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Towards Optimal Planning of EV Charging Stations under Grid Constraints ⋆

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Abstract: At present, the public charging network can not fully satisfy the charging demands of electric vehicles (EVs), which hinders the further development of EVs. In fact, as the key roles of charging service market, the operators need to plan charging stations properly to improve the profit while ensuring qualified charging service. Meanwhile, as the power supplier, the grid requires the charging stations to be deployed properly to lower the generation cost while ensuring safe and stable grid operation. This paper aims to plan the EV charging station (CS) network to improve the comprehensive profit by taking both the operator and the grid into consideration. Firstly, the Voronoi diagram method is used to divide the area to be planned based on the candidate set. Then, a mathematical profit maximization model with electric physical constraints is designed to distribute appropriate capacities for each candidate EV CS locations. The generalized Benders decomposition algorithm is applied to obtain the optimal solution. Finally, the simulation results demonstrate the effectiveness of the proposed algorithm based on a case study which consists of a 56-node distribution system and Xiamen traffic network system.

Keywords: Electric Vehicle, Charging Station, Planning, Operators, Generalized Benders Decomposition.

1. INTRODUCTION

Compared with traditional vehicles, EVs have many advantages such as energy conservation, emission reduction, and power grid optimization. However, the range anxiety troubles the EV users all the time. The abundant construction of fast charging stations can prominently alleviate this trouble. As a matter of fact, the proportion of charging piles in comparison to EV's is only 3:8 in China, far away from sufficient quantity. Besides, the inappropriate locations and capacities of CSs also result in inefficient EV charging. These all means the charging network is in urgent need of construction and optimization (Shukla et al., 2019; Shi and Lee, 2015).

The planning problem of EV CSs has been formulated as different optimal models with different objectives or constraints. Several traffic flow models related to graph theory have been proposed to meet users' charging demands as much as possible (Wang et al., 2013). Based on these traffic flow models, many CS deployment schemes have been proposed to minimize multi-target cost. Rajabi-Ghahnavieh and Sadeghi-Barzani (2016) used the real grid data and traffic data of the northern part of Delane considering construction cost, operation cost, EVs' travel distance cost, and power loss of the grid. Sun et al. (2016) studied how to size and locate charging stations in traffic networks considering grid constraints with budget constraints. A comprehensive planning model was proposed which is optimal for both the transportation network (TN) and the power distribution network (PDN), planning locations and capacities of new CSs, charging spots, TN lines, and PDN lines (Wang et al., 2018). Kong et al. (2019) proposed a novel location planning method of fast charging stations, in order to achieve the overall optimization of operators, drivers, vehicles, traffic condition, and power grid.

Usually, the planning problem relates to the TN, the PDN, the user charging preference, and urban construction. However, the charging service revenue of the operators is rarely considered. Only very recently, several CS placement strategies are proposed to maximize the profit of the operators. Zhang et al. (2018) studied the trade off between cost and revenue of CSs to maximize the profit of the operators, though the grid was not taken into consideration. Lin et al. (2018) identified the optimal location of EV CSs in cities based on Geographic Information System (GIS), then traffic flow data and land-use classifications aggregated charging profiles were utilized to maximize the total profit of new CSs.

Actually, most of these works only focus on satisfying the charging requirements or maximizing social welfare. The voltage power quality and the generation cost are rarely taken into account, which will affect the safe and stable grid operation and decrease the comprehensive profit of the operators. Under this background, this paper takes not only the power quality but also the generation cost into account to maximize the comprehensive profit of the operators while ensuring safe and stable grid operation.

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The highlights of this paper can be summarized as follows:

- The PDN and the TN information are deeply combined to maximize the profit of the operators under the constraints of safe and stable grid operation.
- The mathematical optimization problem is linearized by introducing a new variable in order to apply the generalized Benders decomposition for results.
- The EV users' uncertainties of transferring between adjacent CSs are considered by two scenarios. Parameters of simulations come from the real operating data of CSs and traffic data of vehicles in Xiamen.

