2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)

Online Price-based Vehicle-to-Station Recommendations for EV Battery Swapping

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***Abstract*—We present a framework to integrate the choice of electric vehicle (EV) customers into the vehicle-to-station (V2S) routing problem for battery swapping. Instead of assigning stations to each EV customer directly, we provide a recommendation, including a list of station-price pairs that are available for EV battery swapping services, for customers to choose. Compared with assignment, recommendation is closer to reality for scenarios lacking incentives for the cooperation of customers such as the battery swapping services of private EVs. In this paper, we model customers' behavior by their choice probability given a particular recommendation, which can be readily obtained based on analytics techniques once the real data are available. We propose an online V2S recommendation algorithm, which aims at maximizing the expected revenue of a group of battery swapping stations (BSSs) and ensuring the quality service of EV customers. Leveraging the primal-dual analysis, we show that the loss of revenue due to online EV arrivals is theoretically bounded by a provable competitive ratio. Moreover, numerical tests also validate that the proposed online algorithm can significantly outperform benchmarks in maximizing revenues in online settings.**

***Index Terms*—battery swapping, online recommendation, choice model**

I. Introduction

A. Motivation

Transportation electrification, namely the process of integrating a large fleet of public and private electric vehicles (EVs) into the transportation system, is conceived to be a promising midterm solution to reducing the emission of greenhouse gases and alleviating the demand on fossil fuels. As a key component of the electrification of transportation, various infrastructures for supporting EV refueling have been implemented and commercialized all over the world. Specifically, current EV refueling techniques can be mainly categorized into two aspects, namely, the plug-in charging mode, e.g., [1], [2], and the battery swapping mode, e.g., [3], [4].

Compared with plug-in charging, which usually takes hours, battery swapping can be finished within several minutes. EVs with swappable batteries can swap their depleted batteries (DBs) for fully-charged batteries (FBs) at battery swapping stations (BSSs). The DBs can be either charged locally at the BSSs or gathered to be charged centrally. Currently, without proper coordination and sufficient information of BSSs, EV customers with demand for FBs will choose a BSS based on their preference, which may lead to unpleasant service experience (no battery) or even traffic congestion. These problems trigger a lot of research on vehicle-to-station (V2S) routing problems, where EVs need to be strategically routed to BSSs. For instance, an increasing amount of research has been performed on the V2S assignment problem, where the system operator directly assigns each EV customer to a refueling station with the purpose of achieving a certain system-wide performance. However, private EVs are not committed to a system operator and lack an incentive to cooperate. Thus, it is more interesting and practical to design a V2S routing framework by *recommendation* rather than *assignment*. By V2S recommendation, each EV customer is ensured to have a FB at any recommended BSS, which attracts EV customers to participate. Furthermore, in this paper, we consider a more practical situation where EV customers submit battery swapping requests randomly (both in spatial and temporal domains) and sequentially. We formulate the V2S problem as an online V2S recommendation problem, whose main task is to make real-time recommendations for each EV customer without knowing any future information. Before introducing the technical details of our V2S recommendation problem, in the following we present the related work.

The work was supported by the Innovation and Technology Fund (Project No. ITF/447/16FP) established under the Innovation and Technology Commission of the Hong Kong Special Administrative Region, China.

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B. Related Work

There is a large amount of research performed on plug-in charging. For instance, some literature aims to promote the performance of power grid by leveraging vehicle-to-grid service (V2G). [5] estimated the frequency regulation capacity for V2G services by EV charging scheduling. [6] investigated on decentralized charging control of large populations of EVs and solved the problem through a Nash equilibrium. There are also studies on EV refueling station placement. [7] formulated the EV charging station placement problem and proposed a detailed case study of Hong Kong. Some other research worked on optimizing EV charging schedule with the consideration of time-of-use electricity price in regulated market [8].

Battery swapping requires less refueling time compared with plug-in charging, which makes battery swapping a good complementary to plug-in charging. However, since the restriction of the same type of battery, battery swapping is not as commonly implemented as plug-in charging mode. A relatively small number of literature involves battery swapping. [9] proposed a mixed queuing network (an open queue of EVs and a closed queue of batteries) to model a framework of battery swapping. [10] studied an optimal charging scheduling problem to minimize the charging cost, in the meanwhile, satisfy the FB demand for battery swapping.

