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Mitigating Range Anxiety via Vehicle-to-Vehicle Social Charging System

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***Abstract*—Vehicle-to-vehicle charging/discharging system can provide more flexibility to electric vehicles (EV) with increased range operation. In this paper, we propose the usage of EVs with excess energy than they need as alternative charging points for other EVs that are in need of urgent charge energy. To this end, we develop a mobility model for EVs during their trips and provide communication with other EVs in proximity through a location based social networking system. Simulation results show that such a system can decrease the number of drivers with range anxiety yielding larger number of EVs operating in the area while providing mutual benefits to sellers and buyers without having installation costs of new dedicated charging stations.**

***Index Terms*—Plug-in electric vehicle, grid integration, vehicle-to-vehicle, smart charging, distributed control.**

I. Introduction

Electric vehicles (EV) brought a new aspect to current transportation systems. They have the potential to reduce oil dependence and improve urban air quality. However, there are challenges for the widespread adoption of EVs by consumers. Limited driving range, longer duration for charging, and non-ubiquity of charging stations are the critical barriers to the penetration of electric vehicles.

According to Idaho National Laboratory's (INL) recently released study [1], around 85% of the EV drivers charge their vehicles at home. This is mainly because of the convenience and non-ubiquity of charging stations at other locations. On the other hand, opportunities to charge at workplaces and convenient public "hot spot" locations can extend the electric range without additional battery capacity. Furthermore, with optimal deployments of new charging stations, the overall Return-On-Investment (ROI) could be increased [2]–[4]. However, building new charging stations has additional costs and binds the EVs to areas with grid infrastructure.

Alternatively, energy exchange between EVs can release them from being obligated to get charge from a grid-connected station, yielding more convenience. When an EV is close to running out of charge without a nearby charging station, a second EV with extra charge can transfer the needed energy. This operation is called vehicle-to-vehicle (V2V) charging [5]. There are some recent work in the literature that have studied different aspects of V2V charging. In [6], a V2V charging system is proposed relying on charging of vehicles from mobile energy disseminators (i.e., large vehicles such as trucks and buses) that can carry high capacity batteries, while moving either with plug in electric connection or by electromagnetic induction via loosely coupled coils. However, such a system highly depends on distribution of large size vehicles and suffers from short contact periods and fast moving vehicles. In [7], a semi distributed V2V fast charging strategy is discussed, in which the transfers between the EVs assumed to be performed at swapping stations based on price control. In [8], a special study is performed to increase driving range of EVs by a charge sharing model using inductive power transfer to make them usable as taxicab fleets. However, it assumes power transfers at points such as stoplights which offer only limited durations of charging opportunity.

In this paper, different than these studies, we study the impact of V2V charging system in a city-wide scenario and between all vehicles. Each vehicle's excess charge amounts are determined based on driving habits and EV specifications (i.e., nominal travel range) and made available to other EVs in need. Moreover, inspired by location based social networking applications (e.g., Gowalla [9], Facebook Places [10], and Foursquare [11]), we build such a system through check-ins of EV drivers with related information (i.e., offered charge, location, expected duration), yielding full control of users and privacy preservation.

The proposed system with the sharing of power between EVs has the following benefits. First, EVs which have excess charge (i.e., remaining charge after expected charge amount required to reach next power station is taken out) can sell their powers and gain profit. Second, the range anxiety of the buyer EVs can be reduced by additional charging opportunities (provided by seller EVs). Third, the number of EVs operating without interruption can be increased in the system without adding new dedicated charging stations.

II. EV Charging Framework

Today, most of the EVs in the market utilize conductive charging via either on-board or off-board charging equipment (ac-dc converters). An EV can be charged either at home or at work utilizing a Level 1 or Level 2 electric vehicle supply equipment (EVSE). In addition, much faster charging speeds are possible using high power off-board charging stations. However, they are limited in numbers and require expensive investment. The third option is non-grid connected EV charging. V2V charging is one mode of this operation. As an example, AAA has a service [12] that charges depleted electric vehicles for emergency situations to help the customers get to a nearby charging station. However, utilizing the already available extra charge in other EVs is much more time and cost effective.

The V2V charging can be accomplished via conductive connection or via WPT. While there is not yet any industry demonstrations of V2V WPT charging systems, conductive V2V charging can be accomplished using grid forming EVs such as Via Van [13]. What is needed for an EV to provide V2V charging is a bidirectional on-board charger that can discharge an EV battery. The charging EV can be plugged-in to the energy provider EV with a J1772 compatible charging plug as if it is connected to the utility grid [14]. These type of vehicles are also very promising for their usage of emergency power supply. The concept of providing energy with EVs to individual houses when the grid is lost has a great potential to be implemented in near future [13]. This operation is called vehicle-to-home (V2H).