However the applicable scenario of the method in this paper is that there is no installed CS in the area to be planned.

The remaining of this paper is organized as follows. Section 2 explains the optimal planning model of the CS network. Then the mathematics problem is transformed and solved in Section 3. In Section 4, a case combined with the TN in Xiamen and the 56-node IEEE PDN is studied to validate the method. Followed by Section 5 that concludes this paper.

2. PROBLEM FORMULATION

This paper focuses on how to plan the CS network, which takes both the operators and the power grid into account. As a charging service operator, profit is the primary concern which is revenue minus cost. The revenue of CSs in one day depends on how much the charging requirements of EVs are satisfied. Generally speaking, there is an estimated investment recovery time, so we can allocate the long-term construction cost and the maintenance cost to one day. Meanwhile, according to the EV load and baseload of the PDN, the generation cost can be obtained, which is included in the comprehensive profit of the charging service operator.

2.1 The TN Cost

How to get the potential CS is out of the scope of this paper, due to point of information and urban planning factors, here the CS candidate set $\mathbb{N}_{\mathbb{C}} = \{1, 2, \ldots, N_c\}$ is given. The whole area to be planned is divided into several zones centered by the CS candidate set through Voronoi diagram method. Let u represents the charging piles to be built at candidate set:

$$u_i \leq \tilde{u}_i, \quad u_i \in \mathbb{N}, i \in \mathbb{N}_{\mathbb{C}} \tag{1}$$

where $\tilde{u}_i$ is the spatial upper limit of charging piles number in i^{th} CS. The TN cost including fixed construction cost and the maintenance cost of i^{th} CS can be defined as:

$$C_i^o = S_i(C_{1,i} + C_{2,i}u_i) \tag{2}$$

where $C_{1,i}$ is the fixed construction cost of i^{th} CS, $C_{2,i}$ is the maintenance cost of a single charging pile in i^{th} CS, and S_i is decided by u_i:

$$S_i = \begin{cases} 1, & \text{if } u_i \neq 0 \\ 0, & \text{if } u_i = 0 \end{cases} \tag{3}$$

2.2 The Service Revenue

The service revenue of i^{th} CS can be formulated as:

$$C_i^i = C_{3,i}M_{i,t} \tag{4}$$

where $C_{3,i}$ is the revenue of one single EV in i^{th} CS, $M_{i,t}$ is the served EV number in i^{th} CS during time slot t.

In order to compute $M_{i,t}$, the first-in-first-out $M/M/c/N$ model in queuing theory is employed to simulate the operating processes of CSs (Varshosaz et al., 2019). It is assumed that there are average λ EVs arriving at the CS in each time slot, and there are c charging piles in the CS. Each charging pile can serve μ EVs in each time slot. The EV capacity of the CS is limited to N including the queue. Therefore, service intensity is $\rho = \lambda/(c\mu)$. P_n indicates the probability that there are n EVs in the system, which can be defined as:

$$P_n = \begin{cases} \frac{1}{n!}\left(\frac{\lambda}{\mu}\right)^n P_0, & 1 \leq n \leq c \\ \frac{1}{c^{n-c}c!}\left(\frac{\lambda}{\mu}\right)^n P_0, & c \leq n \leq N \end{cases} \tag{5}$$

$$P_0 = \left[\sum_{n=0}^{c-1} \frac{1}{n!}\left(\frac{\lambda}{\mu}\right)^n + \frac{1}{c!}\left(\frac{\lambda}{\mu}\right)^c \frac{1}{1-\rho}\right]^{-1}, \rho \neq 1 \tag{6}$$

$$P_{i,t}^B = P_N = \frac{1}{c^{N-c}c!}\left(\frac{\lambda}{\mu}\right)^N P_0 \tag{7}$$

where $c = u_i$, $\mu = E/R_{i,t}$. According to the limited system capacity, when the number of EVs in the system is greater or equal to N, the system is blocked. $P_{i,t}^B$ is the blocking probability of i^{th} CS during time slot t, which also represents the proportion of lost EVs in i^{th} CS. These lost EVs arrive at i^{th} CS but can't get the charging service in i^{th} CS.