To solve the V2S routing problem, some work contributes to solving the problem via V2S assignment. For instance, the authors of [11] and [12] studied the centralized and distributed solutions, respectively, to the optimal scheduling problem for battery swapping. The solution of [11] and [12] can achieve a minimal weighted sum of travel distance and electricity generation cost. [13] designed an online bipartite matching approach to deal with the battery swapping assignment problem, where a centralized system operator would assign BSSs to each EV customer. However no theoretic performance guarantee can be shown for the proposed online algorithm. [14] formulated a V2S assignment problem for on-demand mobility system based on a pricing signal. The authors constructed a bi-level optimization problem with the assumption of a potential distribution of customers' choice. However, from a more practical point of view, we take into account customers' choice model and formulate a V2S recommendation problem in this paper.

Different from the aforementioned assignment-based V2S routing, [15] presented an efficient charging scheduling algorithm to recommend charging stations to EV customers, in order to minimize customers' traveling time. [16] provided a real-time charging station recommendation system for EV taxis based on their historical charging data to minimize the total waiting time at charging stations. These research are well performed on plug-in charging mode, where the waiting time as a key component is carefully considered. However, in our paper, we focus on V2S recommendation for battery swapping, where the number of FBs takes an important role, which differentiates our work from the above literature.

C. Our Contribution

Motivated by the above problems, this paper studies an online V2S recommendation problem based on estimated parameters from data analytics without any future information and makes the following contributions. First, we formulate and solve the V2S problem taking into account customers' behavior by recommending BSSs to EVs, which is a more practical setting compared with V2S assignment. Second, we design an online primal-dual algorithm, which guarantees a theoretical performance bound. Third, we present a detailed case study based on the Hong Kong map to validate our theoretical analysis.

II. V2S RECOMMENDATION FRAMEWORK

We consider the V2S recommendation problem for BSSs geographically distributed in different locations of one area. Let $\mathcal{M} := \{1, \ldots, M\}$ denote the set of BSSs. At the beginning of the service time horizon (e.g., one day), each station m has a total number of k_m FBs in store for battery-swapping services. These initial FBs can be obtained by either overnight local charging in BSSs or delivery from a remote charging facility, where collected DBs from all BSSs are charged to FBs centrally for dispatching to different BSSs. We consider the scenario that FBs only come to BSSs at the beginning of the service time horizon, namely, no replenishment. Each BSS can offer battery swapping service with different prices. Let $\mathcal{R}_m := \{r_m^1, \ldots, r_m^{J_m}\}$ be the possible price levels of BSS m and $\mathcal{J}_m := \{1, \ldots, J_m\}$ be the index set of price levels. Without loss of generality, prices are ranked from low to high with the increase of index. Within this area, a population of

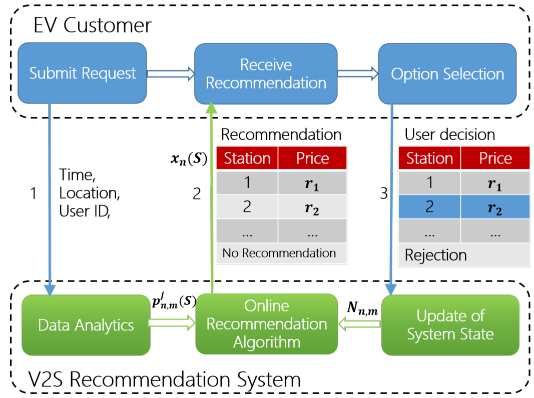


Fig. 1: Illustration of the work flow for the V2SRS.

EV customers are able to adopt battery swapping as their refueling methods complementary to plug-in charging. Let $\mathcal{N} := \{1, \ldots, N\}$ denote the set of EVs, which are indexed based on their arrival sequence.

