customers to travel to farther charging stations with shorter waiting times. For charging stations, the utilization rate increase and average waiting time decrease, indicating that resources are utilized more effectively. This shows that providing valet charging services yields positive externality.

TABLE III

IMPACT OF VALET CHARGING ON CUSTOMERS AND STATIONS

k	Avg Time of Self-Charging Customers (min)			Avg Time of Valet-Charging Customers (min)			Avg Time of All Customers (min)			Stations (avg)	
	Travel	Waiting	Total	Travel	Waiting	Total	Travel	Waiting	Total	ρ	W(min)
0%	14.49	57.28	71.77	-	-	-	14.49	57.28	71.77	0.8273	57.98
10%	14.63	57.03	71.66	14.03	56.89	70.92	14.09	56.90	70.99	0.8276	57.64
20%	14.22	56.70	70.92	14.15	56.58	70.73	14.16	56.60	70.77	0.8312	57.44
30%	14.09	56.46	70.55	14.29	56.6	70.89	14.23	56.56	70.79	0.8325	57.35
40%	14.46	56.36	70.82	14.86	55.61	70.47	14.70	55.91	70.61	0.8306	56.72
50%	14.45	55.82	70.27	15.46	55.53	70.99	14.96	55.68	70.63	0.8337	56.36
60%	14.41	55.57	69.98	15.87	55.46	71.33	14.99	55.53	70.52	0.8362	56.19
70%	14.62	55.69	70.31	16.03	55.45	71.48	15.04	55.62	70.66	0.8378	56.04
80%	14.94	55.33	70.27	15.99	55.49	71.48	15.15	55.36	70.51	0.8422	55.90
90%	15.12	55.24	70.36	16.48	55.23	71.71	15.26	55.24	70.50	0.8415	55.85
100%	-	-	-	16.25	55.19	71.44	16.25	55.19	71.44	0.8460	55.77

TABLE IV

ANALYSIS ON TOTAL DEMAND $\sum_i (\lambda_i^0 + \lambda_i^1)$

Demand (EVs/min)	Cost (10^6 CNY)			Avg Time of Self-Charging Customers (min)			Avg Time of Valet-Charging Customers (min)			Stations (avg)		
$\sum_i (\lambda_i^0 + \lambda_i^1)$	Construction	Operation	Total	Travel	Waiting	Total	Travel	Waiting	Total	s	ρ	W(min)
2	12.059	20.099	32.159	17.09	60.15	77.24	17.57	59.70	77.27	29.8	0.8240	61.86
3	18.639	28.553	47.192	14.88	58.26	73.14	14.91	58.29	73.20	30.7	0.7968	59.35
4	23.839	38.136	61.975	15.07	58.14	73.21	15.43	58.01	73.43	39.3	0.8397	58.81
5	29.099	46.685	75.783	14.57	57.76	72.34	15.52	57.52	73.03	57.8	0.8408	58.29
6	34.499	55.549	90.047	14.96	57.48	72.44	15.07	57.53	72.60	68.6	0.8579	58.42
7	40.848	63.992	104.84	14.09	56.46	70.55	14.29	56.60	70.89	58.3	0.8378	57.35
8	45.978	73.479	119.457	14.59	56.00	70.59	14.63	55.99	70.63	65.3	0.8677	56.34
9	51.578	82.378	133.955	14.99	55.33	70.32	15.21	55.23	70.44	73.3	0.8629	55.86
10	57.557	90.867	148.424	13.73	55.98	69.71	14.15	55.95	70.11	63.6	0.8615	56.73
11	63.057	99.583	162.640	13.59	55.50	69.09	14.78	55.69	70.47	69.7	0.8638	56.20
12	68.857	107.457	176.313	13.81	54.87	68.69	14.09	55.01	69.10	76.1	0.8562	55.90
13	73.117	118.521	191.638	14.68	55.00	69.68	15.62	55.17	70.79	91.0	0.8857	55.19
14	80.336	125.194	205.530	13.18	55.40	68.58	13.73	55.29	69.02	72.6	0.8668	55.98
15	84.616	133.016	217.633	14.24	54.87	69.11	15.03	55.00	70.02	105.4	0.8845	55.34

This phenomenon aligns with economic intuition. When individuals in a system aim to minimize their own interests, there might result in a *prisoner's dilemma* situation, preventing the attainment of global optimality. Thus, valet charging promotes more efficient resource utilization and improves customers' charging convenience while maximizing company profits.