It is assumed that when a CS is blocked, a part of the lost EVs will give up charging directly, while others will transfer to an adjacent CS. The transfer probability is inversely proportional to the distance between these two CSs, which can be given as:

$$p_{ii,t} + p_{i,t}^B = 1, \quad \forall i, t \tag{8}$$

$$p_{ii,t} + p_{i,t}^B\left(\sum_{j\in O(i)} p_{ij,t} + p_{il,t}\right) = 1, \quad \forall i, t \tag{9}$$

$$p_{ij,t} = (1 - p_{il,t})\frac{1/d_{ij}}{\sum_{j\in O(i)} 1/d_{ij}} \quad \forall i, t \tag{10}$$

where $O(i) \in \mathbb{N}_{\mathbb{C}}$ is the adjacent CS set of i^{th} CS, $p_{ii,t}$ is the probability that EVs charge in i^{th} CS without lost, $p_{ij,t}$ is the probability that lost EVs transfer to adjacent j^{th} CS when i^{th} CS is blocked, $p_{il,t}$ is the probability that lost EVs give up charging and leaving directly from i^{th} CS during time slot t, and d_{ij} means the distance between i^{th} CS and j^{th} CS.

Therefore, λ in the queuing theory model finally can be obtained by (11). Considering the possibility that EVs may transfer to an adjacent CS, $M_{i,t}$ can be obtained by (12).

$$\lambda = \lambda_{i,t} + \sum_{j\in O(i)} \lambda_{j,t}p_{ji,t} \tag{11}$$

$$M_{i,t} = \lambda_{i,t}p_{ii,t} + \sum_{i\in O(j)} \lambda_{j,t}p_{ji,t}p_{ii,t}, \quad \forall i, t \tag{12}$$

2.3 The Generation Cost

When EVs are connected to the PDN as some high-power loads, the power flow of the grid will change, especially the power generation cost. The PDN is usually a radial network, which can be represented by a connected directed graph $\mathbb{G} = (\mathbb{N}_{\mathbb{B}}, \mathbb{E})$, where $\mathbb{N}_{\mathbb{B}} = \{1, 2, \dots, N\}$, $\mathbb{E}$ and $\mathbb{N}_{\mathbb{G}} = \{1, 2, \dots, N_g\}$ represent buses, edges and power stations in the grid respectively. Both $\mathbb{N}_{\mathbb{C}}$ and $\mathbb{N}_{\mathbb{G}}$ belong to $\mathbb{N}_{\mathbb{B}}$. The generation cost is minimized by the objective function below in (13), which is a quadratic function of active power (You et al., 2017). The power flow model of a radial distribution network can be described by the distflow equations (14) (Ding et al., 2017).

$$\min_{u,s,s^g,v,l,S} \sum_t \sum_{j\in\mathbb{N}_{\mathbb{B}}} f_{j,t}\left(p^g_{j,t}\right) \tag{13}$$

$$\begin{aligned} s.t. \sum_{k:(j,k)\in\mathbb{E}} S_{jk,t} &= S_{ij,t} - z_{ij} l_{ij,t} + s_{j,t}, \quad j \in \mathbb{N}_{\mathbb{B}} \\ v_{j,t} - v_{k,t} &= 2\,\mathrm{Re}\left(z^H_{jk} S_{jk,t}\right) - |z_{jk}|^2 l_{jk,t},\ j \to k \in \mathbb{E} \\ v_{j,t} l_{jk,t} &= |S_{jk,t}|^2, \quad j \to k \in \mathbb{E} \end{aligned} \tag{14}$$

$$\underline{v}_{j,t} \le v_{j,t} \le \overline{v}_{j,t}, \quad \forall t, j \in \mathbb{N}_{\mathbb{B}} \tag{15}$$

$$\underline{p}^g_{j,t} \le p^g_{j,t} \le \overline{p}^g_{j,t}, \quad \forall t, j \in \mathbb{N}_{\mathbb{B}} \tag{16}$$