While J1772 provides the required low-level communication between the two vehicles (such as max charging limits), IEC/ISO 15118 can serve as the protocol for high-level communication utilizing power line communication (PLC) on the control pilot pin [15]. It is expected in the near future that vehicles that are capable of bidirectional power transfer will come into the market utilizing such communication protocols.

III. Proposed System and Solution

A. Network Model

Today, there are around 50 different EV models in the US market [16]. Table I shows six popular EV types and their specifications. The range of these cars (except Tesla) are between 53 and 93 miles per charge, which is 2 to 3 fold of average commuting distance [17]. However, when an EV driver needs to visit additional places (other than home and work) during the day, he/she may be in need of extra charge for the EV. Charging stations at some work places and at "hot spot" public areas will be the immediate solution in such cases, but they are not ubiquitous yet and driver trips could be in any part of the city.

	Battery Capacity (kWh)	Travel Range (mi)	Charger Power (kW)
Nissan Leaf	24	84	6.6
Chevy Volt	18	53	3.6
BMW i3	22	81	7.4
Mitsubishi MiEV	16	62	3.3
Kia Soul EV	27	93	6.6
Tesla Model S	90	270	10

TABLE I: EV types and their specifications [18].

The trip information of vehicles will need to be shared between vehicles registered to the system. This could be achieved through continuous tracking of EV information (e.g., location (GPS), SOC). However, some drivers might have concerns with such a system due to privacy. A more practical and privacy-preserving scheme that gives the full control into the hands of drivers could be modeled similar to the location based social networking apps [9]–[11]. We assume each driver will download and use a mobile app to participate the system. The app will let them check-in their current status to a centralized server so that other drivers can see the opportunities for buying power. For example, when a driver starts her day, she may check-in with current battery charge level (which is full most probably), and where she is headed to. When she arrives her destination, she may check-in with remaining charge amount and the expected amount of stay at that location. At this moment, she can also decide whether she will allow other drivers to charge their EVs using the excess charge in her EV, which is estimated considering the expected trips in the rest of the day.

Work places are potentially good spots for EV owners as they usually spend most of their times at these locations after their homes. Thus, in this paper, we will specifically focus on the home and work trip patterns and study the V2V charging offerings during work hours. To this end, we analyzed a real dataset [19] to elicit the arrival and departure rates for work places. Figure 2-a shows the arrival and departure time distributions of trips from work places. The arrivals have a peak around 8-9:00 a.m. and a smaller peak around 1:00 p.m. due to returns from lunch activities away from work. Departures have a peak around 5:00 p.m. and a smaller peak around 12:00 p.m., which is again due to eating outside. Gaussian distributions can represent these patterns very well, especially when those smaller peak times are ignored.

B. Problem Statement

We define the problem as follows. Let $\mathbb{N}=\{1, 2, \ldots, N\}$ denote the set of EVs and $\mathbb{M}=\{1, 2, \ldots, M\}$ denote the set of charging stations in an area. We define the range anxiety of the drivers as the minimum state of charge (SOC) level required to drive a certain distance (β). For example, if β = 25 miles, the drivers with EV batteries predicted to provide a distance less than 25 miles will have range anxiety. The set of EV drivers with range anxiety are then defined as[1]:

$$\mathbb{N}_x = \{i \in \mathbb{N} \mid r(i) - \alpha_c(i) - \alpha_a(i) \leq \beta\} \tag{1}$$

where $\alpha_c(i)$ and $\alpha_a(i)$ define the average miles of EV driver i during commuting and additional trips, respectively, and $r(i)$ is the nominal range of the EV i (mi).

The goal is to supply the energy demands of anxious drivers from the available energy suppliers (i.e., charging stations and the other EVs offering[2] their excess charge to other EVs) and reduce the number of drivers with range anxiety.

We represent the problem as a graph. Let $G = (V, E)$ be a graph with vertices representing an EV or a charging station ($|V| = |\mathbb{M} \cup \mathbb{N}|$) and edges defined as links from the vertices

[1] We omitted the time parameter for the sake of simplicity.