Note that we can extend the conclusions to other scenarios. For example, with the advent of Autonomous driving technologies, the entire charging process would only involve electric AVs without drivers. We think the valet-charging service would turn to a "centralized charging routing and scheduling" service provided by the EV company. This new service associated with AVs would be similar to valet-charging, where the only difference is that no real valet staff is needed. We argue that this new service benefits from increasing the average utilization rate of the charging stations, which is conceptually similar to the effect of having the valet-charging service. This is a preliminary analysis. In practice, a comprehensive consideration of AVs requires delving into numerous intricate details. For instance, many valet parking facilities that could support valet charging are located underground, leading to uncertainties arising from communication issues [47]. We leave a numerical study on the new service associated with AVs in the future work.

3) Impact of Valet- and Self-Charging Demand Changes: The number of private EVs is fast growing and relevant technologies are rapidly evolving. For several parameters in the above study, even if we can estimate them well for now, they may change in the near future. Therefore, in this subsection, we assess the potential economic and service performance impacts of changes in these parameters.

First, we vary the total demand. We keep the demand ratio of the two types of customers, i.e., $\sum_i \lambda_i^0 / \sum_i \lambda_i^1$, unchanged at 7:3. However, we vary the total demand $\sum_i (\lambda_i^0 + \lambda_i^1)$ to take on values 2, 3, $\ldots$, 15 EVs per minute, and observe the impact of this variation on the solution and service measures. We report our results in Table IV and describe major observations in the following.

As the total demand increases, the value of each component in the objective function increases accordingly. In terms of service operations, the average long-run travel time of either type of customers would decrease accordingly. This is because more charging stations would be built and the time to visit them would decrease. In addition, the average long-run travel time among valet-charging customers is always longer than the average among self-charging customers. This is because valet-charging service is controlled by the company and its recipients can be arranged accordingly to help improve system-wide service quality, e.g., reducing the waiting times for charging. Next, individual optimality among valet-charging

TABLE V
ANALYSIS OF THE PROPORTION OF VALET-CHARGING CUSTOMERS k

k	Cost (10^6 CNY)			Avg Time of Self-Charging Customers (min)			Avg Time of Valet-Charging Customers (min)			Stations (avg)	
	Construction	Operation	Total	Travel	Waiting	Total	Travel	Waiting	Total	ρ	W(min)
10%	40.438	60.516	100.954	14.77	55.73	70.50	16.68	55.74	72.42	0.8600	56.19
20%	40.638	62.113	102.751	14.86	55.32	70.18	15.55	55.29	70.83	0.8542	56.00
30%	40.848	63.992	104.84	14.09	56.46	70.55	14.29	56.60	70.89	0.8378	57.35
40%	40.438	66.536	106.974	14.95	55.74	70.69	15.37	55.80	71.18	0.8691	55.79
50%	41.518	68.736	110.254	14.52	56.14	70.66	15.46	56.09	71.55	0.8325	56.80
60%	41.818	70.960	112.778	14.37	56.29	70.67	15.74	56.07	71.82	0.8400	56.31
70%	41.678	72.723	114.401	15.52	55.24	70.76	16.03	55.35	71.38	0.8309	55.64
80%	42.158	75.253	117.411	14.29	56.47	70.76	15.45	56.51	71.95	0.8310	56.71
90%	42.458	77.397	119.855	14.22	56.38	70.60	15.70	56.33	72.03	0.8282	56.36

staff is sacrificed for global optimality of the system. Consequently, valet-charging customers would be assigned to charging stations farther away to relieve the congestion at nearby stations. As a result, self-charging customers would benefit. Finally, as the total demand increases, the average long-run waiting time would decrease for both types of customers, thus the total time including travel and waiting would also decrease.