$$\underline{q}^g_{j,t} \le q^g_{j,t} \le \overline{q}^g_{j,t}, \quad \forall t, j \in \mathbb{N}_{\mathbb{B}} \tag{17}$$

$$|S_{jk,t}| \le \overline{S}_{jk,t}, \quad \forall t, j \to k \in \mathbb{E} \tag{18}$$

where

$p^g_{j,t}$	active power generated at j^{th} bus
z_{ij}	complex impedance from i^{th} to j^{th} bus
$l_{ij,t}$	squared current from i^{th} to j^{th} bus
$s_{j,t}$	complex power at j^{th} bus
$v_{j,t}$	squared voltage at j^{th} bus
$\underline{v}_{j,t}\overline{v}_{j,t}$	lower/upper squared voltage at j^{th} bus
$\underline{p}^g_{j,t}\overline{p}^g_{j,t}$	lower/upper active power generated at j^{th} bus
$\underline{q}^g_{j,t}\overline{q}^g_{j,t}$	lower/upper reactive power generated at j^{th} bus
$S_{jk,t}$	complex power of edge from j^{th} to k^{th} bus
$\overline{S}_{jk,t}$	upper complex power of edge from j^{th} to k^{th} bus

where the subscript t means the states of the grid during time slot t, (14) is the power balance constraints in power flow model, (15) is the voltage limits of buses, (16) and (17) denote the active and reactive power limits of power generation buses, respectively. And (18) represents the transfer power limits of lines.

Complex power composed of active power and reactive power can be described as $s_{j,t} = p_{j,t} + iq_{j,t}$. It is assumed that EVs are active loads at CS buses in the grid. The power injection process can be expressed as:

$$p_{j,t} = \begin{cases} p^g_{j,t} - p^b_{j,t} - E/1000 M_{j,t}, & j \in \mathbb{N}_{\mathbb{C}} \\ p^g_{j,t} - p^b_{j,t}, & j \in \mathbb{N}_{\mathbb{B}} \backslash \mathbb{N}_{\mathbb{C}} \end{cases} \tag{19}$$

It can be seen that not only the loads of CS buses will be affected, but also the entire power flow will change in the end.

2.4 The Mathematical Optimal Problem

The planning problem of EV CSs in this paper involves two optimization variables u and $x := (s, s^g, v, l, S)$, which denote charging piles planning and power flow states of the grid respectively. Combining the above factors, the optimization problem can be formulated as follows:

$$\begin{aligned} \max_{x,u} \quad F(x,u) := &\sum_i \left(C_{3,i} \sum_t M_{i,t} - S_i \left(C_{1,i} + C_{2,i} u_i\right)\right) \\ &- \alpha \sum_t \sum_{j\in\mathbb{N}_{\mathbb{B}}} f_{j,t}\left(p^g_{j,t}\right) \end{aligned} \tag{20}$$

$$s.t. \quad G(x,u) = 0, \quad x \in \mathbb{X}, u \in \mathbb{U} \tag{21}$$

where the final objective function is the difference that the service revenue minus the TN cost and the generation cost (20), α is the weighting coefficient utilized to balance the generation cost in optimization, the constraints (21) is transformed from (19), $\mathbb{X}$ indicates that x satisfies the constraints (14) (15) (16) (17) (18). $\mathbb{U}$ indicates that u satisfies the constraints (1) (3) (12).

3. PROBLEM TRANSFORM AND SOLUTION

The generalized Benders decomposition algorithm can be used in mathematical programming problems with complicated optimization variables. And when a subset of the variables is temporarily fixed, the remaining optimization problem should be a linear or convex problem. In our model, when the discrete decision variable u is fixed, remaining objective problem is exactly convex (Jamalzadeh and Hong, 2018; Zhang et al., 2018).

