

Spatio-Temporal Non-Intrusive Direct V2V Charge Sharing Coordination

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Abstract—Direct vehicle-to-vehicle (V2V) charge sharing system has the potential to provide more flexibility to electric vehicle (EV) charging without depending on the charging station infrastructure or building designated parking lots. It can also provide an opportunity to shift peak time utility load to off-peak times. However, the assignment between the EVs that demand energy and the EVs with surplus energy or existing charging stations is a challenging problem as it has to be performed in real time considering their spatio-temporal distribution, availability, and grid load. In this paper, we study this assignment problem specifically in a supplier non-intrusive scenario (without changing their mobility) and aim to understand the potential benefits of a direct V2V charge sharing system. To this end, we present two new algorithms to match the demander EVs to suppliers for charging. In the first one, the maximum system benefit is targeted under multiple system objectives with different priorities and considering the grid load. In the second one, individual EV priorities are taken into account and a stable matching process depending on predefined user preferences is provided. We conduct extensive simulations using real user commuting patterns and existing charging station locations in three different cities together with a newly developed probabilistic EV charging behavior model and EV mobility. Simulation results show that direct V2V charge sharing can reduce the energy consumption of EVs by 20%–35% by providing a closer charging facility compared to the charging station only case, offload grid charging power in peak times by 35%–55%, and help sustain up to $2.2\times$ EV charging requests without building new charging infrastructure, while causing a marginal increase (i.e., 3%–9%) in the energy cycling of supplier EVs. The results also show that the proposed matching algorithms offer 80%–90% more energy consumption reduction compared to the intrusive V2V charging at designated parking lots.

Index Terms—Plug-in electric vehicle, vehicle-to-vehicle charging, sharing economy, matching algorithms.

I. INTRODUCTION

ELECTRIC vehicles (EVs) are expected to transform the modern transportation and energy systems with a reduced foreign-oil dependence and improved urban air quality. Due to

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such potential, mass penetration of EVs is expected in the upcoming years with the increasing investment from auto industry [1]. However, there are some challenges that have to be addressed for the widespread adoption of EVs such as limited charging infrastructure.

Today, the majority of the EV drivers charge their vehicles at home [2] due to the non-ubiquity of charging stations. However, this limits the flexibility and length of trips with EVs. Building new charging stations comes with huge investment costs and still binds the EVs to areas with grid infrastructure. While several alternative solutions such as dynamic/stationary wireless [3] and DC fast charging are proposed, most of the time, they have high installment, labor, and permit costs. Recently, as a promising solution, vehicle-to-vehicle (V2V) charging [4]–[7] has been considered to provide more flexibility to EV charging without depending on a station infrastructure. It aims to connect EVs with excessive electric energy on their board with EVs in need of charge. Thus, EVs can be released from being obligated to get charge from a grid-connected station. This can also help mitigate the negative impacts on the grid due to grid-connected EV charging when EVs are charged during peak hours [8].

In the literature, V2V charging concept has been used with some differences. In the *first scenario* [9]–[11], it is considered for temporary sharing of energy between EVs that are currently connected to a common charging station. Such systems aim to benefit from flexibility on the charging requirements of EVs, and reduce charging costs. That is, an EV with a later deadline to be charged is discharged initially to provide energy to other EVs connected to the station and charged later while still meeting the deadline for charging. While there occurs a V2V power transfer temporarily, the total energy taken from the grid and used in the charging of both vehicles is not reduced compared to the non-V2V case.

In the *second scenario* [12]–[14], V2V charging is considered to happen at designated parking lots through an aggregator, which is a control device that collects all information from EVs and the grid, and execute the V2V operation [4]. Such aggregators can coordinate charging and discharging of a group of EVs connected to it through V2V transfer without directly drawing power from the grid. Thus, they can be installed with a much less cost compared to charging stations that pull power from the grid [15]–[17]. However, there is still a requirement of building designated parking lots connected to an aggregator for energy transfer.



Fig. 1. A Nissan Leaf is transferring energy to a Tesla Model S through a conductive charging cable. A mobile app communicating with both vehicles lets the drivers control the charging process [6], [18].

Indeed, a more flexible and less costly way for V2V charging can be achieved through a direct V2V charge sharing with a DC/DC converter that ties both EV batteries through their fast charging ports. The necessary equipment is carried by one of the vehicles; thus, there is no requirement to build a fixed charging infrastructure. Fig. 1 shows an example of this scenario realized by Andromeda Power [6] with a product called Orca Inceptive. The advantage of using direct V2V charging includes more efficient power transfer and more compact and flexible design.¹ The charging process can also be controlled via a mobile app.

In the literature, several aspects of V2V charging have been studied under the first two scenarios. Some studies look at the impact of pricing in a V2V charge sharing scenario. In [12], an energy exchange market is developed between electric vehicles by setting the prices based on local demand and supply. It has been shown that a lower price could be obtained for charging through a case study using vehicles in Belgium's Flanders region. In [19], a cloud-based V2V energy exchange framework is proposed for demand response management (DRM), and a contract-based electricity trading scheme is designed to increase the generated profit. In another study [14], a game theoretical model (e.g., Oligopoly game) is introduced for price control. Privacy aspect of V2V charging is also integrated to the proposed solutions in some studies. For example, in [20], consortium blockchains are utilized to protect privacy of EVs while optimizing the pricing with an iterative double auction based mechanism. There are also several studies that specifically focus on the matching of suppliers and demanders [17], [21], [22]. However, they mostly consider one-time matching and do not consider the practical scenarios (e.g., it is assumed that supplier EVs have always higher charge than the requested charge by demander EVs).

Contrary to these studies which assume that designated parking lots connected to an aggregator are pre-installed, we study direct V2V charging that can happen without such infrastructure support. To the best of our knowledge, there is one other study

¹This specific unit was designed as a mobile charging station that also supports grid connectivity, thus the hardware used is much larger (as shown in the trunk of a Nissan Leaf on the left), which could be reduced if grid connectivity is not needed. Note that in some cases in practice there may not be enough space to bring the vehicles that will exchange energy next to each other. This could be addressed either by allocating dedicated spots or vehicles can slightly change their location to find available spots next to each other.

that also consider direct V2V charging [23] operating without an aggregator, however, they assume that there are still designated parking lots for V2V charging, and both the supplier EV and demander EV need to move one of these parking lots. However, this will require dedicated supplier EVs and increase the charging service costs. Our proposed V2V charging system does not intrude supplier EVs from their daily mobility patterns; thus, it is more feasible and different than previous work. This is also more preferred way based on our survey results. The EVs with surplus energy (i.e., suppliers) are considered like mobile charging stations that provide energy to demander EVs only when they are stationary (e.g., parked at a workplace with a reserved parking lot next to it for demanders) and willing to do so. Also, the previous work [23] assigns demander EVs to supplier EVs in first come first served manner without considering the matching efficiency. Another significant factor that is oversimplified with a uniform random distribution in all previous works is the amount and the timing of the energy requested by the demander EVs. However, this depends on several factors including vehicle type, driver's commuting pattern and its spatio-temporal distribution as well as the driver's range anxiety that triggers the charging request. Thus, a realistic model considering these points should be developed and considered during the matching of suppliers and demanders.