In terms of facility construction, the average capacity and utilization of each charging station would increase as the total demand increases. Meanwhile, the demand increase would lead to reduction on the average long-run waiting time. Since the growth rate of the capacity is lower than that of the total demand, the utilization would increase. Meanwhile, the waiting time would increase with the utilization and decrease with the capacity by (13). We find that the capacity increase is less than the utilization increase, which is attributed to efficient arrangement of valet-charging customers. Therefore, the waiting time would reduce along with the demand increase. In summary, when demand increases, resources would be utilized more efficiently, and customers would have shorter waiting times.

Next, we vary $k := \frac{\sum_i \lambda_i^1}{\sum_i (\lambda_i^0 + \lambda_i^0)}$, the proportion of customers that use valet charging. We keep the total demand $\sum_i (\lambda_i^0 + \lambda_i^1)$ constant with 7 EVs per minute. We report our results in Table V and describe major observations in the following. First, since the operating cost coefficient of valet-charging customers c_1 is higher than that of self-charging customers c_0, as k increases, the operating cost would increase accordingly. Then same as the result of the demand increase, the waiting time of self-charging customers would be smaller than that of valet-charging customers. Second, the resource utilization would decrease along with the increase of k. This is because when more valet-charging customers become available, more effectively arrangement for them could be done to use the system resource in a more efficient way. However, interestingly, we find that despite the increase in k, there would be no significant change in the expected waiting times of the two types of customers. This is because the added valet-charging customers could be efficiently allocated according to the demand, so it would not likely cause a significant change in the expected waiting time.

4) Impact of Operating Cost Changes: Operating cost includes valet-charging labor cost and charging inconvenience penalty for self-charging customers. The unit-time operating costs of the two types of customers, c_0 and c_1, are set to be $(c_0, c_1) = (27,\ 36)$ CNY/h at the baseline. We vary each parameter independently to take on values 0.1, 0.2, 0.5, 2, 5, 10 times of the baseline value, while fixing the other values at the baseline. We report our results in Table VI and describe major observations in the following. An increase in either c_0 or c_1 would lead to an increase in the construction cost. Consequently, more charging stations would be established to reduce the total charging time to offset the construction cost increase. In fact, all time-related measures in the objective function would decrease due to the same reason, as well as the average utilization rate among stations. The average total charging time for a valet-charging customer would still be longer than that of a self-charging customer. However, we find that the total charging time gap would decrease when c_1 increases more in relation to c_0. If c_1 is significantly greater than c_0, then this gap would be very small.

5) Construction Planning Analysis: In this subsection, we evaluate two construction strategies in response to future demand increase. Strategy 1 is to build charging stations according to the current demand, and expand the charging infrastructure when facing demand increase in the future. Strategy 2 is to build charging stations according to the forecast of future demand at the beginning of construction.

Study 1 – What if the total demand increases in the future?

We consider this planning matter over two periods. We assume that the total demand remains constant at each period, but there is a difference between the two period. We set the total demand to be $\lambda_c = 7$ EVs/min over period 1 and the demand is projected to increase to $\lambda_f \in \{8, 9, \ldots, 15\}$ EVs/min over period 2. We also assume that the proportion of customers that use valet-charging remains at $k = 30\%$.

To compute the cost of strategy 1, we first solve the optimization problem under the total demand of period 1 to obtain an initial construction plan $\mathbf{s} = \{s_j^{(1)}\}$ and its corresponding cost, termed as *period 1 cost*. We then solve the optimization problem under the total demand of period 2 and subject to additional constraints $s_j \geq s_j^{(1)}$ for all charging stations j. We thus compute *period 2 cost* to be the sum of the operating cost of period 2 and the incremental construction cost.

To compute the cost of strategy 2, we first solve the optimization problem under the forecast total demand of period 2 to obtain a one-time construction plan $\mathbf{s} = \{s_j^{(2)}\}$ that would be applied to both periods. To compute the operating cost,