The problem (20) (21) can be transformed into the standard form of generalized Benders decomposition:

$$\begin{aligned} \min_{x,u} \quad & -F(x,u) \\ \text{s.t.} \quad & G(x,u) = 0, \quad u \in \mathbb{U} \cap \mathbb{W} \end{aligned} \tag{22}$$

where

$$\mathbb{W} := \{u : G(x,u) = 0 \text{ for some } x \in \mathbb{X}\} \tag{23}$$

When u is fixed, the problem can be divided into the main problem (24) and the slave problem (25) as follows:

$$\begin{aligned} \min_u \quad & W(u) \\ \text{s.t.} \quad & u \in \mathbb{U} \cap \mathbb{W} \end{aligned} \tag{24}$$

$$\begin{aligned} W(u) := & \min_{x\in\mathbb{X}} -F(x,u) \\ \text{s.t.} \quad & G(x,u) = 0 \end{aligned} \tag{25}$$

where the slave problem is convex with respect to x. The slave problem is converted into dual form:

$$\begin{aligned} \min_{u\in\mathbb{U}} \sup_{\mu\in\mathbb{R}^{2|\mathbb{N}_{\mathbb{B}}|}} & \left\{ \min_{x\in\mathbb{X}} \left\{ -F(x,u) + \mu^T G(x,u) \right\} \right\} \\ \text{s.t.} \quad & \min_{x\in\mathbb{X}} \left\{ \lambda^T G(x,u) \right\} = 0 \quad \forall \lambda \in \mathbb{R}^{2|\mathbb{N}_{\mathbb{B}}|} \end{aligned} \tag{26}$$

where λ and μ are Lagrange multiplier vectors for $\mathbb{W}$ and $W(u)$. This problem is equivalent to:

$$\begin{aligned} &\min_{u\in\mathbb{U}, u_0\in\mathbb{R}} u_0 \\ &\text{s.t.} \quad u_0 \ge \min_{x\in\mathbb{X}} \left\{ -F(x,u) + \mu^T G(x,u) \right\}, \quad \forall \mu \in \mathbb{R}^{2|\mathbb{N}_{\mathbb{B}}|} \\ &\qquad \min_{x\in\mathbb{X}} \left\{ \lambda^T G(x,u) \right\} = 0, \quad \forall \lambda \in \mathbb{R}^{2|\mathbb{N}_{\mathbb{B}}|} \end{aligned} \tag{27}$$

Relax this problem into the following:

$$
\begin{aligned}
\min_{u\in\mathbb{U},u_0\in\mathbb{R}} \; & u_0 \\
\text{s.t.} \quad & u_0 \geq \min_{x\in\mathbb{X}} \left\{ -F(x,u) + (\mu^m)^T G(x,u) \right\} \\
& m = 1,\ldots,n_\mu \\
& \min_{x\in\mathbb{X}} \left\{ (\lambda^m)^T G(x,u) \right\} = 0 \\
& m = 1,\ldots,n_\lambda
\end{aligned}
\tag{28}
$$

The relaxed optimization problem (28) involves discrete variables, thus is nonconvex, but is much simpler to be solved than the original problem (27). In our problem, functions F and G are independent of x and u. In fact, it is exactly the distinction between the PDN and the TN:

$$
\begin{aligned}
F(x,u) &=: F_1(x) + F_2(u) \\
G(x,u) &=: G_1(x) + G_2(u)
\end{aligned}
\tag{29}
$$

where

$$
\begin{aligned}
F_1(x) &= \sum_t \sum_{j\in\mathbb{N}_\mathbb{B}} f_{j,t}\left(p^g_{j,t}\right) \\
F_2(u) &= \sum_i \left(C_{3,i} \sum_t M_{i,t} - S_i\left(C_{1,i} + C_{2,i}u_i\right) \right)
\end{aligned}
\tag{30}
$$

So (28) can be easily transformed into the following (You et al., 2017):

$$
\begin{aligned}
u_0 + F_2(u) - (\mu^m)^T G_2(u) &\geq \min_{x\in\mathbb{X}} \left\{ -F_1(x) + (\mu^m)^T G_1(x) \right\} \\
m &= 1,\ldots,n_\mu \\
(\lambda^m)^T G_2(u) &= -\min_{x\in\mathbb{X}} (\lambda^m)^T G_1(x) \\
m &= 1,\ldots,n_\lambda
\end{aligned}
\tag{31}
$$