A V2S recommendation system (V2SRS) is capable of communicating with EV customers, and serves as the proxy of all BSSs aiming to maximize the total revenues of all BSSs. As illustrated in Fig. 1, interactions between V2SRS and each EV customer are as follows: 1) EV customer n submits a request for battery swapping. Upon receiving the customer information (e.g., time, location and customer ID) associated with the request, the customer's choice probability $p^j_{n,m}(S)$ can be estimated based on data analytics, which will be explained in details in next Sec. II-A. (2) combining this choice probability and the current system state (i.e., the inventory of FBs at all stations), the V2SRS recommends a feasible subset $S \subseteq \mathcal{A}$ of (station, price) combinations with a probability $x_n(S)$ to the customer n, in order to maximize the potential revenue from customer n. Here, we denote the set of all possible combinations by $\mathcal{A} := \{(m, j) | m \in \mathcal{M}, j \in \mathcal{J}_m\}$. (3) after receiving the recommendation S from V2SRS, the customer n accepts one of combinations $(m, j) \in S$ with a probability $p^j_{n,m}(S)$. If the customer n accepts the combination (m, j), then the inventory of FBs of station m decreases by 1, and the system earns a revenue r^j_m. Otherwise, the customer n rejects all recommendations and chooses alternative refueling methods.

A. Customer Choice Model

We model the option selection of EV customer n by $p^j_{n,m}(S)$, quantifying the probability that EV n chooses station m with price r^j_m given the recommendation S. This conditional probability depends on the EV customer's personal preference (e.g., based on service quality at certain BSS), and sensitivity on time and cost (e.g., driving time from the current location to the chosen station, and the service price). For a rational customer, given the recommendation S, $p^j_{n,m}(S)$ satisfies

$$\sum_{(m,j)\in S} p^j_{n,m}(S) \leq 1, \tag{1}$$

$$p^j_{n,m}(S) \leq p^{j'}_{n,m}(S), \quad \forall j' \leq j, \forall m. \tag{2}$$

Inequality (1) holds by definition of conditional probability and $1 - \sum_{(m,j)\in S} p^j_{n,m}(S)$ is the probability that EV customer rejects all the options in the recommendation S.Inequality (2) means that for the same station in a recommendation, customer prefers a lower price. By intuition, the probability to accept a nearby station with a low price will be higher than to accept a remote station with a high price. Our choice model is consistent with the principles of the multinomial logit choice model. We have to point out that the choice probability $p^j_{n,m}(S)$ can be obtained from an online learning process, which is not our main focus in this paper.

B. Offline Formulation for V2S Recommendation Problem

The goal of the V2SRS is to maximize its total revenue before the next replenishment of FBs. We start from formulating an offline revenue maximization problem by assuming the knowledge of arrival information of all EV customers, namely, the arrival sequence $\mathcal{N}$ and the corresponding choice probability $\{p^j_{n,m}(S)\}_{S,(m,j),n}$. $x_n(S)$ is the decision variable determining the probability that the system will recommend S to customer n. The offline revenue maximization problem can be formulated as follows

$$\max_{x_n(S)} \quad \sum_{n=1}^{N} \sum_{S \subseteq \mathcal{A}} x_n(S) \sum_{(m,j)\in S} r^j_m p^j_{n,m}(S) \tag{3}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} \sum_{S \subseteq \mathcal{A}} x_n(S) \sum_{j:(m,j)\in S} p^j_{n,m}(S) \le k_m, \ m \in \mathcal{M}, \tag{4}$$

$$\sum_{S\subseteq \mathcal{A}} x_n(S) \le 1, \ n \in \mathcal{N}, \tag{5}$$

$$x_n(S) \ge 0, \ n \in \mathcal{N}, S \subseteq \mathcal{A}. \tag{6}$$

The offline problem is an efficiently solvable linear program (LP). The objective is to maximize the expected revenue by serving all customers. Note that $\sum_{(m,j)\in S} r^j_m p^j_{n,m}(S)$ is the expected revenue given the recommendation S. Constraint (4) is the inventory constraint, which restricts the total number of consumed FBs in each BSS to be no more than its initial FB inventory. Constraint (5) further restricts that sum of the probabilities for the system to make different recommendations is no greater than 1. Note that V2SRS may offer no recommendations when constraint (5) is not binding. We denote the optimal total revenue by OPT.

