Cooperative between V2C and V2V Charging: Less Range Anxiety and More Charged EVs

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Abstract—Recent years have witnessed a rapidly growth in the number of vehicles on road. It causes environment pollution. Both scientist and companies have paid attention to electric vehicles (EVs) as a clean energy to reduce the oil demands and gas emissions. On the other hand, autonomous electric vehicles have been seen as cutting-edge technology. Self-driving vehicles, and vehicle ride-sharing offered by autonomous EVs are transportation services that have surged quickly. However, use of EVs spread steadily these days because of range anxiety problem and limited charging spots. To overcome these problems, we introduce a novel algorithm for charging problem. Unlike current works, charging strategies are tackled to make the cooperation between V2C and V2V efficiently by proposing an algorithm developed based on the matching theory, then it can offer the sufficient supplier for EVs requested charging service. Simulation results show that the proposed matching based algorithm outperforms the V2C and V2V approaches by 50 % in term of the number of charged EVs. In addition, the range anxiety under our proposal is halved compared with two charging mechanism V2C approach.

Index Terms—smart charging; vehicle to charging; vehicle to vehicle; matching game;

I. Introduction

Recent years have witnessed a rapidly growth in the number of vehicles on road. It causes environment pollution. Both scientist and companies have paid attention to electric vehicles (EVs) as a clean energy to reduce the oil demands and gas emissions. On the other hand, autonomous electric vehicles have been seen as cutting-edge technology. Self-driving vehicles, and vehicle ride-sharing offered by autonomous EVs are interest transportation services, it has surged quickly. However, use of EVs spreads steadily these days because of range anxiety problem and limited charging spots. The range anxiety refers to the worry that batteries will not carry them as far as they want to travel. Due to range anxiety, EVs mostly seek to nearest charging spot whenever being in battery deficiency. There is shortage of charging spots, innovative charging strategies thus are one of permanent solution in order to strongly encourage customers to shift from traditional cars to EVs.

With the development of wireless electric vehicle charging (WEVC) technology, EVs are able to get a charge while driving in near future. This scenario is referred to dynamic electric vehicle charging (DEVC). The WEVC is key idea for the development of autonomous vehicles when they can charge without human assistance. The autonomous cars then can offer broadly some services as ride sharing since visiting CS to re-charging will no longer be a requirement. These EVs are equipped bidirectional charger and known as gridable EVs (GEVs). The GEVs can not only consume the energy from the power grid but also transfer the energy back to the grid by the bidirectional charger. The GEVs from now is mentioned as EVs for short. In this paper, two new technologies vehicle-to-Charging station (V2C) and vehicle-to-vehicle (V2V) are taken into account charging strategies for EVs. V2C means that EVs can charge from power grid at CSs, while V2V shows that EVs can deliver their energy via bidirectional chargers through a local grid, and then distribute the energy among EVs by an aggregator. Therefore, V2V allows a flexible power transfer between the EVs [1].

To overcome range anxiety problem and limited charging spots, we introduce a novel algorithm for charging problem. Unlike current works, charging strategies are tackled to make the cooperation between V2C and V2V efficiently by designing the distributed algorithm for minimizing charging expenditures cost. Our main contributions can thus be summarized as follows:

- A cooperative between V2C and V2V charging (Cooperative) problem (i.e., assign EVs to the best energy suppliers such as minimize the total cost of whole system) is solved in context of not only finding best charging spot for EVs but also sharing energy between EVs. The problem is formulated as mixed-integer optimization problem.
- Since the considered problem is NP-hard, we develop an algorithm based on matching game method [2], [3], which can solve the Cooperative charging problem efficiently.
- Numerical results show that the proposed matching-based algorithm outperforms charging strategies without cooperation V2C and V2V approaches.