However, since $F_2(u)$ and $G_2(u)$ are nonlinear, a binary variable z is introduced to linearize these functions, let:

$$
\begin{aligned}
& z_{i,h} := \{0,1\}, \quad i\in\mathbb{N}_\mathbb{C}, h\in\{1,2,\ldots,\tilde{u}_i\} \\
& s.t. \sum_{h=1}^{\tilde{u}_i} z_{i,h} \leq 1, \quad \forall i
\end{aligned}
\tag{32}
$$

then

$$
\begin{aligned}
u &= \sum_{i=1}^{N_c} z_{i,h} f(h) \\
F_2(u) &= \sum_{i=1}^{N_c} z_{i,h} F_2(h) \\
G_2(u) &= \sum_{i=1}^{N_c} z_{i,h} G_2(h)
\end{aligned}
\tag{33}
$$

The procedures of the generalized Benders decomposition algorithm for solving this model are summarized as Algorithm 1.

Algorithm 1 Linearized Generalized Benders Decomposition

```
Input: λ_{i,t}, α_{ij,t}, ũ_i, C_{1,i}, C_{2,i}, C_{3,i}, N_c, N, E, R_{i,t}, p_{il,t}, and the PDN data 𝔾 = (ℕ_𝔹, 𝔼), ℕ_ℂ, ℕ_𝔾;
Initialization: Randomly set z → u ∈ 𝕌 ∩ 𝕎, get the upper limit of u_0 denoted by ū_0 by solving the dual problem (25);
While True
    Get the lower limit of u_0 denoted by u̲_0 by solving the relaxed master problem (28);
    Update z;
    If ū_0 − u̲_0 ≤ ϵ, where ϵ > 0 is a sufficiently small threshold then
        Return z → u ∈ 𝕌 ∩ 𝕎.
    Else
        Use the updated z to update ū_0 by solving the dual problem (25);
    End if
End while
```

4. CASE STUDY

In this paper, a case study of CSs planning comes from Xiamen island with its TN and PDN information is employed for demonstration. The GPS data of vehicles is distributed in a region of 133 square kilometers for a period of 24 hours in a typical working day. Among all the vehicles in this region, it is assumed that 10,000 EVs have charging demands. By analyzing CS operating data of Xiamen in 2018, it can be seen that the charging probability is time-varying. Furthermore, because of the car's close relation to people's work, the characteristics of charging probability are different on weekdays and weekends as shown in Fig.1. The probability of starting to charge during 19 o'clock is suddenly increase on working days, since that quite a lot people charge their EVs after work. In contrast, the charging probability changes more smoothly on weekends. Hence, charging EV numbers during different time slots can be obtained, when the total number of EVs to charge is known.

Generally, EV users intend to charge in the nearest CS, which is the candidate CS in each zone according to the characteristics of the Voronoi diagram method (Meng et al., 2019). Xiamen island is divided into 18 regions. The candidate locations are the regional centers as shown in Fig.2.

Different candidate locations have different costs, the fixed construction cost of CS $C_{1,i}$ and the maintenance cost of a single charging pile $C_{2,i}$ are listed in Table 1. Due to the spatial limit, each CS can not deploy more than 30 charging piles, with up to 10 EVs in queue. The charging power of fast charging piles is 120kW, and charging requirement of each EV is 40 kWh (Sheikhi et al., 2013). In this case, the expected revenue for charging one EV is \$5 (Zhang et al., 2018). These relevant parameters are listed in Table 2. Besides, other data about PDN such as line data and bus data are provided by a real-world 56-bus distribution grid (Wang et al., 2016). The weight α is set to be 0.04$\$/kWh$ here. All numerical tests are running on a laptop with Intel Core i5-3230QM CPU@2.60 GHz, 8GB RAM, and 64-bit Windows 10 OS.