C. Online Algorithm for V2S Recommendation Problem

In the online setting, for each arriving EV customer n, the system needs to determine the recommendation based on the current system information (e.g., the number of consumed FBs in each station before serving customer n) and its choice probability $p^j_{n,m}(S)$.

The basic idea behind our design of the online algorithm is straightforward. When there is high inventory of remaining FBs, the system operator will sell the FBs with low prices to avoid the risk of having leftover FBs, which are valueless at the end of the day. When the inventory of the FBs is limited, the system operator would like to reserve the small number of FBs to serve the later arriving customers with high tolerance for higher prices, to make more profit. These two cases indicate that myopic policies without considering the inventory level will cause a loss of profit.

We design an online algorithm considering the inventory level by strategically reserving some FBs for future customers who can accept higher prices. The core of this algorithm is to quantify the value of each one unit of the remaining FBs. From intuition, we know that when the remaining inventory decreases, the value of one unit of FBs increases. Then we design a value function ϕ_m of remaining inventory for each station m based on this principle, which is a piece-wise increasing function defined on the fraction of the initial inventory consumed. It satisfies that $\phi_m(1) \ge r^{J_m}_m$ when all FBs are consumed. Thus, when station m has no more FBs, the pseudo-revenue is non-positive and we will not recommend station m to any customer. This ensures constraint (4) holds. The system then can make a decision considering both price levels and the value of remaining FBs to choose the recommendation that can maximize the expected pseudo-revenue. We denote the total revenue earned by the online algorithm by $\mathsf{R_{on}}$. Here, we present our online primal-dual algorithm as the following Algorithm 1. In Algorithm 1, $V_{n-1,m}$ is the number of consumed FBs in station m before customer n comes. $V_{0,m}$ is set to be 0 for all stations. The online primal-dual algorithm will recommend the subset S^* to make a maximal pseudo-revenue for customer n and update the remaining inventory after the customer makes its choice.

Algorithm 1 Online Primal-dual Algorithm

```
V_{0,m} ← 0 for all m ∈ M.
for n = 1, 2,..., N do
    Compute S* by solving (7),

        max_{S∈A} Σ_{(m,j)∈S} p^j_{n,m}(S) ( r^j_m − φ_m( V_{n−1,m} / k_m ) ),   (7)

    where A is the set of all feasible station-price combinations for customer n.
    if the optimal value of (7) is strictly positive then
        Recommend S*.
        if customer n accepts any option (m*_n, j*_n) ∈ S* then
            R_on ← R_on + r^{j*_n}_{m*_n}.
            V_{n,m*_n} ← V_{n−1,m*_n} + 1.
        end if
    else
        Offer no recommendation.
    end if
end for
```

$$\max_{S\in\mathcal{A}} \sum_{(m,j)\in S} p^j_{n,m}(S) \left(r^j_m - \phi_m\left(\frac{V_{n-1,m}}{k_m}\right)\right), \tag{7}$$

Definition 1. *An online algorithm is c-competitive if* $\mathsf{R_{on}} \ge c \cdot \mathsf{OPT}$.

In the next section, we will show the performance of the proposed online algorithm is guaranteed by a competitive ratio when the value function ϕ_m is wisely designed.

III. Online Primal-Dual Analysis

We choose competitive ratio as the performance metric of the online V2S recommendation algorithm. As a theoretical lower bound, competitive ratio quantifies the worst-case performance measure, which is represented by the ratio between the revenue R_{on} of an online algorithm and the revenue of the offline problem OPT.