II. System model and problem formulation

The proposed system model in 1 is comprised of many CSs and EVs. All CSs are controlled by one local aggregator. Each EV obtains charging information of CSs, e.g., number of empty charging spots, available energy amount, from Road Side Unit (RSU).
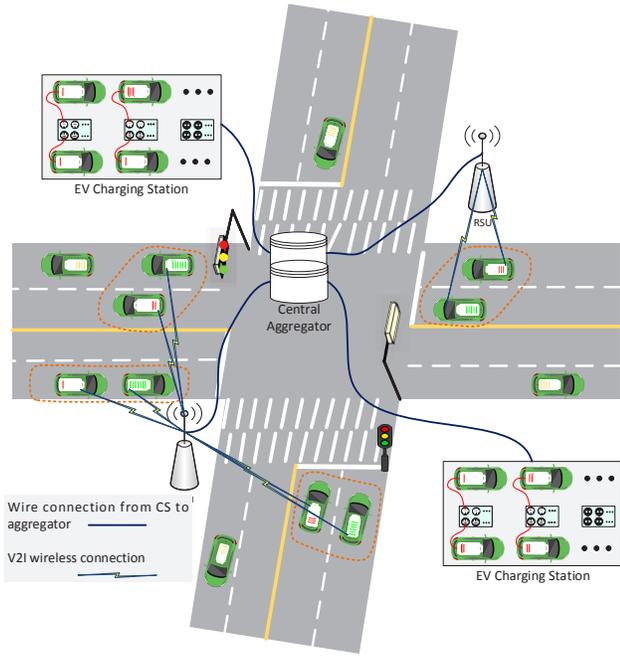
Fig. 1: Proposed system model.

We assume that time is slotted and we study the system for one time period. Each parameter and variable is defined over three sets: a set of CSs $\mathcal{C} = \{1, 2, ..., J\}$, located within the control of one local aggregator as shown in Fig. 1. The set of excess energy EVs (EEVs) and lack energy EVs (LEVs) are denoted by $\mathcal{E} = \{1, 2, ..., E\}$ and $\mathcal{L} = \{1, 2, ..., L\}$, respectively. Two sets, CSs and EEVs, are referred to suppliers set, $\mathcal{S} = \{1, 2, ..J, J + 1, ...S\} | S = J + E\}$. The LEVs is referred as demanders. Each supplier has a capacity of how many demanders can it serve at the same time named as quota $\mathcal{Q} = \{1, 2, ..., S\}$. Then

$$q_s = \begin{cases} \text{\#. of availabe charging spots} & \text{if } s \in C, \\ 1 & \text{if } s \in E. \end{cases} \quad (1)$$

For all LEVs $l \in \mathcal{L}$ and suppliers $s \in \mathcal{S}$, we introduce a binary variable $x_{l,s}$ that indicates whether l is assigned to charge at s or not.

$$x_{l,s} = \begin{cases} 1 & \text{if LEV } l \text{ is charged at supplier } s, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

From EV side, an EV i always tries to pick a CS j as cheap and near as possible. In general, its considerations include charging costs spent if it charges there.

A. Cost models

Cost models of EVs and CSs are devised from EVs charging expenditures and CSs profit, respectively.

Distance matrix Since state of charge (SoC) is a value that determines the current battery capacity as a percentage of maximum capacity, EVs usually either recharge when having low SoC or sell its energy as being at high SoC state. The moving range to a place where a demander and a supplier meet together is essential consideration factor of each demander because their SoC decreases gradually whenever EVs go on

the road. Each demander looks over the suppliers who can maximize their SoC after recharging with smallest energy consumption. Distance matrix keeps track of the distance from demanders to suppliers. Let $\mathcal{D}$ be a L × S distance matrix, such that an element $d_{l,s}$ is normalized distance between demander l and supplier s. The simple additive weighting (SAW) method is applied to measure value of $d_{l,s}$ defined as 3.

$$d_{l,s} = \frac{d_{l,s}^o}{d_s^{\max}}, \forall l \in \mathcal{L}, s \in \mathcal{S} \quad (3)$$

where $d_s^{\max} = \max_l d_{l,s}$, and $d_{l,s}^o$ is considered as original Euclidean distance from l to s.