The main contributions of this paper are:

- We develop a trip-based probabilistic EV charging behavior model inspired by the refueling behavior of fuel-based vehicles.
- We present the results of a survey that is conducted among 153 EV owners in US to show the potential interest and incentive for direct V2V charge sharing.
- We propose two new algorithms to assign the demander EVs to suppliers for charging, targeting the maximum system benefit and the individual satisfaction of participating EV owners separately.
- We design a realistic simulation environment using the real origin (O)-destination (D) patterns of commuters and current charging station infrastructure in three metro areas and provide extensive simulation results.

Note that the goals of this study do not include design optimization of a V2V charger and its performance analysis, which is covered under a different study [24]. The rest of the paper is organized as follows. Section II defines preliminaries including the proposed system model and survey results. In Section III, we give the details of the proposed V2V charge sharing coordination mechanisms. In Section IV, we provide the data-driven simulation settings and extensive simulation results. Finally, the paper is concluded in Section V.

II. PRELIMINARIES

A. System Model

In the proposed V2V charge sharing system, we assume that there is a centralized server and each EV driver uses a mobile app to communicate with the server using cellular infrastructure. The EVs with surplus energy become available (either automatically or manually by the driver) when they are stationary, and their

drivers are willing to serve as a supplier. The EVs in need of energy submits a request to the server to be charged. The charging could happen at either charging stations² in the area or at the supplier EV's location. The server then matches the charge suppliers (i.e., supplier EVs and stations) and demanders in some fixed time intervals based on several factors including the location and the amount of requested energy from demanders, their routes as well as the location, availability, and amount of energy that suppliers can provide. Note that if an EV does not need to be charged during the day, we assume it is fully charged at home during the night.

The main challenge in such a V2V charge sharing system is the coordination of charging requests based on the spatio-temporal distribution of both the demander EVs and the charge suppliers. For example, if a demander EV has a remaining range of r when a charging request is submitted, it should only be matched to the suppliers that are closer than r and will be available by the time it will be there. Moreover, the route of the demander EV should be diverted as little as possible so that it will not waste its energy unnecessarily. Thus, the driving patterns of EVs and the charging station distribution have significant impact. The matching between suppliers and demanders could also be performed for overall system benefit or for the satisfaction of individual demands from EVs (e.g., preference to be matched to the closest). To this end, we propose two different charge sharing coordination mechanisms in Section III-A and Section III-B.

B. EV Charging and Mobility Model

The charging behavior of EVs (i.e., when the driver decides to charge and how much charge he/she requests) is a significant parameter that affects the charge sharing coordination between EVs. Today, most of the charging is completed at homes due to the lack of sufficient infrastructure and drivers' current usage habits of EVs (e.g., commuting only). However, V2V charging provides a ubiquitous charging opportunity for EVs similar to ubiquitous refueling opportunity for fuel-based vehicles thanks to the numerous gas stations. Therefore, the current charging behavior of EVs can show similarities with refueling behavior of fuel-based vehicles in terms of timing. The literature [25]–[27] that analyze the refueling behavior of fuel-based vehicles shows that approximately three quarters of the drivers tend to refuel at the beginning or toward the end of their trips. Such a decision process can also be considered as a natural behavior for the charging of EVs as the drivers may prefer not to interrupt their trips. Therefore, in order to develop a similar charging decision model for EVs, we first model the mobility of EVs based on trips and then develop a stochastic charging decision model at trip start and end times.

We assume each EV i has a range of r_i and makes a set of trips during the day. It starts with a commute from home to work. When the lunch time comes, there could be an optional lunch trip and come back to work. After work, during commuting to

²In this study, we consider L2 stations only as they constitute the majority of the public stations available today. We assume only one charging port at every station. The charging prices through stations and V2V suppliers are also assumed the same as our focus is to study efficient matching based on spatio-temporal distribution of demanders and suppliers.

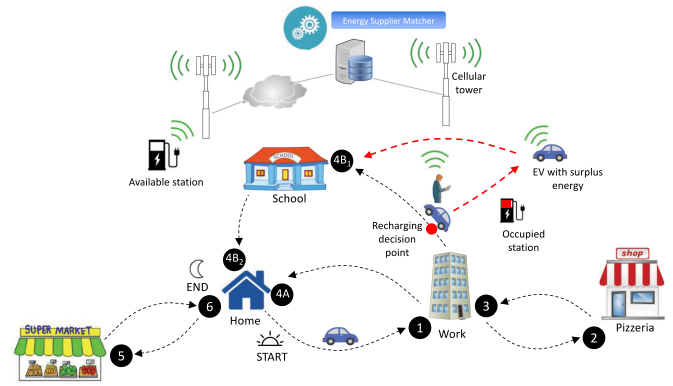


Fig. 2. An example set of daily trips of an EV including a trip to a supplier EV's location to be charged.

home, there could be an additional/unplanned trip (e.g., school) around the route. Another additional trip (e.g., market and recreation) can also exist after coming back home and staying a while. For example, a sample set of trips of an EV i can be $T_i = \{t(h, w), t(w, l), t(l, w), t(w, a), t(a, h)\}$. Each trip has a starting time, t_s , and ending time t_e and each trip's distance in miles is represented by $\Delta(h, w)$. When an EV requests a charge, the server assigns either an available charging station or a supplier EV with sufficient surplus energy. Then, the EV goes to that supplier's location from the current position in its trip. Once the charging is conducted at the intended amount and duration, it leaves from there towards the destination of its current trip. An example daily trip schedule of an EV including a visit to a supplier is illustrated in Fig. 2.

The charging decision is modeled as a stochastic decision process around trip beginnings and ends based on the range anxiety of the drivers. As it is found that the refueling decision is also related to the quantity of fuel remaining in their tank [25]–[27], we make an analogy to two common factors, namely, the low fuel light and $\sim 1/4$ of the tank, used in fuel-based vehicles and define β and $\beta + \kappa$ as the low and high range threshold values, respectively. If an EV will have a range less than zero by the time it arrives the current trip destination, it makes an immediate charging request before starting the trip. If the range at destination will be more than zero but less than β , it decides to charge with an increasing probability from the trip start time. If a decision is not made by the time it arrives destination, an immediate decision is made. Moreover, if range at the destination will be greater than β but less than $\beta + \kappa$, it decides to charge only at trip start time with some probability. Note that if such a decision is not made, it will be still safe for the driver to drive to the destination and make another decision there depending on the expected range at the next destination. Algorithm 1 and Algorithm 2 summarize this stochastic decision process.

Another significant parameter in the charging request is the amount of the requested energy. As the charging of EVs takes longer compared to the refueling in current technology, we consider partial charging in the amount of sufficient energy that will make the EV travel back home at the end of the day with at

Algorithm 1: ChargingDecider(O, D, β, κ, p).

Inputs: Origin (O) and destination (D) of current trip;
 β : low range threshold; κ : high range threshold;
 p : probability of charging at a time unit.

- 1: \mathbb{R}_i : Range at location i
- 2: t : current time
- 3: **if** $\mathbb{R}_D = \mathbb{R}_O - \Delta(O, D) \leq 0$ **then**
- 4: Charge(1, D) // find a supplier immediately
- 5: **else if** $0 < \mathbb{R}_D \leq \beta$ **then**
- 6: $s \leftarrow t$ // first time noticed that range at D will be $\leq \beta$
- 7: **while** notDecidedYet & have not arrived to D yet **do**
- 8: // decide charging with an increasing probability based on the time passed since s
- 9: Charge($1 - (1 - p)^{(t-s+1)}$, D) as $t \leftarrow t+1$
- 10: **end while**
- 11: **if** arrived to D & notDecidedYet **then**
- 12: Charge(1, D)
- 13: **end if**
- 14: **else if** $\beta < \mathbb{R}_D \leq \beta + \kappa$ **then**
- 15: Charge(p , D) // decide charging with probability p
- 16: **end if**

Algorithm 2: Charge(p, D).