We analyze the competitive ratio of our proposed online algorithm by an online primal-dual approach. The dual problem of the offline primal problem (1) is

$$\min_{\lambda_m,\mu_n} \quad \sum_{m=1}^{M} k_m\lambda_m + \sum_{n=1}^{N} \mu_n \tag{8}$$

$$\text{s.t.} \sum_{(m,j)\in S} \lambda_m p^j_{n,m}(S) + \mu_n \geq \sum_{(m,j)\in S} r^j_n p^j_{n,m}(S), \tag{9}$$

$$n \in \mathcal{N}, S \subseteq \mathcal{A},$$

$$\lambda_m, \mu_n \geq 0,\ m \in \mathcal{M}, n \in \mathcal{N}. \tag{10}$$

Here, we will introduce the basics of the online primal-dual analysis method. First, we show the online algorithm produces a feasible primal variable $\boldsymbol{x}$ and achieves the primal objective $P(\boldsymbol{x})$, which is easily verified by our online setting. Then, we show feasible dual variables $(\boldsymbol{\lambda}, \boldsymbol{\mu})$, which can be found based on $\boldsymbol{x}$ and achieves a dual objective $D(\boldsymbol{\lambda}, \boldsymbol{\mu})$. In order to ensure our online algorithm can achieve a competitive ratio c, we need to guarantee $cD(\boldsymbol{\lambda}, \boldsymbol{\mu}) \leq P(\boldsymbol{x})$.

We set dual variables $\lambda_m = \mathbb{E}[\phi_m(V_{N,m}/k_m)]$, and $\mu_n = \mathbb{E}[U_n]$, where U_n is defined as the pseudo-revenue earned by serving customer n. $U_n = r^j_m - \phi_m(V_{m,n-1}/k_m)$ for $\forall(m,j) \in S^*$, if customer n accepts the combination (m,j), otherwise $U_n = 0$. μ_n is the expectation of U_n. Note that randomness of U_n consists of two dimensions. First, the recommendation S is based on the system state $V_{n-1,m}$ (i.e., the number of consumed FBs by previous $n-1$ customers), which depends on the realization of previous $n-1$ customers' choices. Second, customer n will make choices based on the choice probability $p^j_{n,m}(S)$. Since, ϕ_m and U_n are nonnegative, we can verify constraint (10).

For each $n \in \mathcal{N}$, the algorithm will make a decision based on the current system information (e.g., remaining FBs) to earn a maximal pseudo-revenue. Therefore, we can have the conditional expectation for any $S \subseteq \mathcal{A}$:

$$\mathbb{E}[U_n|V_{n-1,m}] \geq \sum_{(m,j)\in S} p^j_{n,m}(S)\left(r^j_m - \phi_m\left(\frac{V_{n-1,m}}{k_m}\right)\right). \tag{11}$$

Given the number of consumed FBs in different stations, the system will recommend the corresponding subset S^* to earn a maximal pseudo-revenue, and thus the left hand side (LHS) of (11) is greater or equal to an arbitrary subset S. Then, by using the tower property of conditional probability, we take an expectation for both sides of (11) and take the summation over all combinations included in subset S

$$\begin{aligned}\mu_n &= \mathbb{E}[\mathbb{E}[U_n|V_{n-1,m}]] \\ &\geq \mathbb{E}\left[\sum_{(m,j)\in S} p^j_{n,m}(S)\left(r^j_n - \phi_m\left(\frac{V_{n-1,m}}{k_m}\right)\right)\right].\end{aligned} \tag{12}$$

Because ϕ_m is an increasing function, we have

$$\lambda_m = \mathbb{E}\left[\phi_m\left(\frac{V_{N,m}}{k_m}\right)\right] \geq \mathbb{E}\left[\phi_m\left(\frac{V_{n-1,m}}{k_m}\right)\right]. \tag{13}$$

Thus, by substituting (12) and (13) in to the LHS of (9), we can verify (9) .