Charging time. It is assumed that V2V charging has the fixed charging rate. Charging time thus is observed only under V2C scenario. the charging rate depends on charging levels. There are three charging levels. Level 1 uses standard 120V electrical outlets. Most home electronics are level 1 chargers. Level 2 charger uses standard 240V electrical circuits, and is used by most public CSs. The last one is level 3, DC fast charging, that uses ultra high-power 480V circuits at public CSs [4]. Since charging spots at public CSs are mostly equipped by charging level 2, we suppose that all CSs in our model use charging level 2. Charging rate at j, ω_j, is in range $[3.7, 19.2]$ kw power delivery. Let $\mathcal{T}$ be a L × J charging time matrix, where element $t_{l,j}$ is the normalized of charging duration time that needs to fill charging demand of l, r_l, at j. The normalized $t_{l,j}$ is:

$$t_{l,j} = \frac{t_{l,j}^o}{t_j^{\max}}, \forall l \in \mathcal{L}, j \in \mathcal{C} \quad (4)$$

where $t_{l,j}^o$ is the original charging time of EV l associated with CS s with charging efficiency rate η is:

$$t_{l,j}^o = \eta * \frac{r_l}{\omega_j}, \forall l \in \mathcal{L}, j \in \mathcal{C} \quad (5)$$

Charging fee and profit. Generally, electricity prices can be various at different times of day. It is low price at off-peak load time and high price at peak time. In our design, all CSs are controlled by an aggregator. Then, the aggregator manages the charging fee based on electric load of whole area. The charging fee at any CSs thus has the same price at the same time. Then charging fee is taken into account only under V2V charging scenario. On smart grid, EVs now are not only energy consumers but also energy suppliers since it can sell its surplus energy to LEV. In a natural way, EEV e only sell their surplus energy if they can get profit from electricity price differences. It means that the buying electricity price of EEV e, γ_e, is smaller than the selling price δ_e that they will offer to LEV l. Then, LEV l have to pay EEV e charging fee on the selling energy amount from EEV j. The buying and selling price of each EEV are different to each other. On the electricity market, each EEV can joint to auction mechanism to seek who can pay it with highest price. Let $\mathcal{I}$ be a L × E charging fee matrix, where element $i_{l,j}$ is normalized based on the charging fee that LEVs i have to pay back EEVs e who they exchange the energy with. That charging fee $i_{l,e}^o$ is calculated as follows:

$$i_{l,e}^o = r_l * \delta_e, \forall l \in \mathcal{L}, e \in \mathcal{E} \quad (6)$$

Then,

$$i_{l,e} = \frac{i^o_{l,e}}{i^{\max}_e}, \forall l \in \mathcal{L}, e \in \mathcal{E} \tag{7}$$

For EEVs side, a profit matrix $\mathcal{M}$ is defined to store the revenue of EEVs e that comes from the electricity price differences. The revenue of EEV e pertaining to the charging demand of LEV l is:

$$m_{e,l} = \frac{m^o_{e,l}}{m^{\max}_l}, \forall l \in \mathcal{L}, e \in \mathcal{E} \tag{8}$$

where $m^o_{e,l} = (\delta_e - \gamma_e) * r_l, \forall l \in \mathcal{L}, e \in \mathcal{E}$

To sum up, a charging activity of LEVs l related to two types of cost, distance cost and charging cost. The charging cost is considered as either charging time if LEVs charge at CSs or charging fee if they exchange energy with EEVs.

B. Problem formulation

Our objective is minimize the charging expenditures, including distance cost and charging cost, of all LEVs by cooperating V2C and V2V charging. The cooperative charging problem can be stated as follows:

$$\mathbf{min} \quad \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \alpha d_{l,s} x_{l,s} + \beta t_{l,s} x_{l,s} + \zeta e_{l,s} x_{l,s}, \tag{9a}$$

$$\text{s.t.} \quad \sum_{s \in \mathcal{S}} x_{l,s} \leqslant 1, \forall l \in \mathcal{L}, \tag{9b}$$

$$\sum_{l \in \mathcal{L}} x_{l,s} \leqslant q_s, \forall s \in \mathcal{S}, \tag{9c}$$

$$\sum_{l \in \mathcal{L}} x_{l,s} r_l \leqslant A^{\max}_s, \forall s \in \mathcal{S}, \tag{9d}$$

$$x_{l,s} = \{0,1\}, \forall l \in \mathcal{L}, s \in \mathcal{S}. \tag{9e}$$

In 9, constraint 9b ensures that each EV can be served at most one supplier; additionally, constraints 9c and 9e ensure each supplier cannot provide the service to more customers than its possible resources, involving capable of quota and power. Since, the number of EVs are vast, problem 9 is a non-convex, and integer problem, which is difficult to solve for a realistic setting. Therefore, by using matching game, we present practical algorithm which is suitable for a large-scale dense networks of EVs.

