# Charging Station Selection Optimization Based on Electric and Traffic Information

Zhe Zhou, Qinglai Guo, *Senior Member, IEEE*, Hongbin Sun, *Senior Member, IEEE*, Kai Zhang

***Abstract*—With the increase of electric vehicles (EVs) and charging stations (CSs), how to maximize the benefits of all parties and maintain the efficiency and security of both power system and traffic network is an important research topic. To address these issues, we propose a game-theoretic price-setting framework to select the optimal CSs based on the total cost of EVs. To combine electric information, Security Index (SI) is innovatively introduced in the demand function, which impacts the price after game. SI is also used in distance calculation to revise the spatial distance to electrical distance. Besides, based on geographic information, route planning is achieved by revised Dijkstra algorithm. The simulation results demonstrate the effectiveness of the framework in balancing the load distribution compared with no SI-revised method.**

***Index Terms*-- Electric Vehicles, Security Index, Non-cooperative oligopoly game; Fuzzy programming**

## I. INTRODUCTION

The rapid booming of electric vehicles (EVs) is foreseeable. Data from International Energy Agency (IEA) shows that by 2015, the number of EVs has achieved one million worldwide and it is still rocketing. However, without proper charging regulation, the quick implementation of large scale EVs may lead to disastrous consequences, such as overload of the grid and decreasing power quality. Therefore, choosing the appropriate charging station (CS) for EVs is of great significance to reduce side effect that EVs have on the grid.

Demand response offers some desirable solutions to these problems. A smart charging control based on TOU price can reduce the peaks and meet the requirement for demand response[1]. Fuzzy control method is used in the modeling of multiple EVs, which act as distributed storage devices to flatten the load profile [2]. However, it is far from enough to solve all the challenges such as CS selection problem when EVs are running out of batteries.

As more charging operators enter the market, the discussion for guiding drivers' behavior by charging price has great significance in the electricity market. Robust Stackelberg model is established under uncertain demand and provides robust solutions in changing scenarios[3]. And mean field game can be applied to analyze the economic benefits when pure EVs enter the energy market[4]. While in our case, we use non-cooperative oligopoly game to set the charging price and guide the drivers to choose the optimal CSs.

The charging behaviors of EVs have the coupled characteristics of both traffic network and power system. Many factors should be considered including the time for driving, waiting and charging. Intelligent transportation system (ITS) can be combined with game theory model to reduce the total traveling time[5]. A fast-charging navigation system, which contains ITS module and power system control module, can navigate the drivers to the CS with the minimum total time[6].

Charging behaviors require the geographic information of CSs and economical route planning. Some studies take into account of road network, weather and traffic information and provide route-guiding service. Google Map API and Yahoo! API is also used to collect real-time traffic and weather data and releases the estimated energy consumption via mobile phones or maps[7]. Based on driving range and origins and destinations of EVs, the number of charging and route planning can also be estimated[8]. In our model, both electrical and traffic information are adopted to help alleviate EVs' impact on the grid.

## II. MAIN PROCEDURES AND IMPORTANT CONCOEPTS

### *A. Main Procedures*

The main procedures are as follows: first, EVs get the positioning information of CSs and send out charging demand to the CSs which are within reach. Then, based on the requests and electrical information, CSs set the charging price by distributed non-cooperative oligopoly game. They also combine the knowledge of station charging capacity (SCC) and security index (SI). Finally, EVs decide on the optimal CSs based on the total cost of charging and traveling. The procedures are illustrated in Figure 1.