- 1: $r \leftarrow$ random number between $[0,1]$
- 2: **if** ($r \leq p$) **then**
- 3: Submit a request for a charging to the scheduler
- 4: Go to the supplier assigned by the scheduler
- 5: Go to D from supplier's location after charging
- 6: **end if**

least β range. We also assume that there is a minimum energy, \mathcal{E}_{min} , that will be requested to be reasonable.

C. Incentives for Supplier EVs

We assume that there will be incentives (e.g., service fee) for EVs with surplus energy to share their charge. These incentives will come from (i) utility companies that will utilize V2V charging to shift peak time EV charging to off-peak times [8], [14], (ii) EV manufacturers who will see a more sustained EV growth without heavily relying on new and expensive station installations, and (iii) (demander) EV owners who will have more spatio-temporal flexibility for charging their vehicles. These incentives are assumed to be sufficient enough to help supplier EV owners replace their batteries when they age faster due to additional charge cycling and to make additional profit. The detailed analysis of the amount of incentives is out of the scope of this paper, however, in order to test the practicality of the V2V charge sharing and see if there will be enough incentives for suppliers from demanders, we have conducted an IRB-approved survey among 153 EV owners³ in US. Table I

³Participants are recruited from Electric Auto Association members and online forum site Reddit/ElectricVehicles subgroup users. Each participant is compensated with a \$10 Starbucks gift card. Survey can be reached at <https://tinyurl.com/v2v-sharing>.

TABLE I
SURVEY RESULTS AMONG 153 EV OWNERS IN US

	A	B	C	D
How would you be interested in joining V2V charge sharing network? A) Supplier only B) Receiver only C) Both D) None	6%	21%	40%	33%
Which form of V2V charging would you use? A) By driving to supplier's location B) By asking supplier to come (not exclusive)	72%	59%	N/A	N/A
How much would you be willing to pay for supplier EV service? A) \$5 B) \$10 C) \$15 D) \$20	46%	40%	10%	4%
At least how many users in your area would make you interested in joining V2V charge sharing? A) 10 B) 10-30 C) 30-50 D) More	24%	40%	22%	14%

shows the summary of responses to some questions in the survey. The results show that 67% of survey respondents said they would use V2V charge sharing as a supplier, receiver or both. 72% of them said they would use V2V charging in the case where they need to drive to the supplier (i.e., non-intrusive to the supplier), compared to the 59% of them which said they would use it in the case they ask suppliers to come their location. 46% said they would pay \$5 and another 40% said they would pay \$10 for supplier's service (in addition to the charging cost). Moreover, 86% of responders said they would need at most 30–50 users to join such a network. Based on these results, we expect that even in areas with smaller number of EV owners participating to V2V sharing, there will be both suppliers who will be willing to share their surplus energy with others, and there will be receivers who will value their service and pay to suppliers. Note that these results are with incentives based on payments from demanders and will be more profound with the additional incentives that might come from the utility operators and EV manufacturers.

In order to model the willingness of EV suppliers for sharing in the proposed system, we assume EVs that expect to have at least $\beta + \kappa$ range by the end of the day will be potential suppliers, and they will be able to share until at least they will have β range. However, we assume that only γ percentage of these potential EVs will be willing to be real suppliers (to consider the not interested or not available EV owners) and notify the system about it. This decision will be made at the beginning of each availability period (i.e., when not moving between the trips), thus, a potential EV can go on and off on this supplier behavior during the day.

III. DIRECT V2V CHARGE SHARING COORDINATION MECHANISMS

In this section, we first provide a maximum bipartite matching based V2V charge sharing coordination to achieve the maximum system efficiency. Then, we propose a stable matching based solution aiming to increase individual satisfaction of participating EV owners.

A. System-Oriented Matching With Multiple Objectives

In a V2V charge sharing system, as the server knows the current charging requests (triggered by Algorithm 1 and 2) from demander EVs and availability (i.e., when they are not moving

and willing to serve as a supplier) of all suppliers, it can aim to optimize the system efficiency by providing maximum service to all requests. Assume that the set of EVs is denoted by \mathbb{N} and at the current moment (i.e., t) there is a subset, \mathbb{S} , of supplier EVs each represented with a tuple of $(\mathcal{E}_i^S, l_i, t_s, t_e)$, where \mathcal{E}_i^S is the surplus energy that can be supplied to demander EVs between times t_s and t_e , and l_i is its stable location during that time frame. We define the supplier EVs as the set of EVs which will have at least $\beta + \kappa$ mileage in their remaining range by the end of the day (i.e., t_{end}). That is:

$$\mathbb{S} = \{i \in \mathbb{N} \mid \mathcal{R}_i(t_{end}) > \beta + \kappa\}, \text{ where,}$$

$$\mathcal{R}_i(t) = r_i - \left(\sum_{\substack{\forall(o,d) \in \mathcal{T}_i \\ (o,d).t_s < t \\ (o,d).t_e > t}} \Delta(o, d) \right) - \underbrace{\Delta(o, l_i)}_{(o,d).t_s < t \\ (o,d).t_e > t}$$

$$\Delta(i, j) = \text{trip distance between } i \text{ and } j \quad (1)$$

Here, $\mathcal{R}_i(t)$ represents the remaining range in the battery of EV i at time t . The energy that this EV can supply then is:

$$\mathcal{E}_i^S = (\mathcal{R}_i(t_{end}) - \beta) \lambda_i \quad (2)$$

where, λ_i represents the average energy consumed per mile in the EV i . Note that this will vary for different EV types.

Similarly, there is a subset, \mathbb{D} , of demander EVs each represented with a tuple of $(\mathcal{E}_i^D(t), l_i(t), t)$, where $\mathcal{E}_i^D(t)$ is the function of demanded energy starting at t and $l_i(t)$ is the function of EV's location.

$$\mathbb{D} = \{i \in \mathbb{N} \mid \text{a charging decision is made for } i\} \quad (3)$$

$$\mathcal{E}_i^D(t) = \max\{\mathcal{E}_{min}, (\beta - \mathcal{R}_i(t_{end})) \lambda_i\} \quad (4)$$

Demander EVs can request energy during a time frame in which they can still be moving within some limits, while supplier EVs are assumed to be available only when they are stable. The set of charging stations, \mathbb{T} , is also considered to include only the available charging stations at that moment.