TABLE VI
ANALYSIS OF UNIT-TIME OPERATING COST c_0 AND c_1

Operating Cost (CNY/h)		Cost (10^6 CNY)			Avg Time of Self-charging Customers (min)			Avg Time of Valet-charging Customers (min)			Gap of Total Time (min)	Stations (avg)	
c_0	c_1	Construction	Operation	Total	Travel	Waiting	Total	Travel	Waiting	Total		ρ	W(min)
2.7	36	39.018	29.171	68.189	15.08	59.83	74.91	15.26	59.73	74.99	0.08	0.8784	61.85
5.4	36	37.798	34.041	71.839	17.47	58.67	76.14	17.43	58.73	76.15	0.01	0.9161	60.69
13.5	36	38.998	45.118	84.116	16.09	56.41	72.49	16.40	56.42	72.82	0.33	0.8952	56.80
27	36	40.848	63.992	104.84	14.09	56.46	70.55	14.29	55.60	70.89	0.43	0.8378	57.35
54	36	41.178	104.238	145.416	14.32	55.60	69.91	14.44	55.67	70.11	0.2	0.8410	56.47
135	36	47.118	216.870	263.988	13.76	53.34	67.10	14.44	53.38	67.82	0.72	0.7432	53.43
270	36	50.778	406.210	456.988	14.10	52.16	66.26	14.91	52.30	67.21	0.95	0.6839	52.34
27	3.6	39.778	44.210	83.988	15.22	56.31	71.54	22.37	60.85	83.22	11.68	0.8802	61.19
27	7.2	39.238	46.513	85.751	14.56	57.17	71.73	17.34	57.37	74.71	2.98	0.8899	57.84
27	18	40.238	53.365	93.603	15.91	55.61	71.51	16.39	55.63	72.02	0.51	0.8600	56.59
27	36	41.078	63.992	105.070	14.09	56.03	70.12	14.58	55.97	70.55	0.43	0.8530	56.11
27	72	41.578	87.329	128.907	14.79	55.41	70.20	15.14	55.31	70.44	0.24	0.8372	55.81
27	180	43.878	154.198	198.076	14.79	54.14	68.93	14.92	54.09	69.01	0.08	0.7954	54.18
27	360	45.438	264.335	309.773	14.92	52.99	67.90	15.01	52.94	67.95	0.05	0.7704	53.06

TABLE VII
COST WITH RESPECT TO THE INCREASE IN TOTAL DEMAND (10^6 CNY)

λ_f	Strategy 1			Strategy 2			Gap		
	prd 1	prd 2	NFV	prd 1	prd 2	NFV	prd 1	prd 2	NFV
8	105.070	78.966	205.050	107.757	73.479	202.787	2.687	−5.487	−2.263
9	105.070	93.948	220.032	112.759	82.378	217.689	7.689	−11.570	−2.343
10	105.070	108.566	234.650	117.512	90.867	231.881	12.442	−17.699	−2.769
11	105.070	122.694	248.778	122.440	99.583	246.511	17.370	−23.111	−2.267
12	105.070	136.123	262.207	128.205	107.457	261.303	23.135	−28.666	−0.904
13	105.070	151.074	277.158	132.950	118.521	278.061	27.880	−32.553	0.903
14	105.070	164.765	290.849	139.288	125.194	292.340	34.218	−39.571	1.491
15	105.070	176.837	302.921	143.462	133.016	305.170	38.392	−43.821	2.249

Gap = Strategy 2 − Strategy 1

TABLE VIII
COST WITH RESPECT TO THE INCREASE IN VALET-CHARGING CUSTOMERS PROPORTION (10^6 CNY)

k_2	Strategy 1			Strategy 2			Gap		
	prd 1	prd 2	NFV	prd 1	prd 2	NFV	prd 1	prd 2	NFV
40%	105.07	66.233	192.317	105.005	66.536	192.542	−0.065	0.303	0.225
50%	105.07	69.341	195.425	106.179	68.736	196.1508	1.109	−0.605	0.7258
60%	105.07	72.177	198.261	106.949	70.96	199.2988	1.879	−1.217	1.0378
70%	105.07	73.72	199.804	106.442	72.723	200.4534	1.372	−0.997	0.6494
80%	105.07	76.897	202.981	107.324	75.253	204.0418	2.254	−1.644	1.0608
90%	105.07	79.355	205.439	107.379	77.397	206.2518	2.309	−1.958	0.8128

Gap = Strategy 2 − Strategy 1

we resolve the optimization problem under the total demand of each period, respectively, and subject to additional constraints $s_j = s_j^{(1)}$ for all charging stations j. In this case, *period 1 cost* is the sum of the construction cost of period 1 and the operating cost of the period; whereas *period 2 cost* is just the operating cost of period 2.