III. MATCHING BASED COOPERATIVE CHARGING

The cooperative between V2C and V2V charging (Cooperative) problem can be formulated as a *two-side matching game*, where each LEV will be assigned to at most one supplier. We assume that an arbitrary supplier s can serve a maximum number of its quota q_s at particular time. A matching game is defined by two separate sets of players. Each set of players evaluate one of another side using well-defined preference relations [2], [3]. The concept of preferences is used to model the common and conflicting interest. The preference profiles built by the LEVs and the suppliers are denoted $\mathcal{P}_l, \mathcal{P}_s$, respectively. Let the tuple $(\mathcal{L}, \mathcal{S}, \succ_{\mathcal{L}}, \succ_{\mathcal{S}})$ is our *many-to-one matching* design. Here, $\succ_{\mathcal{L}} \triangleq \{\succ_l\}_{l \in \mathcal{L}}$ and $\succ_{\mathcal{S}} \triangleq \{\succ_s\}_{s \in \mathcal{S}}$ represent the set of the preference relations of LEVs and suppliers, respectively [5].

Definition 1 A matching is defined as a function from the set $\mathcal{S} \cup \mathcal{L}$ into the set of $\mathcal{S} \cup \mathcal{L}$ such that:

1) $|\mu(l)| \leq 1$ and $\mu(l) \in \mathcal{S} \cup \emptyset$.
2) $|\mu(s)| \leq q_s$ and $\mu(l) \in \mathcal{L} \cup \emptyset$.
3) $s \in \mu(l)$ if only if $\mu(l) = s$.

Algorithm 1: Matching based Cooperative between V2C and V2V charging

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Input : $\mathcal{P}_l, \mathcal{P}_s, \mathcal{Q}, \forall l, s$
Output: a matching μ

1 initialize: $\mu^0 = [0]_{L \times S}$;
2 Calculate the preference lists of LEVs and suppliers using Equation (10) and Equation (11) ;
3 Acceptance matrix $\mathcal{X} = \{(l,s)|(l,s)$ prefer to each other;
4 Updated quota matrix $\mathcal{Q}$;
5 Initialize temporary rejected matrix $\mathcal{R}$;
6 **While** $\mathcal{R}$ is nonempty:
7 *Step 1:l* $\longleftarrow$ remove one element from $\mathcal{R}$;
8 *Step 2:* LEV $l \in \mathcal{L}$ sends its preference vector $\mathcal{P}_l$ to the next supplier that is going to apply;
9 *Step 3:* Supplier $s \in \mathcal{S}$ updates its applicant list. The supplier s ranks the applicants by ((11)) and selects first $\mathcal{Q}(s)$ LEVs and rejects the rest;
10 *Step 4:* Update acceptance matrix $\mathcal{X}$, for $\forall l \in \mathcal{L}$;
11 *Step 5:* $\mathcal{R} \longleftarrow \mathcal{R} \cup$ LEVs rejected;
12 return a matching μ;

LVE Preferences. To avoid range anxiety, LEV l needs to be recharge as soon as possible whenever it sends a charging request. How fast a supplier can serve a LEV is based on the moving time (from l to s) and charging time. Therefore, each LEV l firstly seeks a closest and fastest supplier s to minimize the range anxiety. Secondly, they focus on a supplier who can offer a saving charging service by observing charging fee. Therefore, LEVs l will choose suppliers s with smallest charging expenditures. Then, ab LEV l rank a supplier s based on the following ranking function:

$$R_l(s) = \begin{cases} \sum_{s \in \mathcal{S}} (\alpha d_{l,s} + \beta t_{l,s}) x_{l,s} & \text{if } s \in \mathcal{C}, \\ \sum_{s \in \mathcal{S}} (\alpha d_{l,s} + \zeta i_{l,s}) x_{l,s} & \text{if } s \in \mathcal{E}. \end{cases} \tag{10}$$