From the overall system's point of view, the goal should be supplying the needs of as many demander EVs as possible. To this end, we formulate the problem as a maximum weighted bipartite matching problem. That is, let $G = (V, E)$ be a graph with vertices representing an EV or a charging station ($|V| = |\mathbb{S} \cup \mathbb{D} \cup \mathbb{T}|$) and edges defined as links from the vertices of EVs that are in need of energy to the rest of the vertices that can supply the demanded energy. More formally:

$$V = \mathbb{D} \cup \mathbb{S} \cup \mathbb{T} \quad (5)$$

$$E = E_1 \cup E_2 \quad (6)$$

$$E_1 = \{(i, j) \mid \forall i \in \mathbb{D}, \forall j \in \mathbb{S} \text{ s.t.}$$

$$\mathcal{R}_i(t) \geq \Delta(i, j) \text{ \&}$$

$$\mathcal{E}_j^S(t) > \mathcal{E}_i^D(t) + \mathcal{R}_\Delta \lambda_i, \text{ where,}$$

$$\mathcal{R}_\Delta = \mathcal{R}_i(l_i(t), l_j, d) - \mathcal{R}_i(l_i(t), d) \quad (7)$$

$$E_2 = \{(i, j) \mid \forall i \in \mathbb{D}, \forall j \in \mathbb{T} \text{ s.t.}$$

$$\mathcal{R}_i(t) \geq \Delta(i, j) \quad (8)$$

Note that due to the trip to and from the supplier to the current trip destination, demander EVs should ask for additional energy on top of the energy they actually need to have β miles by the end of the day. This can be found by the mileage difference (\mathcal{R}_Δ) between indirect trip to destination through this supplier ($\mathcal{R}_i(l_i(t), l_j, d)$) and the direct trip ($\mathcal{R}_i(l_i(t), d)$) multiplied by the energy consumption rate per mile (λ_i). The total demanded energy should be less than the energy that the supplier EV can provide. It should be noted that an available charging station is assumed to provide as much energy as the EV needs as long as it is available. However, in either case, the current range of the EV should be larger than the distance to the energy supplier (i.e. $\mathcal{R}(i) \geq \Delta(i, j)$) so that EV can travel to supplier's location without depleting its energy.

Once the graph is formed with edges between demanders and suppliers representing potential assignments, we propose a new matching algorithm on the graph that aims to achieve multiple objectives at the same time in some prioritized order. The *first goal* is to maximize the number of EVs matched to an energy supplier. Since there can be multiple ways of achieving the same number of maximum matchings, as a *second goal* in peak hours, we give priority to the EVs with surplus energy over the charging stations in order to offload the power demand from the grid. We assume that V2V suppliers are provided incentives to adopt delayed charging [28] strategy (working in coordination with grid operator) and start charging their vehicle at home after peak hours (e.g., after midnight) while providing energy into the market before peak hours. Finally, among the matchings with same number of supplier EVs, as a *third goal*, we give priority to the supplier EVs that cause smaller detour cost \mathcal{T}_Δ , defined as:

$$\mathcal{T}_\Delta = \mathcal{T}(i, j, d) - \mathcal{T}(i, d), \text{ where}$$

$$\mathcal{T}(i, j, d) = \frac{\mathcal{R}_i(l_i(t), l_j, d)}{v_i} + \frac{\mathcal{E}_i^D(t) + \mathcal{R}_\Delta \lambda_i}{C_j}$$

$$\mathcal{T}(i, d) = \frac{\mathcal{R}_i(l_i(t), d)}{v_i} \quad (9)$$

Here, v_i is the average travel speed of demander EV i , C_j is the charging rate⁴ of supplier j , $\mathcal{T}(i, j, d)$ is trip duration to destination through supplier j , and $\mathcal{T}(i, d)$ is the direct trip duration from demander EV i 's current location to current trip destination d (see Fig. 3). Note that $\mathcal{T}(i, j, d)$ includes not only the traveling time to the supplier but also the time for charging at the supplier.

Putting all these together, the objective and graph can be formulated as:

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

$$y_i = \sum_{\forall j \in \mathbb{S} \cup \mathbb{T}} x_{ij} < 2, \forall i \in \mathbb{D} \quad (10)$$

⁴The charging power increases very slightly during DC charging between 10-60% of SOC [29], [30]. We assume here that it is constant similar to previous work [31], [32]. Moreover, we assume that the V2V supplier can provide the maximum power that can be achieved without violating any SOC or DOD limits.

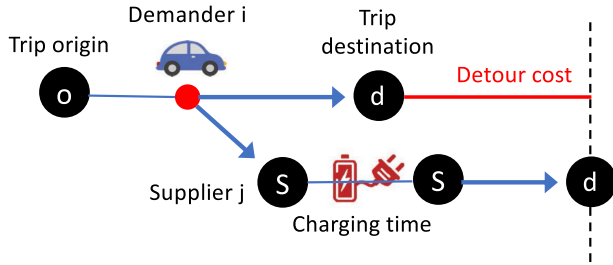


Fig. 3. Graphical representation of the detour cost, which is defined as the time loss in current trip due to the supplier visit and charging.

$$\sum_{\forall i \in \mathbb{D}} x_{ij} < 2, \forall j \in \mathbb{S} \cup \mathbb{T} \quad (11)$$

$$x_{ij} = \begin{cases} 1 + \mu_{ij}/Z, & \text{if } i \leftrightarrow j \in \mathbb{S} \\ 1, & \text{if } i \leftrightarrow j \in \mathbb{T} \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

$$\mu_{ij} = 1/\mathcal{T}_{\Delta} \quad (13)$$

(10) ensures that there will be only one supplier for each demander EV. (11) ensures that there will be only one demander assigned to each supplier EV or a station. (12) sets x_{ij} to 1 if it is matched to a charging station, or to a number between 1 and 2 if matched to a V2V supplier. Thus, in the maximum weight matching, V2V suppliers will be preferred as aimed by the second goal. The decimal part of the x_{ij} (when assigned to V2V supplier) is set inversely proportional with the detour cost so that the V2V suppliers causing smaller detour cost will be preferred in the light of the third goal. μ_{ij} , in (13) is the reciprocal of detour cost, and Z is a very big number (e.g., $\gg \sum_{\forall ij} \mu_{ij}$) that ensures that the sum of decimals in x_{ij} s of all matched supplier EVs will be less than 1. This ensures that if there is an additional demander matching possible even to a charging station (which has a weight 1), it will be preferred rather than having fewer users matched even they are all assigned to V2V suppliers, to comply with the first goal which has priority over the second goal. Note that y_i in (10) is defined as the sum of weights of links (x_{ij}) from demander i and has an upperbound of 2. This allows only three options for the demander (i) being assigned to a station, (ii) being assigned to a V2V supplier or (iii) left unassigned (which will not be the case if there is an available supplier). y_i 's being less than 2 does not allow two station assignments to the demander.

Note that in off-peak times, we simply update (12) as follows to invalidate the second goal and find the matching that achieves the minimum total detour cost among the matchings with maximum cardinality (i.e., maximum users matched):

$$x_{ij} = \begin{cases} 1 + \mu_{ij}/Z, & \text{if } i \leftrightarrow j \in \mathbb{S} \cup \mathbb{T} \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

To solve the maximum weighted bipartite problem, we transform it to an instance of an assignment problem and solve it with Hungarian algorithm [33]. The complexity of this algorithm is

Algorithm 3: Stable-Demander-Supplier-Matching

($\mathbb{D}, \mathbb{S}, \mathcal{L}$).