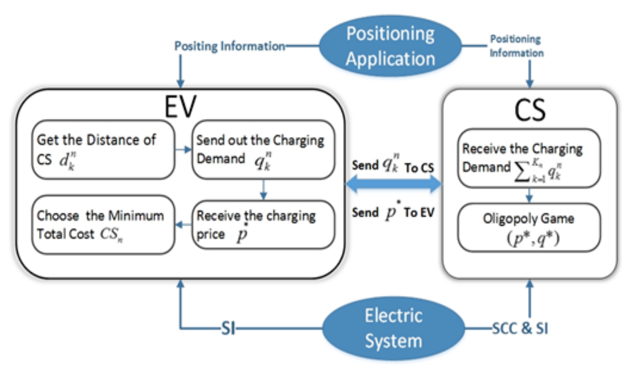


Figure 1 Main procedures of the model

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Qinglai Guo* is the corresponding author.Qinglai Guo, Hongbin Sun are all with Tsinghua Berkeley Shenzhen Institute (TBSI) and Department of Electrical Engineering, State Key Laboratory of Power Systems, Tsinghua University.

*B. Security Index(SI)*

Considering the power quality and thermal stability of power system, security index (SI) is introduced to illustrate the stability margin and assess the security of power system based on the predicted electrical load[9].

*SI* is defined as follows, charging load (CL) represents the total charging load in this CS, station charging capacity (SCC) is the largest electrical load that this node could offer. When the load exceeds the node capacity, the corresponding CS connected to this node will be labeled "unavailable". And their relationship is as follows:

$$SI = 1 - CL / SCC \tag{1}$$

*SI* is normalized to [0, 1.0], the closer to 1, the system is more stable.

## III. Oligopoly Game-Theoretic Framework

The principle for EV and CS is the maximization of their own profits[10]. The price competition among CSs can be modeled by oligopoly game. Because price is more concerned here than quantity, Bertrand's oligopoly game is established and the charging demand of EVs is assumed to be irrelevant with charging price.

*A. SI-revised Charging Station Modeling*

For simplicity, assuming that the generation utility is directly operating the CS, so the demand function of generation utility is also applicable to CS. Each CS can be described by a linear demand function denoted by quantity $q$ and price $p$ [10].

$$q = A - Bp \tag{2}$$

The total charging demand EVs send to the CS is:

$$A = \sum_{k=1}^{K_n} q_k^n, K_n \le N \tag{3}$$

$K_n$ is the number of EVs which send charging demand to certain CSs. $N$ is the total number of EVs. $q_k^n$ is the charging request sent by $k$ th EV.

$B$ is the elastic coefficient of demand function, which represents the amount of demand decreasing with the unit increase of price. $A$ and $B$ are decided by the market situation and specific to each to each charging station[10]. To take into account of the electrical information, SI is innovatively introduced in $B$. We hope that for the CS with smaller stability margin, the demand elasticity is also smaller, which corresponds to more necessary goods in economics. Therefore, $B$ is as follows:

$$B = B_{Initial} \times SI \tag{4}$$

Through the simulation, it can be proved that CS with larger SI will be adjusted to decrease their price in order to attract more EVs[10].

*B. Differentiated Product*

Cross-elasticity describes the relation between differentiated products. It is defined as the demand change of $CS_n$ caused by unit price change of $CS_m$ [10].

$$\varepsilon_{nm} = \frac{\partial q_n / q_n}{\partial p_m / p_m} \tag{5}$$

where $p_m$ is the unit price change of $CS_m$, $q_n$ is the energy demand of $CS_n$.

$f_n$ is the function to demonstrate the interaction reaction, $p_n$ and $q_n$ are the price and quantity offered by $CS_n$:

$$f_n = f_n(q_1, q_2, \ldots, q_{n-1}, q_{n+1}, \ldots, q_N) = f_n(\mathbf{q}_{-n}) \tag{6}$$

For each $CS_n$, the supply-demand relation is as follows:

$$q_n = A_n - B_n p_n - f_n(\mathbf{q}_{-n}) \tag{7}$$

The interaction function is：

$$f_n(\mathbf{q}_{-n}) = \sum_{m=1, m\neq n}^{m=N} \varepsilon_{nm} q_m \tag{8}$$