Suppliers Preferences. There ae two types of suppliers, CSs and EEVs. Because the charging service given by CSs is public service, it is assumed that charging service policy at CS is first come first serve. A LEV l will be served before a LEV l' if it is near CSs than l'. On other hand, EEVs provide personal charging service, they thus only care about their profit. Hence, each supplier s ascendingly ranks the LEV l according to the following ranking function:

$$R_l(s) = \begin{cases} \sum_{l \in \mathcal{L}} d_{l,s} x_{l,s} & \text{if } s \in \mathcal{C}, \\ \sum_{l \in \mathcal{L}} [\sigma d_{l,s} + (1-\sigma)(1-m_{l,s})] x_{l,s} & \text{if } s \in \mathcal{E}. \end{cases} \tag{11}$$

As mentioned earlier, cooperative charging problem is formulated as many-to-one matching problem. Therefore, the our goal is to find a *stable matching*, which is key concept as optimal result by using matching game. To seek a stable matching, the deferred-acceptance algorithm is deployed [6]. A stable matching is verified through the concept of blocking pair defined as follows:

Definition 2 A matching μ is stable, if only if no pair of $\{(l,s)|l \in \mathcal{L}, s \in \mathcal{S}\}$ blocks the matching. That is, $\nexists (l,s)$ s.t $l >_s \mu(s), s >_l \mu(l)$.

The result of this algorithm, μ, is a stable matching.
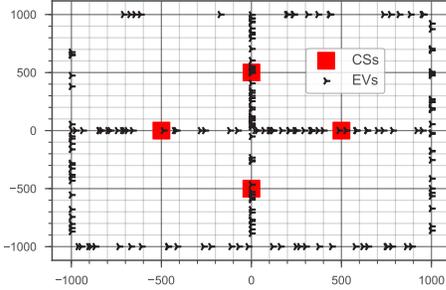
IV. NUMERICAL RESULTS

Fig. 2: Grid-like road network

For our simulations, we consider a system with 4 CSs, and 200 vehicles distributed over city with 2000m x 2000m size. The grid-like road network is shown in Fig. 2. The number of chargers equipped at CS is randomly chosen from the range $[5, 8, 10, 15]$ [7]. Simulations parameters are given in Table. **??**simulParameters. EV types of each EV are uniformly assigned to one of six popular EV types as in Table. II [8].

TABLE I: Simulation parameters

SoC	State of charge	$[0.1, 1]$
γ	Buying price of EEVs	$[6.7, 12.4]$
δ	Selling price of EEVs	$[13, 15]$
η	Charging efficiency rate at CSs	0.95
ω	Charging rate at CSs	$[3.7, 19.2]$
α β ζ	Weight factor	1
σ	Tunable parameter	0.5

TABLE II: EV types and their Charger rates

	Battery Capacity (kWh)	Charger rate (kW)
Mitsubishi MiEV	16	3.3
Chevy Volt	18	3.6
BMW i3	22	7.4
Nissan Leaf	24	6.6
Kia Soul EV	27	6.6
Tesla Model S	90	10

For comparison purposes, we first compare the proposed algorithm which is denoted as Cooperation with two different strategies. The first one is with V2V charging scheme, matching game with EV - optimal stable matching that assign charging slots to EVs in each CSs such that no EV can increase its profit. The second one is with V2V scheme that assign the anxious EV to a surplus EV how no pair matched EV can find another better partner except the currently matched ones. All results are obtained by averaging over a large of number of independent simulation runs, each of which realizes random location and number of both anxious EV and surplus EV. Charging demand, selling amount, and quota of each CSs are also randomly generated. Results corresponding to the only charging at CS, only wireless charging from EV to EV, and cooperation charging between V2C and V2V are denoted as V2C, V2V, and Cooperative, respectively. We evaluate the performance of the proposed algorithm with $EVs = [50, 100, 150, 200]$.
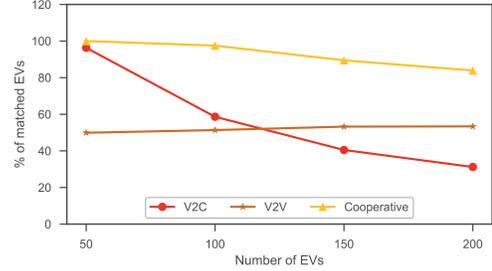