Inputs: \mathbb{D} : the set of demander EVs; \mathbb{S} : the set of suppliers;

\mathcal{L} : preference lists of demanders/suppliers

```

1: for each demander EV  $d_i$  and each supplier  $s_j$  do
2:    $\mathcal{M}(d_i) = \emptyset, \mathcal{M}(s_j) = \emptyset$  // No partners yet
3: end for
4: while  $\exists d_i \mid \mathcal{M}(d_i) == \emptyset$  do
5:    $d_{new} \leftarrow d_i$ 
6:    $s_{next} \leftarrow \text{top}(\mathcal{L}(d_{new}))$ 
7:    $d_{cur} \leftarrow \mathcal{M}(s_{next})$ 
8:   if  $d_{cur} == \emptyset$  then
9:      $\mathcal{M}(s_{next}) \leftarrow d_{new}$ 
10:     $\mathcal{M}(d_{new}) = s_{next}$ 
11:   else if  $d_{new} \succ_{s_{next}} d_{cur}$  then
12:      $\mathcal{M}(d_{cur}) = \emptyset$ 
13:      $\mathcal{L}(d_{cur}) = \mathcal{L}(d_{cur}) - s_{next}$ 
14:      $\mathcal{M}(s_{next}) = d_{new}$ 
15:      $\mathcal{M}(d_{new}) = s_{next}$ 
16:   else
17:      $\mathcal{L}(d_{new}) = \mathcal{L}(d_{new}) - s_{next}$ 
18:   end if
19: end while
20: return  $\mathcal{M}$ 

```

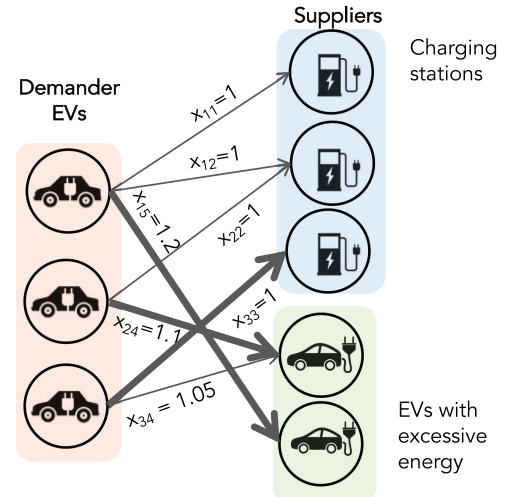


Fig. 4. An example system-oriented matching between demander EVs and suppliers.

$O(V^3)$. The result of the assignment on a sample problem is shown in Fig. 4.

B. Individual EV-Oriented Stable Matching

In the previous section, the matching of demander EVs with suppliers is conducted considering the overall system efficiency. However, in practice, each demander and supplier EV may have their own preferences from their own perspectives. For example, a demander EV may want to be charged by the eligible suppliers that can let it go back to its destination as quickly as possible (i.e.,

minimum detour cost, \mathcal{T}_Δ). Similarly, a supplier EV may prefer charging the demander EVs that will buy the largest amount of energy first to make more profit. Thus, a design without considering individual EV preferences may not be attractive to users, and unstable conditions may appear (i.e., demander and supplier pairs preferring each other over their assigned partners). To address this concern, in this section, we propose a new algorithm that results in a stable matching between demanders and suppliers.

In our problem, the demander EVs and suppliers at the current decision moment (i.e., t) represent either side of the stable matching problem. The critical part is how the preference lists are formed at the scheduler. To this end, we propose different criteria for demanders and suppliers considering the goals from their perspective. For the preference list of demander EVs, we first find the list of available supplier EVs and charging stations that can serve this demander. Then, we sort them in ascending order of the detour cost (i.e., \mathcal{T}_Δ) they would cause from the demander's original route. To form the preference lists of supplier EVs, we first find the list of demander EVs that this supplier can provide the demanded energy. Then we sort them in descending order of the demanded amount as suppliers prefer the demanders that will bring more profit to them. Then, a stable matching between suppliers and demanders needs to be found such that there does not exist a demander and a supplier EV that prefer each other rather than their assigned pairs.

To define the problem more formally, let $\mathcal{L}(i)$ denote the preference list of a user i (i.e., demander or supplier), and let $\mathcal{M}(i)$ denote its partner in the matching \mathcal{M} . If it is not matched yet, $\mathcal{M}(i) = \emptyset$. We utilize $j \succ_i k$ notation to express that user i prefers j to k . A matching \mathcal{M} will be stable if there does not exist any blocking pair $\langle d, s \rangle$ such that $d \in \mathcal{L}(s)$, $s \in \mathcal{L}(d)$ and $s \succ_d \mathcal{M}(d)$ and $d \succ_s \mathcal{M}(s)$. Note that if a demander d is not matched yet but if the supplier s prefers d over what it is matched, i.e., $d \succ_s \mathcal{M}(s)$ and $\mathcal{M}(d) = \emptyset$, that also creates a blocking pair. Similarly, $\langle d, s \rangle$ will be blocking pair with $s \succ_d \mathcal{M}(d)$ and $\mathcal{M}(s) = \emptyset$. Moreover, if they are left unmatched, i.e., $\mathcal{M}(d) = \emptyset$ and $\mathcal{M}(s) = \emptyset$, it will be also be a blocking pair to stable matching.

To solve the problem and guarantee a stable matching, we adapt the Gale-Shapley stable marriage assignment algorithm [34] to our problem to find a demander optimal solution, where each demander is matched with his/her most preferred supplier as much as possible by letting them propose to the suppliers in the order of their preference lists. As there could be unequal number of suppliers and demanders at the time of an assignment, we apply specific termination conditions⁵ as presented in [35]. Algorithm 3 shows the steps of finding a guaranteed stable matching between demander EVs and suppliers. Initially, every demander and supplier has no partner in the matching, \mathcal{M} . Until all the demander EVs are assigned, a new demander, d_{new} , not assigned yet is selected. The demander d_{new} proposes to the

⁵If there are fewer demanders than suppliers ($|\mathbb{D}| < |\mathbb{S} \cup \mathbb{T}|$), the algorithm stops when $|\mathbb{D}|$ of the suppliers have been asked, and if there are more demanders than suppliers ($|\mathbb{D}| > |\mathbb{S} \cup \mathbb{T}|$) the algorithm stops when each demander is either being kept in suspense by some supplier or has been refused by all the suppliers.

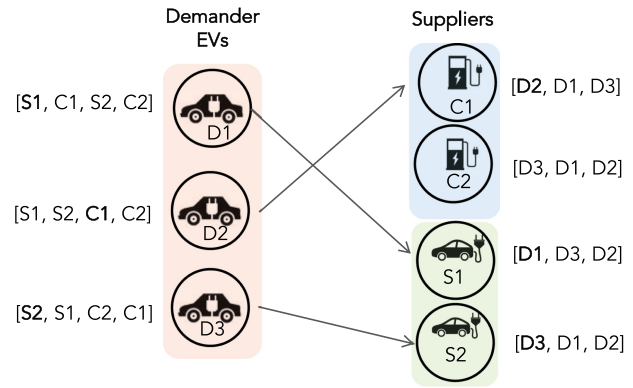


Fig. 5. An example stable matching of demander EVs with supplier EVs and charging stations.

supplier (s_{next}) at the top of its preference list, $\mathcal{L}(d_{new})$. If that supplier EV has not been assigned to any other demander EV yet, it immediately accepts this proposal. However, if it is already assigned to another demander EV (i.e., d_{cur}), it checks if it prefers the new demander more than the current one matched ($d_{new} \succ_{s_{next}} d_{cur}$). If that is the case, it is reassigned to d_{new} and d_{cur} is unmatched. s_{next} is also removed from previous demander's preference list ($\mathcal{L}(d_{cur})$) to make it propose to its next preferred supplier. If the old demander is preferred over the new one, the supplier s_{next} rejects the proposal of demander d_{new} , then s_{next} is removed from demander d_{new} 's preference list. This process stops when all demanders are matched to a supplier or aforementioned specific termination conditions are met for unequal number of suppliers and demanders.