The optimization model given in Section 2 and the algorithm given in Section 3 are employed to obtain optimal locations and capacities of EV CSs among the candidate locations, which is the optimal strategy. Its results are illustrated in Table 3. In order to compare the performance of the proposed model and algorithm, the average strategy

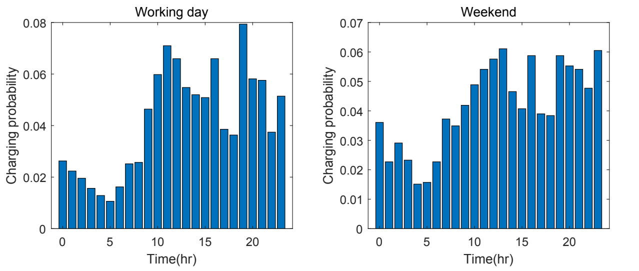

Fig. 1. The charging probabilities during one typical day

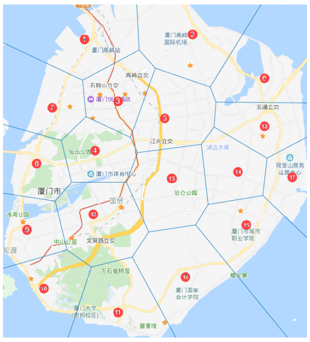

Fig. 2. CS candidate set and divided region

Table 1. The construction and the maintenance cost of candidate locations

Locations	1-2	3-5,13-14	6,12,18	7-10,15-17	11
$C_{1,i}$	150	200	150	150	200
$C_{2,i}$	35	40	40	30	30

Table 2. Operating parameters of CS and EV

Parameter	Value	Unit
N_c	18	-
N	c+10	-
$\tilde{u}_i$	30	-
$C_{3,i}$	5	dollar per EV
E	120	kW
R	40	kWh

Table 3. Optimal strategy CS planning results

Locations index	1	2	3	4	5	6	7	8	9
u_i	11	22	18	0	14	20	11	10	0
Locations index	10	11	12	13	14	15	16	17	18
u_i	0	0	22	0	15	22	0	15	11

and the traffic flow strategy are proposed as the benchmarks. These two strategies will build the same number of charging piles as the optimal strategy, but the distribution is different. The average strategy averagely distributes all charging piles into every candidate location. In the traffic flow strategy, the charging pile number in each candidate location are positive linear with the EV number originally wanted to charge there.

The relationship between the number of EVs initially arrived at each CS and the number of charging piles in each CS under the optimal strategy can be seen in Fig.3. It is obviously that candidate locations with few EVs would

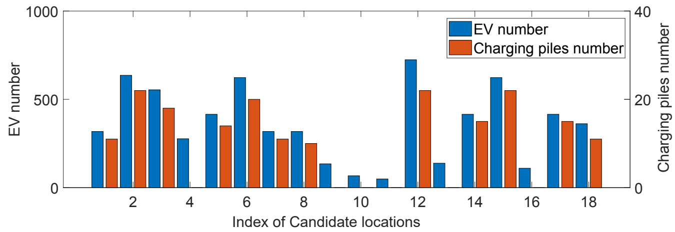

Fig. 3. Arrived EV number and planning results under optimal strategy

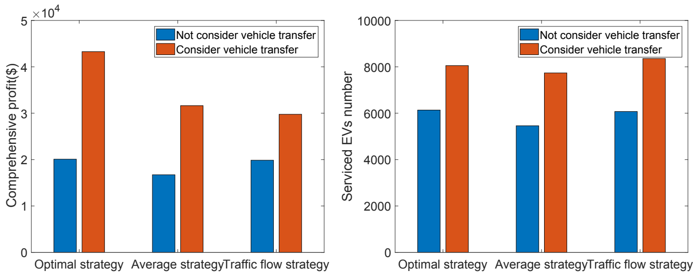

Fig. 4. Total profit and serviced EV number under different strategies

not build a CS, EVs have to transfer to an adjacent station to charge.