We consider the length of each period to be one year and use an opportunity cost rate $i_0 = 20\%$ to quantify the monetary value of time. We compute the Net Future Value (NFV) to compare the two strategies, i.e., NFV = period 1 cost $\times$ $(1 + i_0)$ + period 2 cost. We report our results in Table VII.

When comparing strategies 1 and 2 in terms of period 1 cost, strategy 1 incurs a lower cost than strategy 2, since strategy 1 would build the infrastructure more closely following the present demand. However, when comparing the two strategies in terms of period 2 cost, since strategy 2 would build the infrastructure more closely following the future demand, strategy 1 would lead to a higher construction cost and a higher operating cost than strategy 2. Hence, there would be a tradeoff between the two strategies. In our case, when the forecast demand of period 2 is small (8 – 12 EVs/min), strategy 1 is less costly overall; otherwise, strategy 2 is a better choice.

Study 2 – What if the proportion of valet-charging customers increases in the future?

We consider an increase of the proportion of valet-charging customers in the future. We still consider this planning matter over two periods. We assume that the total demand is kept at 7 EVs/min. We further assume $k_1 = 30\%$ in period 1, and k increases to $k_2 \in \{40\%, 50\%, \ldots, 90\%\}$ in period 2. We apply the same two strategies as before. We report our results in Table VIII.

Strategy 2 is always worse than strategy 1 regardless. As noted before, this is because valet-charging customers can be allocated more flexibly than self-charging customers. In this study, period 1 has more self-charging customers compared to period 2. Hence, strategy 1, which focuses on period 1 more than strategy 2, would naturally achieve a lower cost.

VI. DISCUSSION OF CHOICE BETWEEN SELF- AND VALET-CHARGING

We admit it is likely people to become more sensitive to charging process time as the technology becomes mature and its implementation in real world becomes more noticeable. The price sensitivity may significantly affect their choices on the charging station. The decision between self- and valet-charging will move from exogenous to endogenous. In other words, the assumption could become less justifiable as the technology moves along. We thus added the following discussion in the revised manuscript to point out the limitation of the current work depending on the exogenous assumption.

We consider the following utility functions:

$$U_V = R - F(P)$$
$$U_S = R - G(T) - \Gamma$$

where U_V represents the utility of choosing valet-charging, incorporating the reward of charging an EV (denoted as R)

and a disutility function of service cost P (denoted as $F(P)$). U_S is the utility of choosing self-charging; $G(T)$ is a disutility function of charging process time T, consisting of both travel time and waiting time; and Γ represents the charging inconvenience. We assume that Γ follows a distribution with a cumulative distribution function (CDF) H. When $U_V > U_S$, in other words, if $\Gamma > F(P) - G(T)$, users choose to use valet-charging service, and vice versa.

We assume that the total demand at node i is denoted as λ_i. At equilibrium, self-charging customers at demand point i have a charging process time of T_i^*, and we assume that $\Gamma_i^* = F(P) + G(T_i^*)$. Consequently, the demand of the two types of customers at demand node i can be expressed as:

$$\lambda_i^0 = \lambda_i H(\Gamma_i^*)$$
$$\lambda_i^1 = \lambda_i \bar{H}(\Gamma_i^*) = \lambda_i (1 - H(\Gamma_i^*))$$

Under the above, we can incorporate the customer choice between self- and valet-charging into the model. Currently, there are several challenges as we move forward. First, we need explicit expression of functions F(P), G(T), and the distribution H. To suggest meaningful management insights, we would need to conduct thorough and comprehensive customer surveys to obtain sufficient data to fit H. Second, the resultant lower-level problem would become a double equilibrium problem, which becomes more challenging to analyze than the problem discussed in our current paper. We would need to prove the existence and uniqueness of equilibrium to ensure the feasibility of the upper-level location problem. Third, even if the problem is feasible, a new efficient algorithm has to be designed for the lower-level problem. For example, we could consider an alternating iterative algorithm, which alternately computes the equilibrium between choosing the self- and valet-charging services for customers, and the equilibrium among self-charging customers in their choice of charging stations.