The running time of the algorithm is $O(V^2)$ and it guarantees that a stable matching will be found [34], [36]. This is because, by the design of algorithm, it will not be possible to find a demander, d , and a supplier s that will prefer each other over their matched pairs. If d prefers s to its current supplier, d must have asked s before asking to current supplier. If s accepted it at that moment but ended up matched with another demander, s must have rejected d for some other demander that it prefers, thus does not prefer d more than its current demander. If s rejected d 's proposal, s was already matched with some demander it liked more than d . An example matching is illustrated in Fig. 5.

IV. SIMULATIONS

To evaluate the performance of the V2V charge sharing system and the matching algorithms, we have built a Java based custom simulator. In this section, we first discuss how several simulation components are modeled, and then provide the results.

A. Data-Driven EV Mobility

The mobility model of EVs affects the performance of the V2V charge sharing performance directly. Not only the routes followed by EVs and the associated trip costs but also the spatio-temporal distribution of demander EVs and suppliers affect the matching results.

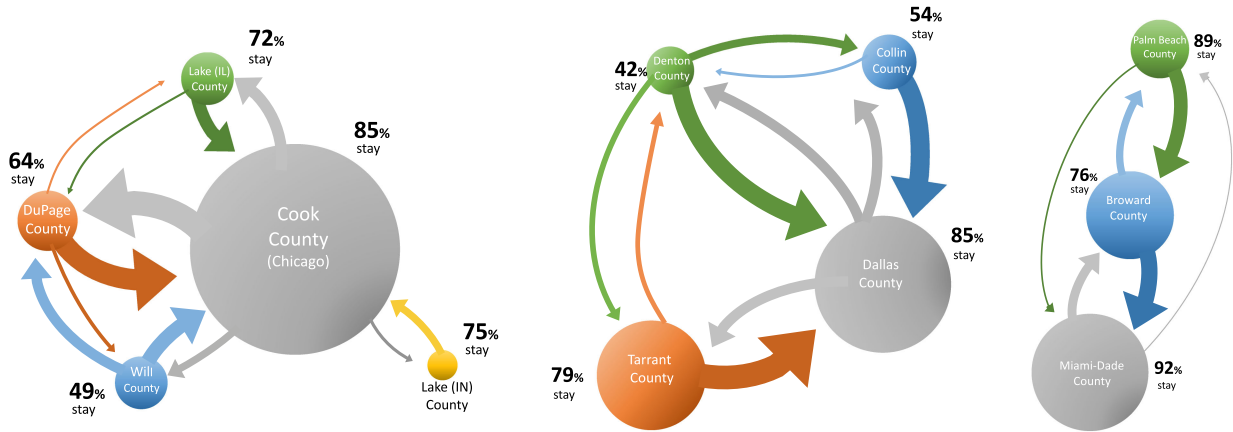


Fig. 6. Origin-destination commuting patterns between the counties of the three metro areas: (i) Chicago, (ii) Dallas and (iii) Miami. The size of the circles represents relative resident population in the counties and the thickness of the lines between counties represents the transition rates between counties during commuting.

There are various approaches adopted for the movement of vehicles [37]. Some models are designed with high complexity and lots of low level details (e.g., lane changes) as the quality of communication links in vehicular ad hoc networks is highly sensitive to distance between vehicles and RSUs. However, our focus in this paper is to conduct a macro-scale analysis of V2V charge sharing system, and we need high level distribution of distances between vehicles and charging stations. Thus, we use a simple stochastic model, namely Constant Speed Motion model [38], in our simulations. The model limits the movement of vehicles on a graph that represents the road topology. Vehicles move towards their destination over the edges on the graph using a random speed in some range. The speed of the vehicle is set to $v = v_{min} + (v_{max} - v_{min})\eta$, where η is a uniformly distributed random variable in $[0, 1]$. The route of the vehicle is determined by running a shortest path algorithm between the origin and destination nodes. The model can potentially include the pause times and some variations due to acceleration and deceleration of the vehicle at the intersections. However, they would affect only the trip times from an origin to a destination, for which we can get the same impact with reduced average speed range for vehicles.

Additionally, the commuting patterns of EVs need to be injected realistically to the simulations. To this end, we analyzed National Household Travel Surveys (NHTS) [39] that provides statistics from the vehicle based trip behaviors. We extracted the Origin-Destination (O-D) patterns of three metro areas, namely, Chicago, Dallas and Miami. Fig. 6 shows the neighbor counties considered for each metro area together with the transition rates between the counties. The graphic is depicted in a way such that the size of the circles represents relative resident population in the counties, and the thickness of the lines represents the transition rates between counties during commuting. For example, in Chicago, 85% of the residents living in the Cook county stay in the county for work, while 8% of them goes to DuPage county.

NHTS statistics also shows that an average commuter duty cycle comprises four trips (matching to trips defined in

Section II-B) and covers a distance of 20 miles. Trip 1 is the morning commute to work, trip 2 is a noon-hour trip (e.g., lunch), trip 3 is an evening commute from work, and trip 4 is an evening trip. Even though commuting represents around one third of the urban driving in the city [40], approximately three quarters of the drivers refuel their vehicles on the way to or from home [26]. Thus, in our simulations, we focus on commuting behavior but consider all other trips with multiple purposes under the additional trip category. Each EV has initially been assigned to a county for its home and work location based on the ratios in Fig. 6. The exact locations of home and workplaces as well as the trips inside the counties are determined based on the residential and workplace distributions (obtained from city zoning information and population densities). County lands are divided into a grid, and each grid cell is marked as a residential or workplace area. The selection of home and work locations are determined probabilistically based on the densities of residential and workplace cells, respectively.

Each EV is assumed fully charged at home. Based on the arrival and departure time distributions obtained from a real dataset [41], the first trip (i.e., home to work) start time is decided with a Gaussian distribution $G(\mu, \sigma^2) = (8, 1/2)$. That is, it starts on average at 8 am with a standard deviation of 30 minutes. Similarly, work to home trip is decided with a departure time decided with $G(17, 1/2)$. Additional trips are generated for lunch and after work or after coming back home in the evening. The probabilities used during their generation and the rest of the simulation settings⁶ regarding the parameters used in the algorithm designs are shown in Table II. In order to take into account the workplace charging [2], we also let 15% users charge their vehicles at work if they notice a charging need while at work.

⁶These values are selected based on different rationale. For example, β is set to the weighted average of user responses in the survey. C is decided based on the specifications of available V2V chargers and expected charging speed demanded in survey. We have also used some reports (e.g., for lunch time [42]) and our common sense to set them to reasonable values.