From above, we prove the feasibility of the primal and dual variables obtained from the online setting. Now we show how to achieve a performance guarantee of our online algorithm. By applying weak duality, we can obtain

$$\begin{aligned}\mathsf{OPT} &\leq \sum_{m=1}^{M} k_m \mathbb{E}\left[\phi_m\left(\frac{V_{N,m}}{k_m}\right)\right] + \sum_{n=1}^{N}\mathbb{E}[U_n] \\ &= \sum_{n=1}^{N}\mathbb{E}\left[\sum_{m=1}^{M} k_m\left(\phi_m\left(\frac{V_{n,m}}{k_m}\right) - \phi_m\left(\frac{V_{n-1,m}}{k_m}\right)\right) + U_n\right].\end{aligned} \tag{14}$$

To achieve a competitive ratio c, we need to ensure $cD(\boldsymbol{\lambda}, \boldsymbol{\mu}) \leq P(\boldsymbol{x}) = \sum_{n=1}^{N}\mathbb{E}[R_n]$, where R_n is the revenue by serving customer n. Thus, we enforce the following inequality holds for realized sample path of customer's choice

$$\sum_{m=1}^{M} k_m\left(\phi_m\left(\frac{V_{n,m}}{k_m}\right) - \phi_m\left(\frac{V_{n-1,m}}{k_m}\right)\right) + U_n \leq \frac{R_n}{c}. \tag{15}$$

Note that the LHS of (15) is the term inside the expectation in (14). Suppose customer n fails to get battery swapping service (either the system offers no recommendation or customer n rejects all options). Then we have $V_{n,m} = V_{n-1,m}$, $U_n = 0$, and $R_n = 0$, which indicates (15) will always hold when a customer fails to get the service. If customer n chooses one option (m,j), we have $V_{n,m} = V_{n-1,m} + 1$, $U_n = r^j_m - \phi_m(V_{n-1,m}/k_m)$, and $R_n = r^j_m$, then we rewrite (15)

$$\begin{aligned}&k_m\left(\phi_m\left(\frac{V_{n-1,m}+1}{k_m}\right) - \phi_m\left(\frac{V_{n-1,m}}{k_m}\right)\right) \\ &+ r^j_m - \phi_m\left(\frac{V_{n-1,m}}{k_m}\right) \leq \frac{r^j_m}{c}.\end{aligned} \tag{16}$$

Theorem 1. *If we can design the value function ϕ_m for any swapping station m, and any customer n, which satisfies* (16)*, then the online primal-dual algorithm can achieve the competitive ratio c.*

The proof for Theorem 1 is straightforward through the above analysis.

A. Value function design

Now, we have changed our problem into how to design a value function ϕ_m to ensure the validity of (16) for all (m,j), and furthermore to maximize the competitive ratio c. When $k_m \to \infty$ (actually, the number of initial FBs is very large), we can have

$$\begin{aligned}&\lim_{k_m\to\infty} k_m\left(\phi_m\left(\frac{V_{n-1,m}+1}{k_m}\right) - \phi_m\left(\frac{V_{n-1,m}}{k_m}\right)\right) \\ &= \lim_{k_m\to\infty} \frac{\phi_m(w_m + 1/k_m) - \phi_m(w_m)}{1/k_m},\end{aligned}$$

where w_m is the consumed fraction of the initial inventory in station m, namely, a multiple of $1/k_m$. As explained in Section

II, we design ϕ_m as a piece-wise increasing function, and set the value on the each segment border L_m^j exactly the price r_m^j. The segment border $L_m^j \in [0,1]$ is the ending point for each piece (L_m^{j-1}, L_m^j) of ϕ_m, and $L_m^0 = 0, L_m^{J_m} = 1$. Then we can rewrite (16) for each piece (L_m^{j-1}, L_m^j) of ϕ_m

$$\phi_m'(w_m) - \phi_m(w_m) \le r_m^j(\frac{1}{c} - 1). \quad (17)$$

Then we solve the differential function to get the value function ϕ_m at each piece (L_m^{j-1}, L_m^j) by binding the inequality. Setting $\phi_m(L_m^{j-1}) = r_m^{j-1}$ and $\phi_m(L_m^j) = r_m^j$, we can obtain $\phi_m(w_m) = Ae^{w_m} - r_m^j(1/c - 1)$, where