[2] In this paper, we assume this is offered with a fix price per kWh. Impact of different pricing strategies in a market environment will be the subject of our future work.

of EVs that are in need of power to the rest of the vertices that can supply the demanded power. More formally:

$$\begin{aligned} V = \quad & V_1 \cup V_2 \cup V_3, \text{ where} \\ & V_1 = \mathbb{N}_x,\ V_2 = \overline{\mathbb{N}_x} \text{ (or } \mathbb{N} - \mathbb{N}_x\text{) and } V_3 = \mathbb{M} \quad (2) \\ E = \quad & \{(i,j) \mid \forall i \in V_1, \forall j \in V_2 \text{ that satisfies} \\ & \qquad \mathcal{E}(i) \geq \Delta(i,j) \ \&\ req(i) \leq \mathcal{E}(j) - 2\Delta(i,j) \\ & \qquad \text{and } \forall i \in V_1, \forall j \in V_3 \text{ that satisfies} \\ & \qquad \mathcal{E}(i) \geq \Delta(i,j)\} \quad (3) \end{aligned}$$

$$\begin{aligned} \text{where,} \quad req(i) \ &= \ |\mathcal{E}(i)| \\ \mathcal{E}(j) \ &= \ \begin{cases} r(j) - \alpha_c(j) - \alpha_a(j) - \beta, & \text{if } j \in \overline{\mathbb{N}_x} \\ \infty, & j \in \mathbb{M} \end{cases} \\ \Delta(i,j) \ &= \ \text{trip distance between i and j} \end{aligned}$$

Here, $\mathcal{E}(j)$ represents the power that nodes with excess power can offer, and absolute value of it ($|\mathcal{E}(i)|$) gives required power amount for nodes with range anxiety. The graph definition above generates an incomplete bipartite graph. The objective function is to maximize the number of EVs matched to an energy supplier node[3]:

$$\max \sum_{\forall i} y_i \qquad s.t.$$

$$y_i = \sum_{\forall j \in V_2 \cup V_3} x_{ij}, \forall i \in V_1 \quad (4)$$

$$\sum_{\forall j \in V_2 \cup V_3} x_{ij} \leq 1, \forall i \in V_1 \quad (5)$$

$$\sum_{\forall i \in V_1} x_{ij} \leq 1, \forall j \in V_2 \cup V_3 \quad (6)$$

$$x_{ij} \ = \ \begin{cases} 1, & \text{if } i \text{ is assigned to } j \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

Note that an EV with energy demand can only be assigned to another EV that can supply this demand including the travel costs[4] (i.e., $req(i) \leq \mathcal{E}(j) - 2\Delta(i,j)$) or a charging station that are not assigned to other EVs and can provide as much power as the EV needs (thus, $\mathcal{E}(j) = \infty$ for $j \in \mathbb{M}$) . In either case, the current range of the EV should be larger than the distance to the energy supplier (i.e. $\mathcal{E}(i) \geq \Delta(i,j)$) so that EV can travel to supplier's location without depleting energy.

There can be multiple ways of matching all EVs with energy demand to energy suppliers. However, depending on the current remaining capacity (C_R) on the grid, another constraint can also be set to keep the load on grid within its current capacity so that energy suppliers are forced to be selected from the EVs with excess powers as much as possible.

$$\sum_{\forall i \in V_1} \sum_{\forall j \in V_3} x_{ij}(req(i) + 2\Delta(i,j)) \leq C_R \quad (8)$$

[3]We assume each EV will only be assigned to a single energy supplier. However, the problem and the graph could be modeled such that multiple energy suppliers can be assigned to one EV in need of power. This increases the complexity of the problem but could be solved with reduction to multi-traveler Salesman Problem (mTSP) with quota.

[4]We assume EVs will go back to their original location once they receive the power they need.

C. Proposed Solution

In the proposed system, when the EV drivers login to the system[5], they can find other EVs that offer their excess charge or they can sell[6] their excess charge to others. The information shared with the system is under the control of the drivers and happens through location based check-ins. The system can collect the requests from the drivers to find energy suppliers (within a time frame) and match them with energy suppliers that reported excess energy. Since we modeled the problem as a weighted bipartite graph, the system can use a maximum weighted bipartite matching algorithm to find the optimum matching.

To solve the maximum weighted bipartite problem, we transform it to an instance of a network flow problem and solve it with Fold-Fulkerson algorithm [21]. The complexity of this algorithm is $O(VE)$.

IV. Simulation Case Study

We have built a custom discrete event simulator in Java to evaluate the proposed system. As a case study, we simulated a network of EV drivers in Richmond metro area.