TABLE II
SIMULATION SETTINGS

Parameter	Value
Number of EVs	[10-100]k
Probability of having lunch	0.5
Lunch duration	[20-40] minutes
Lunch location range (from work)	10 miles
Probability of having additional trip after work	0.5
Probability of having additional trip in the evening	0.5
Additional trip duration	[20-40] minutes
Additional trip location range (from work/home)	10 miles
Speed range for EVs (v_{min} , v_{max})	[30-50] mile/hour
Charging decider lower limit parameter (β)	25 miles
Supplier surplus range upper limit parameter (κ)	25 miles
Supplier willingness parameter (γ)	0.05
V2V charging power rate (C)	20 kW

TABLE III
EV TYPES AND THEIR SPECIFICATIONS

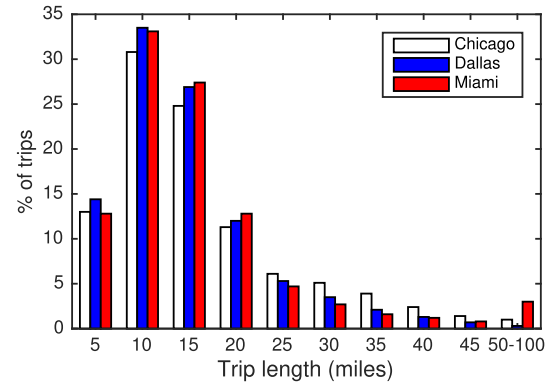
EV Model	Battery Capacity (kWh)	EV Range (mi)	Charger Power (kW)	Assumed Market Share (%)
Nissan Leaf	30	107	6.6	25
Tesla Model S	100	315	10	20
Chevy Bolt	60	238	3.6	18
Tesla Model X	90	238	10	12
BMW i3	33	114	7.4	9
Hyundai Ioniq	28	124	7	9
Kia Soul EV	27	93	6.6	7

B. EV Specifications and Charging Infrastructure

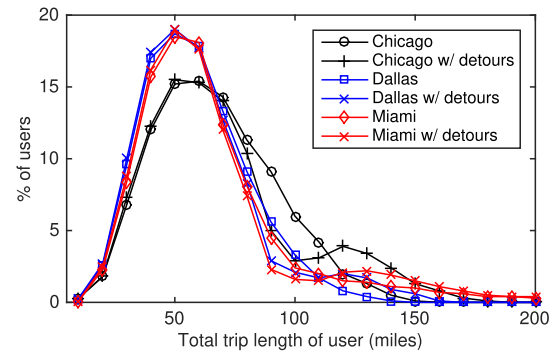
The variety of available models in EV market has been increasing rapidly as the auto industry invests more. In Table III, we show seven popular models that are available in the market today. We use these EV types together with their associated specifications including the battery capacity, range, and charger power in our simulations for a realistic model. Average energy consumption rate (λ_i) of each EV is obtained by dividing the battery capacity of the EV by its range (kWh/mile). The range of these vehicles are more than the average commuting distance [40], but we also assign the EVs with longer ranges to users with longer commutes. However, when an additional trip is needed during the day, some of these vehicles may force their drivers find extra charge (through Algorithm 1 and 2) due to the range anxiety. Nearby charging stations will be the immediate solution in such cases, but there may not be any available one in their vicinity due to the insufficient station infrastructure. We extracted the locations of L2 charging stations available to public in the three metro areas considered from [43]. In total, we found 572 such stations in Chicago, 462 stations in Dallas, and 469 stations in Miami within the counties considered in Fig. 6. In the simulations, when an EV decides to charge, it looks for available stations and other EVs with surplus energy and is matched with one of the suppliers as defined by the matching algorithms.

C. Performance Metrics

We evaluate the performance of the proposed V2V charge sharing system and coordination mechanisms based on the following metrics:



(a)



(b)

Fig. 7. (a) Distribution of all trip lengths. (b) Distribution of total trip lengths of users.

- **Maximum sustainable EV count:** The maximum number of EVs whose charging requests all can be matched with available suppliers (e.g., stations, supplier EVs).
- **Energy consumption reduction (%):** This is the decrease in the total energy consumption of all EVs through proposed algorithms compared to the scenario where all EVs are charged at nearest charging stations. Note that with closer suppliers matched, EVs consume less energy.
- **Peak charging load reduction (%):** This is the ratio of the reduction in the charging power demand from the grid during peak times with the introduction of V2V charging compared to all EVs charged at stations.
- **Battery energy cycling increase (%):** This is the increase in the total energy cycling (i.e., charging/discharging) of supplier EV batteries.

D. Results

We first provide some statistics about the trips generated during simulations. Fig. 7 shows the distribution of all trip lengths and total trip lengths of users. Average trip lengths are 14.0, 12.2 and 14.6 miles in Chicago, Dallas and Miami, respectively. Due to the long rectangular area covered in Miami, there are more EVs with long trip lengths (i.e., ratio of trips with 50–100 miles is higher than it is in other cities as shown in Fig. 7a). The largest average total mileage per user is obtained in Chicago (i.e., 62.1 miles) due to the largest area covered while

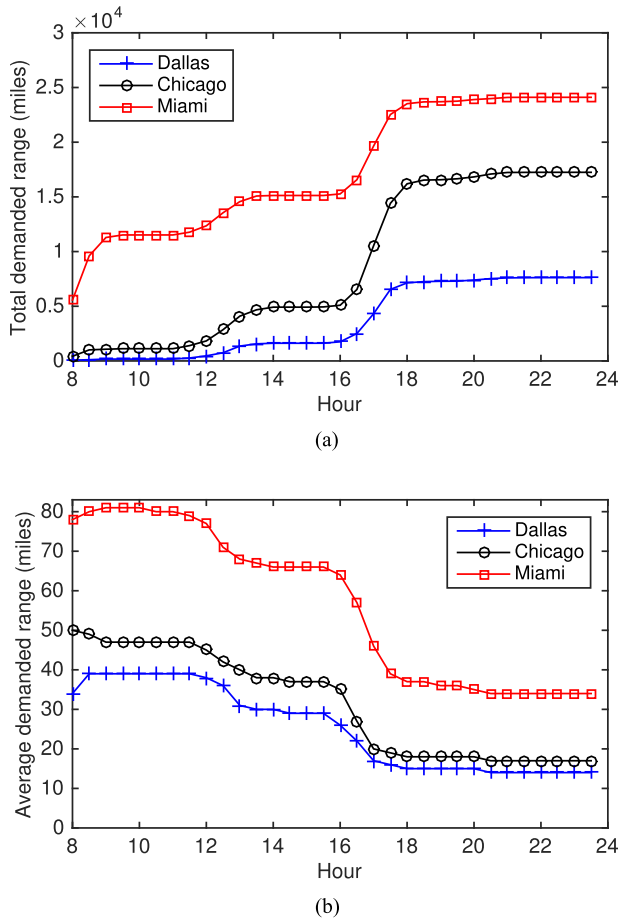


Fig. 8. (a) Total demanded range from all EVs. (b) Average demanded range by EVs with range anxiety.

the smallest is obtained in Dallas (i.e., 53.6 miles). Fig. 7b shows the total trip length distribution with and without detours. The latter represents the case where there were no detours needed due to charging needs. As the users demand for energy (on average, 9%, 13% and 8% of all users in Dallas, Chicago and Miami, respectively) and stop by suppliers, their total trip lengths increase due to the detours. We can also observe this in Fig. 7b, as the ratio of users with more than 70 mile total trip lengths (and having EVs with lower ranges) is shifted and distributed to 100–150 mile range.