$$A = \frac{r_m^j - r_m^{j-1}}{e^{L_m^j} - e^{L_m^{j-1}}}, \quad (18)$$

$$c = \frac{1 - e^{-(L_m^j - L_m^{j-1})}}{1 - r_m^{j-1}/r_m^j}. \quad (19)$$

Therefore, c must be set to $min_j \frac{1-e^{-(L_m^j - L_m^{j-1})}}{1-r_m^{j-1}/r_m^j}$ to make (17) hold on each piece. Then we want to maximize the minimal value of $\frac{1-e^{-(L_m^j - L_m^{j-1})}}{1-r_m^{j-1}/r_m^j}$, for $\forall j \in \mathcal{J}_m$, which is achieved by setting $\frac{1-e^{-(L_m^j - L_m^{j-1})}}{1-r_m^{j-1}/r_m^j}$ equal for all $j \in \mathcal{J}_m$. In this way we can derive each segment border L_m^j. Since, $r_m^0 = 0$ and $L_m^0 = 0$, we can derive the competitive ratio c

$$c = \min_m 1 - e^{-L_m^1}. \quad (20)$$

We can also derive the value function ϕ_m by substituting c and L_m^j into (17) and binding the inequality. Interested readers can refer to [17] for more details about the design of the value function ϕ_m.

IV. SIMULATION RESULTS

In this section, we evaluate the performance of our online recommendation model and validate our algorithm by a case study of Hong Kong (HK). We consider the total 18 districts 4 swapping stations and mark them on a HK map. Each BSS has two different prices (low, high) for battery swapping. All FBs are the same with a capacity $\mathcal{C}= 20kWh$. Based on the different electricity price of the three areas of Hong Kong (New Territories, Kowloon and Hong Kong Island), we set two different prices for the 4 swapping stations. Suppose we have N EV customers in one day, and we will vary the total number of EV customers by a loading factor (LF), which is the average number of customers for one unit of initial FBs.

A. Choice Model of Customers in HK

In this subsection, we show how we estimate the choice model of EV customers.

- CASE 1. If there is only one combination (m, j) in the subset S, we estimate the choice probability based on both the distance $d_{n,m}$ between the location of customer n and BSS m and the price level r_m^j. In this case, we denote the probability by $p_{n,m}^j$ when only one combination (m, j) is recommended.

$$p_{n,m}^j \propto \frac{1}{(d_{n,m}, r_m^j)}. \quad (21)$$

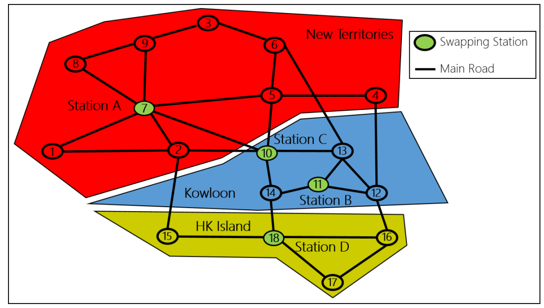


Fig. 2: An illustration of Hong Kong map, including 18 districts and main roads.

TABLE I: SERVICE LOAD SPLIT

	Percentage of Customers Split		
	New Territories	***Kowloon***	***HK Island***
Station A	61%	16%	11%
Station B	25%	62%	2%
Station C	14%	21%	$< 1\%$
Station D	$< 1\%$	$< 1\%$	85%
Total	100%	100%	100%

- CASE 2. If there are more than one options in the subset S, the customer will have a probability $p_{n,m}^j(S)$ based on the given subset S. For any customer n, we can obtain the probability $p_{n,m}^j(S)$ based on the multinomial choice model as

$$p_{n,m}^j(S) = \frac{p_{n,m}^j}{\sum_{(m,j)\in S} p_{n,m}^j + p_0(S)}, \quad (22)$$

here, $p_0(S)$ is the probability the customer will not accept any option in subset S.

We assume that for any customer $n \in \mathcal{N} : \{1, \ldots, N\}$, it can submit a request for FBs at any location on the roads of HK. We use the population density in each district to estimate the potential FB demand density. When a random request appears, the online V2SRS can know the location of that customer, and it estimates the probability $p_{n,m}^j(S)$ for any (station, price) combination in S.