A. EV Charging Patterns

Understanding drivers' trip and charging patterns is essential to model an efficient power sharing network model between EVs. Literature has lots of data from conventional gasoline vehicles [17], [22]. For example, in [23], authors analyze the driver behaviors at different metropolitan cities and by considering the current charging station deployments and current ranges of EVs, they study the feasibility of EV usage by these drivers. They show that 60% of the drivers will need travel adaptation in their up to 5% of trips, which drops drastically when the comfort zone (i.e., minimum required charge level) goes lower.

As there are not many EVs on the roads today, there is very limited real dataset for EVs. One effort towards this goal is the dataset obtained from Electric Vehicle (EV) Project launched in 2009 by U.S. Department of Energy national laboratories in partnership with automotive companies. Table II shows the statistics obtained from the EVs (i.e., Nissan Leaf) volunteered to participate in early days of the project. As the statistics show, EVs are usually charged at home and once a day (probably due to convenience and not many public charging stations available). Thus, miles traveled between charging events is around average daily miles traveled. However, there are 3-4 trips between charging events, which can be explained with the additional trips (e.g., lunch activities, school drop-off/pick-up) other than just home-work and work-home trips.

[5]Communication with app server is achieved through cellular connections, however, for the environments with limited cellular connectivity, efficient delay tolerant communication based on the analysis of vehicle to vehicle interactions could be utilized [20].

[6]In this paper, we focus on the potential benefits of V2V charging system and impacts on reducing range anxiety. Therefore, in current scope, we assume the costs of charging the vehicles at charging stations and from V2V offering vehicles are the same.

In our mobility model, we consider all these factors for a realistic simulation.

	Mean	Median	Max
Trip distance (miles)	6.9	4.0	100.6
Daily miles traveled	30.3	26.8	227.7
# trips between charging events	4.2	3	
# charges per day	1.05	0.99	3.22
Trip distances between charging events (miles)	28.8	27.1	101

TABLE II: EV driving and charging statistics [24].

B. Simulation Setting and Results

The system consists of N EV drivers. Each EV type is randomly selected from the set of six EV car models in Table I. Each EV driver is assigned a home and a workplace location based on the city residential (i.e., suburbans) and workplace area densities (i.e. downtown, universities, malls). We assume each EV driver charges its car battery at home fully, commutes to work and comes back home. The work place arrival and departure hours and rates are determined based on the distributions in Figure 2-a. Then, in order to simulate the irregular activities throughout the day, we added additional trips uniformly distributed in range of [0-20] miles from their workplaces. With all these, our goal was also to match the daily trip distributions seen in several datasets [19] and average commute duration of 25 miles.

We obtained the locations of currently available charging stations in the area from [25]. There are 48 charging stations as shown in Figure 1. Most of the EVs are located at car dealers around highways 60 and 250 and at public places in downtown Richmond.

We assume each EV driver check-ins to the system with the predicted time of stay at their current location and their excess charge amounts that can be transferred to other EV owners.

In simulations, we compare the performance of the system when there is V2V charging system in addition to the dedicated charging stations and when there is only charging stations. Comparison is done in terms of number of drivers with range anxiety. In the simulations, we set $\beta = 25$.

In Figure 2-b, we show the benefit of utilizing V2V charging system (i.e., EVs and stations used as energy suppliers) compared to the current system in which the charge needs of the EVs with range anxious drivers is supplied only from available charging stations. As the number of EVs in the network increases, the charging stations will not be able to satisfy the demand. Thus, anxious driver percentage increases (after 75 EVs). On the other hand, as V2V system brings opportunity to supply the charges needed from other EVs' excess charge levels, the anxious driver percentage starts increasing very lately and slowly.

Figure 2-c and 2-d show the count and percentage of anxious drivers (before energy suppliers used), respectively, and the count and percentage of the station chargers (i.e., supplier) and V2V chargers used to lift the anxiety of these drivers (i.e., by supplying the energy needs). The default

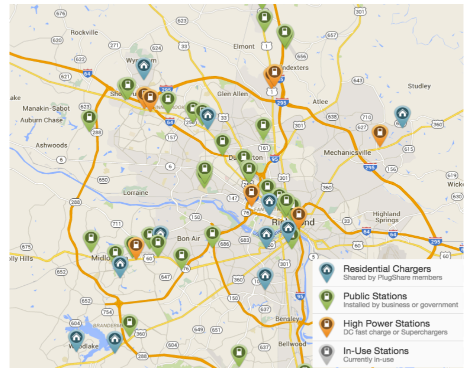

Fig. 1: EV charging stations deployed in Richmond metro area [25].

setting used in the simulations generates around 40% anxious drivers independent of EV counts. These EV drivers then look for energy suppliers. The number of stations selected as energy supplier increases to some point (i.e., 30), then for the rest of the anxious driver EVs, other EVs offering V2V charging are selected. Note that, the station chargers do not reach to 48, which is the available count in the area. This is because some EVs offer better opportunity (i.e., cost efficient) than stations.