However, the competitive relationship among CSs is not known by other generation utilities. CS has conjectures about the slope of his competitors called conjectural variations (CV). We have:

$$q(q_n, \mathbf{q}_{-n}) = q(p_n, \mathbf{p}_{-n}) \tag{9}$$

Also, there is:

$$\frac{dq_n}{d\mathbf{p}_n} = \frac{\partial q_n}{\partial p_n} + \frac{\partial q_n}{\partial \mathbf{p}_{-n}} = \frac{\partial q_n}{\partial p_n} + \sum_{m=1, m\neq n}^{m=N} \varepsilon_{nm} \frac{\partial p_m}{\partial p_n} \tag{10}$$

CV is defined as the price variation of other CSs if the price of $CS_n$ changes, which is denoted by $\delta_n$.

$$\delta_n \triangleq \frac{\partial \mathbf{p}_{-n}}{\partial p_n} \triangleq \sum_{m=1, m\neq n}^{m=N} \varepsilon_{nm} \frac{\partial p_m}{\partial p_n} \tag{11}$$

$\mathbf{p}_{-n}$ refers to the charging price of CSs other than $CS_n$.

*C. Differentiated Product Oligopoly Game (DPOG)*

N-players DPOG $\{\mathrm{N}, \{p_n\}, \{\pi_n\}\}$ decides on the charging price selling to EVs, and $\mathrm{N} = \{1, 2, ..., N\}$ represents $N$ CSs, CS tries to maximize their own profits, that is:

$$\max_{p_n} \pi_n = p_n q_n - C_n, \text{for all } n \in \mathrm{N} \tag{12}$$

Suppose the cost function $C_n$ of $CS_n$ is:

$$C_n = a_n q_n^2 + b_n q_n + c_n (a_n > 0, b_n > 0, c_n \ge 0) \tag{13}$$

When achieving the equilibrium point, no CS is going to get extra benefits by changing his strategy unilaterally. The results are obtained by solving the following equations:

$$\begin{gathered} \frac{\partial \pi_1}{\partial p_1} = 0 \\ \vdots \\ \frac{\partial \pi_N}{\partial p_N} = 0 \end{gathered} \tag{14}$$

## IV. CHARGING STATION SELECTION OPTIMIZATION

It is reasonable for travelers to choose the CS with the lowest cost. Charging costs can be considered in two aspects------traveling distance and charging fees.

### A. *Traveling Distance*

The traveling distance varies with different routes. To quantify the distance and balance the electrical load, a SI-revised Dijkstra algorithm is proposed to calculate the shortest route.

*1) Dijkstra algorithm:* Dijkstra algorithm is the most classical and widely used algorithm in finding the shortest route (SR)[11].

Suppose a weighted graph $G=(V,E)$ , $V$ is the vertex set, $E$ is the arc set. The set $V$ is divided into two groups. One is the set $S$ including the vertexes whose SRs have already been calculated. The other group $U$ includes all the remaining vertexes, which are later added from $U$ to $S$ in the ascending order of SR. The algorithm ends when $S$ equals $V$ . During the process, the SR from the source node $v$ to $S$ is always no longer than that of $v$ to $U$ .

*2) Revised Dijkstra algorithm:* To combine the information in the electric power system, the spatial distance is transformed into electrical distance through SI.SI is used as the penalty factor to increase the equivalent distance when the node is near to the stability margin[9].

$$D' = -In(SI)D \tag{15}$$

$D$ is the spatial distance obtained by Dijkstra algorithm, $D'$ is the revised electrical distance.

What worth mentioning is that the final choice of the selected CS is made by the drivers. While this method encourages drivers to arrive at the "right" CS, EVs may consume more energy to be more electrical-friendly. Therefore, drivers should be given economic compensation, which we haven't covered yet.