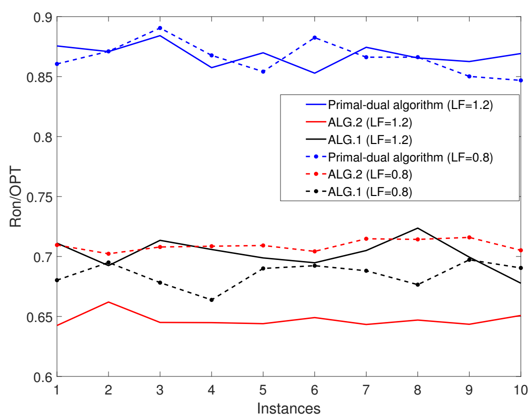
B. Performance Analysis of Load Balancing across Areas

We name the 4 swapping stations as Station A, Station B, Station C and Station D in Fig. 2. The initial number of FBs of the corresponding stations are 400, 600, 400 and 200 respectively, which are fixed and will not be replenished in one day. We have to point out that the number of initial FBs can also be optimally placed, which will be a long-term planning problem. In this paper, we focus on balancing the service load in different areas to ensure each customer will be recommended a station with available FBs for swapping. By splitting the customer flow to nearby areas, we can achieve a maximal total revenue and avoid the FBs consumed too fast in some of the BSSs.

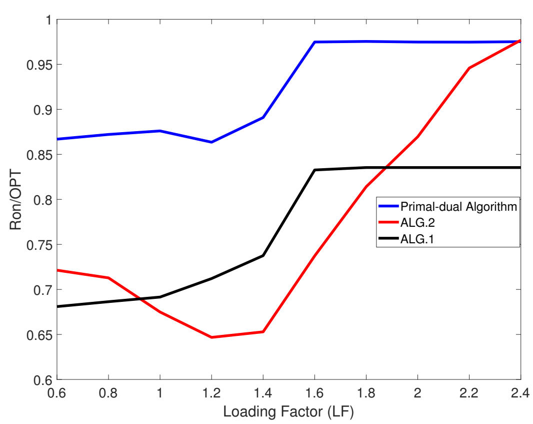
From the numerical results in Table I, (1) we can identify that the customers who accept recommendations from V2SRS in New Territories, Kowloon and HK Island are further split into the 4 swapping stations. (2) only low percentages of customers in New Territories and Kowloon go to HK Island for FBs, and low percentage of customers in HK Island go to the other two areas. This shows the rationality that few customers are willing to travel far away across tunnels (between Kowloon and HK Island) for FBs.

C. Comparison with Heuristic Online Algorithms

In this subsection, we compare the performance of our proposed online algorithm with two heuristic algorithms (AlG.1 and ALG.2). ALG.1 and ALG.2 always recommend feasible stations with low prices and high prices, respectively, without considering the inventory level. In Fig. 3 (a), we compare the test results of the three algorithms for 10 instances with two LFs (0.8, 1.2), and measure the performance of these algorithms by the ratio $\mathsf{R_{on}}/\mathsf{OPT}$, where $\mathsf{R_{on}}$ is the revenue of online algorithms. Note in each instance, we have different customer sequences and random customer choices. In Fig. 3 (b), the performances of these algorithms are compared by different LFs, which validates that our online primal-dual algorithm achieves a good performance for a large range of customer size. Note for ALG.2, the ratio gets close to 1, when LF becomes large enough. It is reasonable that ALG.2 can sell out all FBs with high prices, when the customer size is very large.



(a) Performance comparison for 10 instances (LF=0.8,1.2)



(b) Average performance comparison for different LFs

Fig. 3: Performance comparison between primal-dual algorithm and heuristic algorithms

V. Conclusion

In this paper, we formulate an online V2S recommendation problem with the consideration of customers' choice model. We design an online primal-dual algorithm, which is guaranteed to have a bounded performance. In particular, we conduct a case study based on a real Hong Kong map. From the data analysis of 18 districts in Hong Kong, we estimate EV customers' choice model to achieve both customers' service quality guarantee and total revenue maximization. The simulation results show that our proposed online algorithm can achieve a competitive ratio of 0.5898 and outperforms other heuristic algorithms.

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