In Figure 2-e, we show the impact of Tesla Model S cars in the distribution. As these EVs have bigger batteries than the batteries of other EV models, they not only supply the daily consumption needs of their owners but also they can help supply the demand from other EVs through V2V charging. When there is no Tesla cars in the system, all charging stations are used after some point (i.e., 175 EVs), while this is never reached when there are Tesla cars. This is because Tesla cars can also serve as charge resources to other EVs in the system with their excess charge amounts, which is more than other EVs. Finally, in Figure 2-f, we show the impact of remaining capacity in grid (no Tesla case). We assumed there are 200 EVs in the network in this case. The percentage of EVs that are matched increases until a certain grid capacity. After it reaches some value, the system could not get any more benefit of grid even though there is more capacity. Moreover, when the grid capacity decreases, V2V system supply energy of more EVs in need.

V. Conclusion

In this paper, we introduced a V2V charging framework that allows EV drivers with range anxiety buy energy from other EVs that have excess charge. The system is controlled and maintained by a location based social networking system which assigns an energy supplier (i.e., charging stations or other EVs offering V2V charge transfer) to each EV with range anxiety through solving maximum weighted matching algorithm. To evaluate the performance of the system, we studied a city-wide scenario with real charging station locations and different EV model distributions. Simulation results show that the proposed system decreases the number of EVs with range anxiety compared to the current system in which the energy

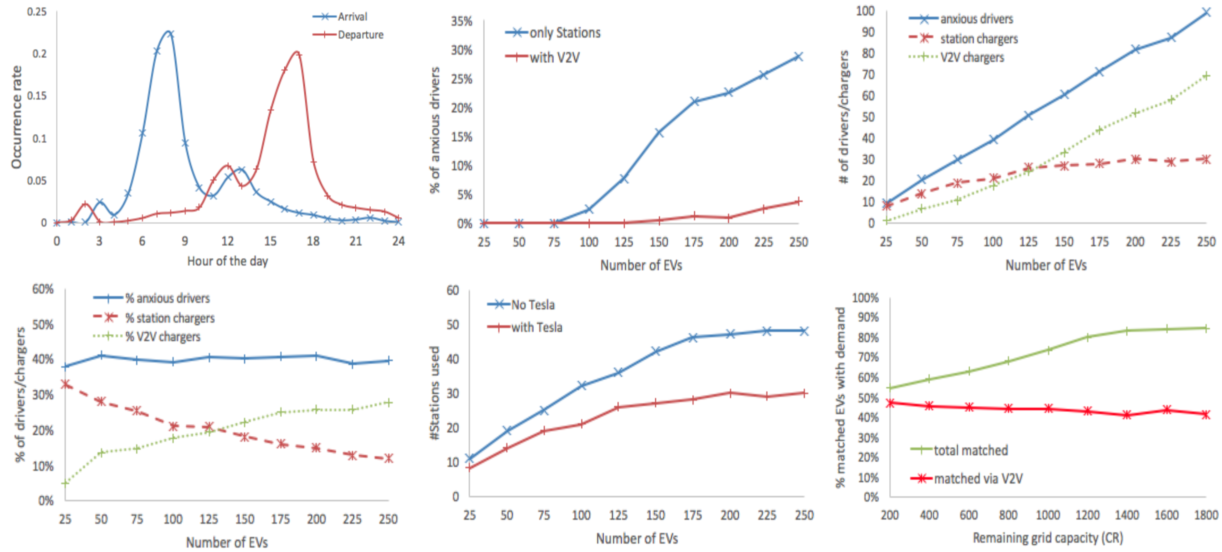

Fig. 2: a) Arrival and departure times for work, b) Percentage of anxious drivers c (d) Number (percentage) of anxious drivers and the split of station and V2V chargers for these anxious drivers, e) Percentage of anxious drivers with and without Tesla, f) Percentage of matched EVs vs. grid capacity.

demands are only supplied from deployed charging stations. This results in fewer drivers with range anxiety and lets larger number of EVs operating in the area without installing new charging stations. The proposed social charging system gives full control to the EV drivers while preserving their privacy and proving a mutual benefit environment for both the seller and buyer EVs.

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