### B. *Charging Fees*

Based on the positioning information and state of charge (SOC), EVs send out their charging demand $q_k^n(kWh)$ to the CSs that are within reach. $\overline{q}_c^n(kWh/km)$ is the energy consumption per unit of distance, $d_{kn}$ is the distance of EV $k$ from current location to the $nth$ CS. The charging demand at the starting point is $q_k^{ch}$ , which is a random amount from the minimum traveling demand to the full SOC state. Therefore, the charging demand $q_k^n$ of EV $k$ is:

$$q_k^n = \overline{q}_c^n d_{kn} + q_k^{ch} \tag{16}$$

Besides, EV's remaining energy must be enough to support it to reach the chosen CS.

$$d_{kn} < d_{th} = \frac{q_k^r}{\overline{q}_c^n} \tag{17}$$

$q_k^r$ is the remaining SOC of the battery, $d_{th}$ is the maximum distance EV can reach before batteries run out.

When EV chooses to charge at $CS_n$, the charging fees can be expressed as follows, $p_n$ is the electricity price at $CS_n$ :

$$\text{Cos}\,t_{EV,i} = q_k^n p_n = (\overline{q}_c^n d_{kn} + q_k^{ch}) p_n \tag{18}$$

### C. *Minimization of EVs' Costs*

The cost of EV includes charging fees and charging price, which is a multi-objective problem[11]. For multiple objectives, one of the ideas is to transform the multiple objectives to single objective. Fuzzy programming takes into consideration that not all the objectives can reach the optimal values at the same time and tries to achieve a balance, especially when their boundaries are indistinct[12].

*1) Fuzzy programming method:* Suppose $U$ is the domain, the fuzzy set $\tilde{A}$ on $U$ is defined as $\forall x \in U$ , $x$ belongs to $\tilde{A}$ by a certain $\mu(\mu \in [0,1])$ , $\mu$ is called as the membership function of $X$ to $\tilde{A}$ .Membership functions have different forms, linear distribution is applied here:

$$\mu_i(f_i) = \begin{cases} 1 & f_i \le f_{i,\min} \\ \dfrac{f_{i,\max} - f_i}{f_{i,\max} - f_{i,\min}} & f_{i,\min} \le f_i \le f_{i,\max} \\ 0 & f_{i,\max} \le f_i \end{cases} \tag{19}$$

*2) Procedures:* The procedures go as follows:

- Transform each objective to the minimization form.
- Calculate the minimum under each objective.
- Define the membership function of each objective.
- Transform the multi-objective functions $g_i$ to a single one and decide the weight $\lambda_i$ .

$$L = \max[\sum_{i=1}^{n} (\lambda_i g_i)^p]^{\frac{1}{p}} \tag{20}$$

## V. CASE STUDY

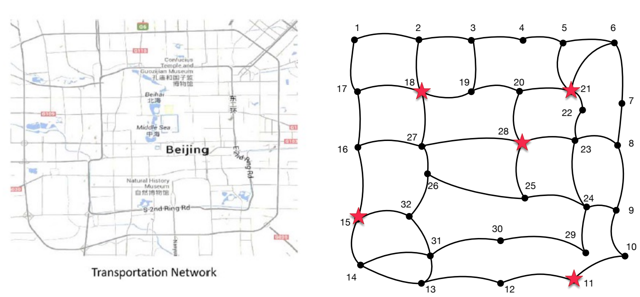


Figure 2 Transport network and topological graph

The simulation system used a $30 \times 30km$ region of Beijing-center road network, containing five rapid-charging stations, which is labeled as red five-pointed star. The transport network and corresponding topological graph are shown in Figure 2[6][10].

To validate the feasibility of the proposed model, the given area is served by 5 CSs and 960 EVs. The EVs are assumed to be distributed uniformly in the whole area. For the simplicity of calculation, we assume that each node is with 30 EVs. The volume of the battery is 24kWh, and the consumption rate is $1/6kWh/km$ . The differentiation of products is caused by the cost function. And the elasticity coefficient for all CSs $\varepsilon_{nm}=0.5$ .The initial SOC for EVs $N(7.8,1)$ , which is approximately 0.33 $SOC_{full}$(full at 24kWh) and EVs stop charging when achieving 0.8$SOC_{full}$.