Fig. 3: Comparison percentage of matched EVs Cooperative charging with V2C, and V2V.

Firstly, we investigate the performance of three approaches mentioned above through the number of EVs that can reserve the service. The experiment is performed by fixing capable of resources and distributing the number of EVs in range $[50, 200]$. The results is shown in Fig. 3. Without cooperative mechanism, both V2C and V2V approaches are more ineffective than Cooperation way. When the charging demand surges unexpectedly, inadequate charging spots rises speedily at CSs. The percentage of matched EVs under V2C solution thus goes down rapidly. Meanwhile, each EV still has strong probability in finding a surplus EV and purchasing energy as expanding the number of EVs. That why the efficiency of V2V is lower than Cooperation scheme, but it is more stable than V2C method. By utilizing charging resources adequately, the proposed algorithm brings the positive result in term of increasing number of charged EVs.
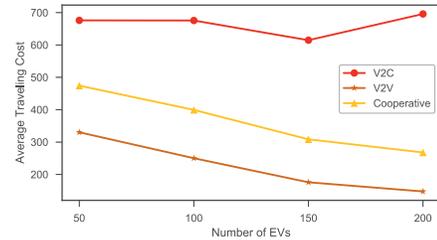

Fig. 4: Average traveling cost of V2C, V2V, and Cooperative Charging, for different number of EVs.

In addition, we evaluate the average traveling cost of the Cooperative algorithm under different algorithms. Since distance between EVs is closer than those from CS to EV, V2V provide the smallest average traveling cost. However, compared the number charged EVs served under V2V way with those value of Cooperative, Cooperative method can provide the charging service for nearly double time. Therefore,

Cooperative approach continually outperforms V2V approach. For the V2C approach, our proposed scheme chooses distributively suppliers to serve the charging requests in the way that minimize the total cost of whole system. Based on matching game, our proposal constantly ensures that no EVs can reach better supplier out of the supplier found by matching game. The Cooperative approach, therefore outruns extremely V2C approach.

We further demonstrate the efficient of the proposed algorithm with network size $EVs = 200$ and number of independent simulation running time = 100. It is observed from Fig. 5. The percentage of anxious EVs of the Cooperative method is less than 0.3 % whereas most of the values of others are more than 0.55%. The charged EVs almost doubles under our proposed algorithm. Similarly, the average total cost criteria to measure the achievement of Cooperative approach has shown that the range anxiety is declined significantly, roughly 50 percents compared with V2C manner. These results once again led to an affirmative determination of reducing the range anxiety and growing the charged EVs.
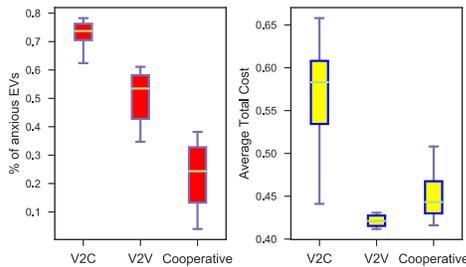

Fig. 5: Comparison of performance of Cooperative charging with no. of EVs = 200 and no. of independent simulation runs = 100.

V. Conclusion

In this paper, we have proposed the matching based method that can cooperative between V2C and V2V charging, then it can decrease range anxiety and increase number of charged EVs. We have investigated our proposal numerically by comparing it to two types of charging mechanism, V2C and V2V. Numerical results have shown that our algorithm can improvement in terms of the range anxiety, and the number of charged EVs. Prediction of electric demand by using deep learning to seek an optimal charging plan will be considered in the future work.

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