Due to the above challenges, we consider this part as a future research direction.

VII. Conclusion

In this paper we present a novel facility location optimization problem in the area of electric vehicle charging infrastructure development, by considering two different EV-charging service modes (i.e., self-charging and valet-charging). While previous studies on EV charging station location optimization considered these charging service modes, no study incorporated them simultaneously in the same charging station location optimization model. The model formulated in this paper is a bi-level location optimization model, where the lower level problem is a game that models self-charging customers' station choice behaviour. Existing commercial solvers can only solve this model on a very small scale. To overcome this difficulty, we design a construct-improve heuristic to solve the lower level game and embed it into an adaptive large neighbourhood search to solve the upper level location-allocation problem. Note that in our method, the queuing performance measure, i.e., expected waiting time, is evaluated repeatedly in both the upper and lower level problems. Thus, the algorithm is not affected much for solving discrete location optimization problems where the underlying queue is assumed to be G/G/1 or M/G/s or more complex, as long as the queuing outcome can be expressed with a closed-form expression of the number of servers and expected demand arrival rate.

We conduct a case study in a sizable district of Shanghai, and examine how sensitive the optimal location solution is to changes in the total demand, demand distribution between the two customer types, and hourly operating costs. In response to possible changes in future demand, we propose and compare two construction planning strategies. We draw meaning insights including a framework to help charging assistance service providers choose strategies under different opportunity cost rates and demand forecasts.

In the future, we propose to pursue the following research items. First, the impact of charging time on the utility of self-charging users is expected to become more significant in the future. Hence, it is worthwhile considering the choice between self- and valet-charging for the users. Second, we will consider additional EV charging modes such as battery swapping in the facility location context. The introduction of battery swapping stations will not only result in multiple service modes, but also expand the options and strategies for charging infrastructure development. It is further challenging to model diverse customer behaviors in choosing these service modes and conduct data-driven modeling.

Appendix A
Proof of Lemma 1

For all $i \in I$, if $T_i^* \neq \min_j\{t'_{ij} + \bar{W}(a_j, s_j)\}$, we must have $T_i^* > \min_j \left\{t'_{ij} + \bar{W}(a_j, s_j)\right\}$, and there must exist one j_0 such that $j_0 = \arg\min_j\{t'_{ij} + \bar{W}(a_j, s_j)\}$ and $t'_{ij_0} + \bar{W}(a_{j_0}, s_{j_0}) < T_i^*$. By equation (9), $t'_{ij_0} + \bar{W}(a_{j_0}, s_{j_0}) = T_i^*$ if $p_{ij_0} > 0$. Then we know that $p_{ij_0} \leq 0$. Since $p_{ij_0} \in [0, 1]$, it implies that $p_{ij_0} = 0$. This derivation contradicts to $t'_{ij_0} + \bar{W}(a_{j_0}, s_{j_0}) > T_i^*$ if $p_{ij_0} = 0$. The lemma result follows. □

Appendix B
Proof of Lemma 2

Consider the following game. Each demand node i is regarded as a participant in the game. Fraction $\{p_{ij}\}_j$ is the strategy for participant i. Payoff for each participant i is $\left(-\max_{j\in J, p_{ij}>0}\left\{t'_{ij} + \bar{W}(a_j, s_j)\right\}\right)$, which means participant i wants to minimize the longest total process time that a self-charging customer from demand node i takes.

$\bar{W}(a_j, s_j)$ is monotonically increasing with p_{ij}. Thus, in this game, when a Nash equilibrium is reached, self-charging customers from the same demand node i will have the same total processing time, and this time must be the minimum one among all stations. Otherwise, participant i could adjust his strategy by decreasing p_{ij}'s with a higher processing time and increasing p_{ij}'s with lower processing time to reach a better payoff. Therefore, this game and (P2) can be described in the same mathematical form.

Note that this new game is a pure strategy game with continues strategy spaces. It is easy to check that this continuous game satisfies the conditions proposed by Reny [48]. Therefore, a Nash equilibrium of this game and (P2) exists. □

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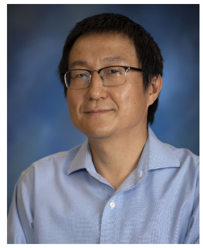

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