When the CS is blocked or not built in a region, only a part of EV users will transfer to an adjacent station with a distance-related probability, while others will not transfer, but leave directly without charging. The comparison of the comprehensive profit with three strategies are shown in Fig.4 (left), it can be found that when considering the transfer of EVs, the profitability of operators adopting optimization strategies is 36.83% higher than the average strategy, and 45.38% higher than the traffic flow strategy. When the transfer of EVs is not considered, the profitability of operators adopting optimization strategies is 20.04% higher than the average strategy, and 1.12% higher than the traffic flow strategy.The comparison of serviced EVs number with three strategies are shown in Fig.4 (right), it can be seen that the traffic flow strategy serves the most EVs at about 83.57%, the optimal strategy following closely at about 80.52%, the average strategy is the lowest at 77.37%. Here all three strategies can achieve the service rate at least 50% in two scenarios, which are valid charging service.

In short, compared with the average strategy, the optimal strategy is superior in two aspects. Compared with the traffic flow strategy, the optimal strategy can get 45.38% more profit with only losing 3.05% EV users, which has great marginal benefits. It can be said that the operators can adopt the optimal strategy to achieve a good balance between charging service and profitability.

In order to explore the impacts of the fixed construction of each CS $C_{1,i}$ and the maintenance cost of each charging pile $C_{2,i}$ on the optimization of the CS network, more numerical simulations are conducted by adjusting $C_{1,i}$ and $C_{2,i}$. We set the range of these costs as $[0.1C_{1,i},\ 1.5C_{1,i}]$ and $[0.1C_{2,i},\ 1.5C_{2,i}]$, respectively. The numerical results for the total TN cost, the number of charging piles, the

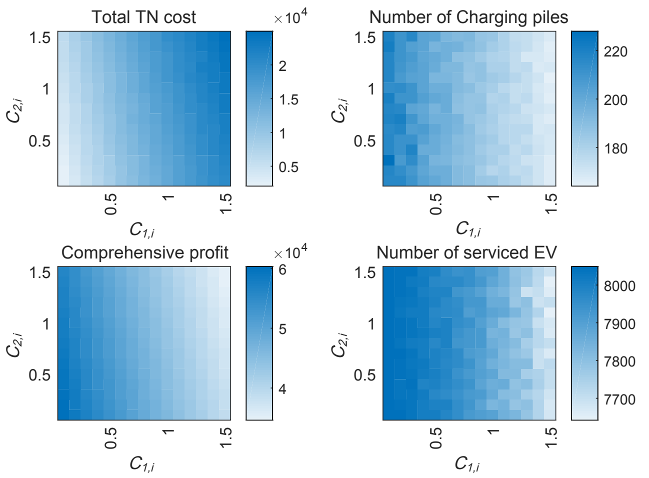

Fig. 5. The effects of $C_{1,i}$ and $C_{2,i}$ on the decision of the planning results.

comprehensive profit of the operators, and the number of serviced EVs can be seen in Fig. 5.

From the simulation results, it can be found that $C_{1,i}$ and $C_{2,i}$ affect the profit of the operators greatly. Furthermore, $C_{1,i}$ will increase the total TN cost more greatly due to its high price. When $C_{1,i}$ or $C_{2,i}$ increases, the total TN cost will increase, while the number of charging piles, the number of serviced EVs, and the comprehensive profit will decrease. That is because the operators need to make a trade off between the mainly TN cost and the service revenue. Some possible CSs and charging piles will not be planned, such that the comprehensive profit for the charging service operators can be maximized.

5. CONCLUSION

In this paper, an optimal charging stations planning strategy is raised for the charging service operators to maximize the comprehensive profit considering both traffic and the power grid. Especially, the generation cost of the grid is included in the comprehensive profit of the operators. To minimize the side effect caused by charging station loads, several critical constraints like voltage deviation and power balance are taken into consideration. The complicated mixed-integer programming problem is solved by linearized generalized Benders decomposition algorithm. The effectiveness of our algorithm is validated by comparing with two other regular planning methods. The impacts of the construction and the maintenance cost on charging stations planning are discussed. In the future, how to deploy new charging stations based on the existed will be marked in our calendar.

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