After calculation, the total energy requested to each CS is in Figure 3.

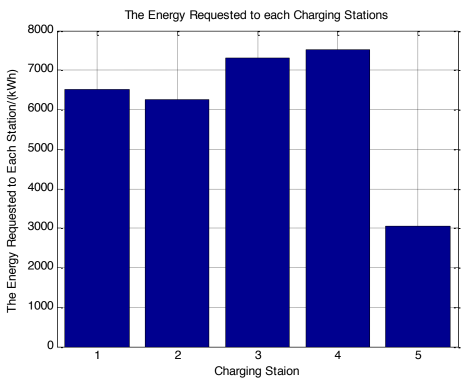


Figure 3 Total charging demand received by CSs

### A. Cost/Revenue/Price Comparison v.s. CV

When CV starts changing from 0.2-2, the total cost comparison of proposed method and the closest station in Figure 4. When the cost gets higher, the objective value becomes smaller. It can be concluded that no matter whatever CV is, the cost has been reduced greatly compared with choosing the closest station. Besides, the total cost has little to do with the variation of CV.

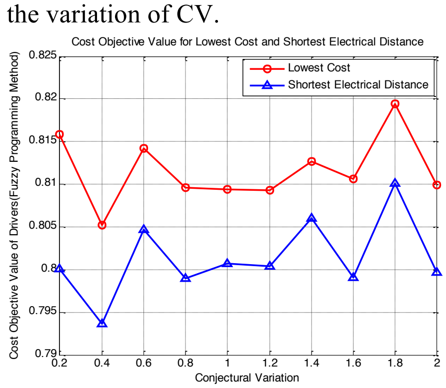


Figure 4 Objective values for lowest cost & shortest electrical distance

Figure 5 shows that when CV varies from 0.2-2, the average price of CS compared with Bertrand equilibrium. It can be concluded that the price gets higher than that of DPOG when taking the competitors into account. And the closer the interaction, the higher the price will get. The price of Bertrand Equilibrium is stable with the variation of CV, because it is corresponding to the case that CV=0.

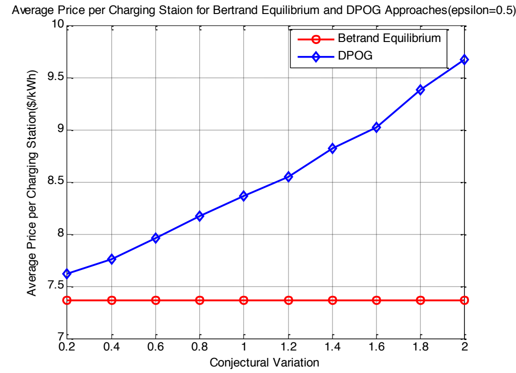


Figure 5 Average price of CSs for Bertrand and DPOG approaches

Figure 6 shows that when CV changes from 0.2-2, the revenue of CSs compared with that of Bertrand Equilibrium. When CV gets bigger, the revenue increases accordingly.

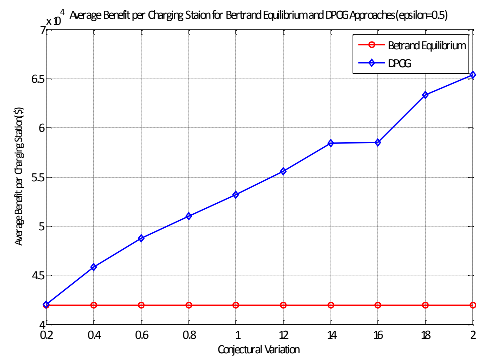


Figure 6 Average benefit of CSs for Bertrand and DPOG approaches

### B. The Function of Security Index(SI)

When SCC corresponding to certain CS increases and keep the charging demand remain the same, then SI becomes bigger.

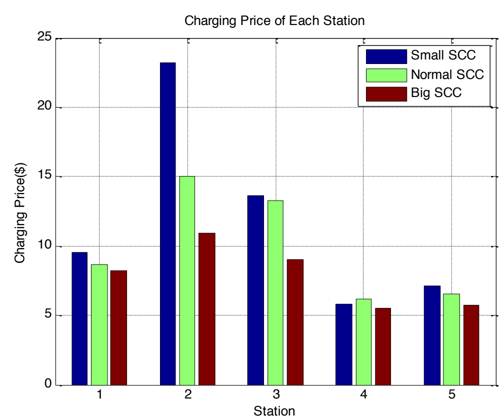


Figure 7 Charging price of CS with the change of SCC

Figure 7 shows that with the increase of SI, the price after game will decrease. And this will attract more EVs to charge at the stations with larger capacity or SCC.

*C. Mean & Variance of Security Index(SI)*

Figure 8 and Figure 9 shows that when CV changes from 0.2-2, the mean and variance of SI in comparison with the shortest spatial /electrical distance.

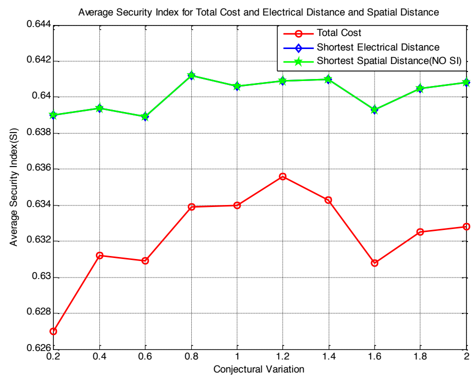


Figure 8 Average SI of total cost/shortest electrical distance/shortest spatial distance

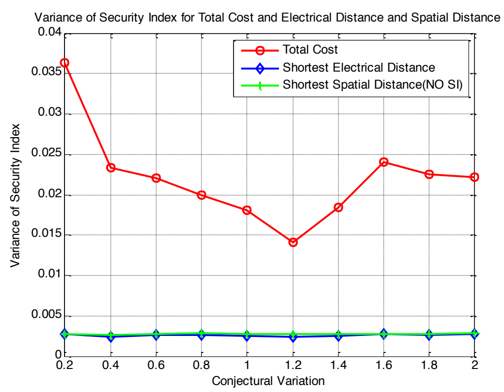


Figure 9 Variance of SI of total cost/shortest electrical distance/shortest spatial distance

It can be concluded that the average value of SI of the shortest spatial /electrical distance is much higher than of the total cost, and the variance is much lower. This means that the shortest distance term can be really helpful in balancing the electrical load, thus in helping the CS alleviate the over-loading stress. And if the security of power system becomes more important, the weight of distance can be adjusted higher to get more uniformly distributed load.

Besides, we notice that shortest electrical distance performs slightly better than the spatial one. The reason for the small gap is that SCC and locations of CSs are relatively even. And their difference will become more obvious when SCC and locations vary greatly and the SI-devised term will show the function of balancing the load better.

## VI. Conclusion

This paper presents a game-theoretic price-setting framework to select the optimal CSs based on the electric and traffic information. The game-theoretic price setting uses distributed oligopoly game and product differentiation, which models the non-cooperative competition between CSs. Security Index (SI) is introduced in the pricing game and traveling cost calculation, which incorporates the real-time data of power system. Besides, the traffic information is adopted in the charging request and route planning. Finally, fuzzy programming method is adopted to handle the multi-objective optimization of EVs with the flexibility of adjusting the weight of each goal. The simulation results show that SI is able to reflect the interaction between EVs and CSs, and help adjust the charging price to balance the electrical load and alleviate the over-loading stress of CSs.

Future work will combine the price policy and establish a more comprehensive simulation platform to take into account of time cost and make it more applicable in realistic scenario.

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