Next, we look at the distribution of demanded range by the EVs in the simulations. Fig. 8a shows the total demanded range (i.e., $\sum \mathcal{E}_i^D(t)$) during the day in the three cities. As the EVs start the day with full battery, the first demands usually come after 8 am. The demand stays low until lunch time for the cities except Miami. This is because we cover a larger region with the Miami counties compared to others and the EVs with longer commuting distances might decide to charge even in the morning hours (e.g., right after they complete first trip or so). Such EVs may also need multiple charging during the day. In Fig. 8b, we show the average range demanded by the EVs. Earlier demander EVs usually ask for larger ranges, thus the initial average is high for each city. But they all stabilize around 20–40 mile range,

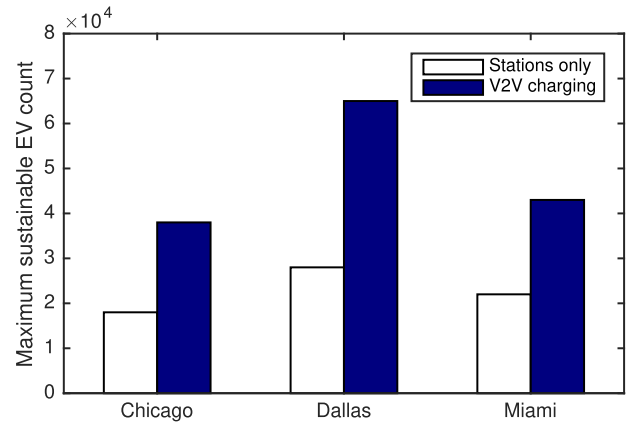


Fig. 9. Maximum sustainable EV count with current charging station infrastructure vs. with V2V charging.

with demander EVs in Miami having the largest average, due to the same reason of large area consideration.

To understand how V2V charge sharing can help satisfying the charging needs without building new charging stations, we compare the maximum sustainable EV counts with only charging stations and with V2V charging introduced. That is, we increase the number of EVs in the simulations until the first demander EV is not matched to any available supplier (station or supplier EV). Fig. 9 shows these EV counts for each city. Dallas area infrastructure can sustain the largest number of EVs (i.e., 30 k) among all three cities with the current infrastructure. Note that while Chicago has the largest number of stations available, due to the large size of the area considered and the distribution of the stations in the area, it cannot sustain the largest number of EVs. When V2V charge sharing is introduced, with the settings used in Table II, we observe that maximum sustainable EV counts will increase in 2–2.5 times for all cities. This is because V2V charge sharing can provide more charging opportunity and can help supply the needs of more EVs. Note that these are with EVs with surplus energy used as mobile charging stations when they are not moving (i.e., non-intrusive). Thus, it could be achieved with less incentives compared to the case where suppliers are asked to provide charging service in demander's location (e.g., Uber style) or a meeting point (e.g., designated parking lot).

In Fig. 10, we provide the energy consumption reduction obtained by proposed matching algorithms as well as by the first come first served (FCFS) based matching compared to the charging station only scenario. Note that while the actual charge need (i.e., $\mathcal{E}_i^D(t)$) from EVs is the same for all cases, due to the travel to the supplier locations, the total charging amounts (i.e., $\mathcal{E}_i^D(t) + \mathcal{R}_\Delta \lambda_i$) may change. With V2V charge sharing, more potential suppliers are introduced; thus, closer suppliers are found, resulting in 20–35% decrease in the total charging amounts. By design, in stable matching, EVs prefer being matched with suppliers that provide smaller detour cost (i.e., \mathcal{T}_Δ) from the original route. However, in maximum weighted bipartite matching, the main goal is to increase the matchings to supplier EVs as much as possible and later consider the detour cost due to the trips to suppliers. Therefore, stable matching offers more energy consumption reduction compared to maximum

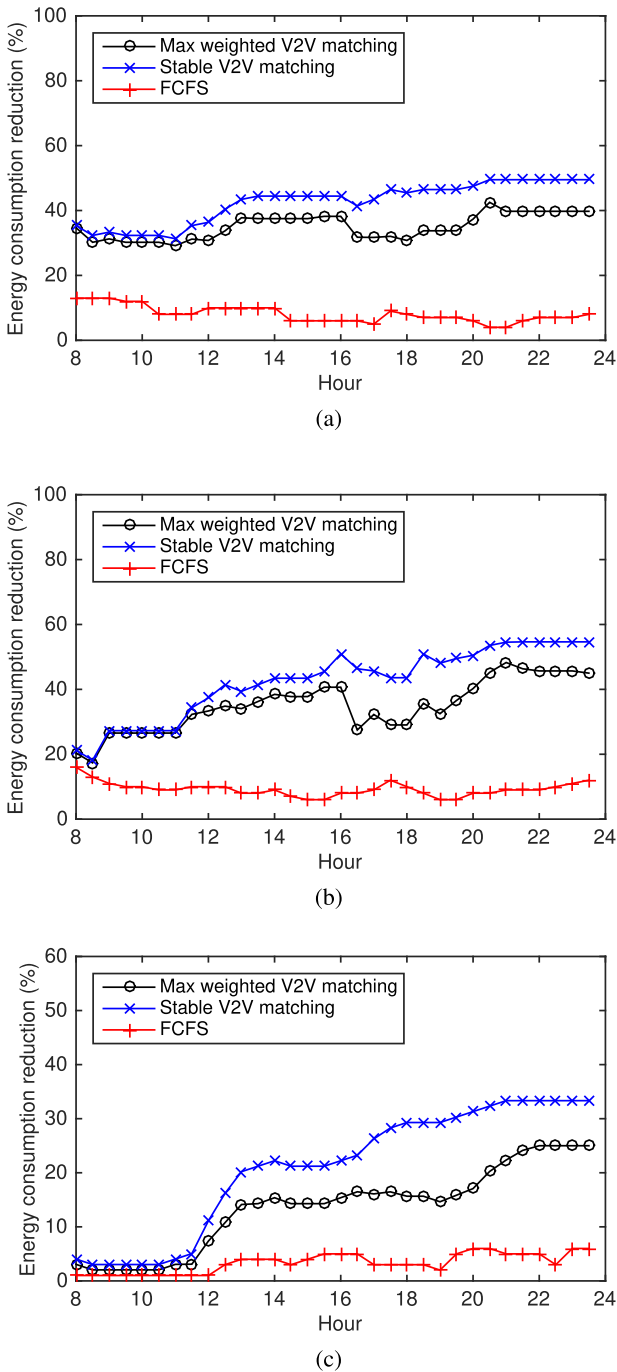


Fig. 10. Energy consumption reduction with proposed matching algorithms in three cities. (a) Chicago. (b) Dallas. (c) Miami.

weighted bipartite matching. However, both algorithms perform better compared to FCFS, as expected. Comparing the results in different cities, we observe that reduction is the least in Miami. This is because the actual energy needs is higher in Miami (as shown in Fig. 8) due to larger area, thus the reduction is less.

Next, we look at peak charging load reduction from the grid with V2V charging. V2V suppliers can help reduce the charging power demand from the grid by providing energy to demanders during the day and charge themselves during off-peak hours.

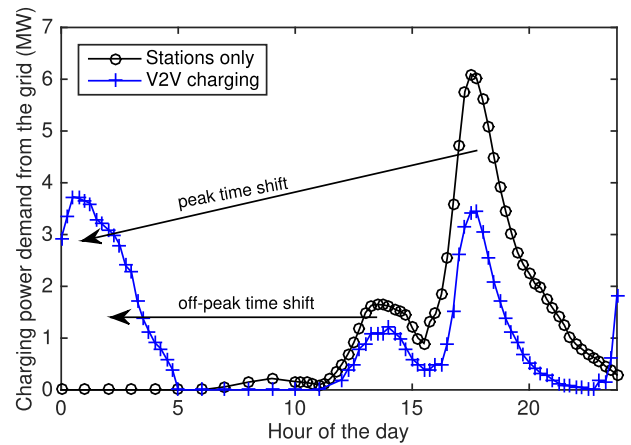


Fig. 11. Comparison of charging power demand from the grid with V2V charging vs. with station only charging (Dallas).

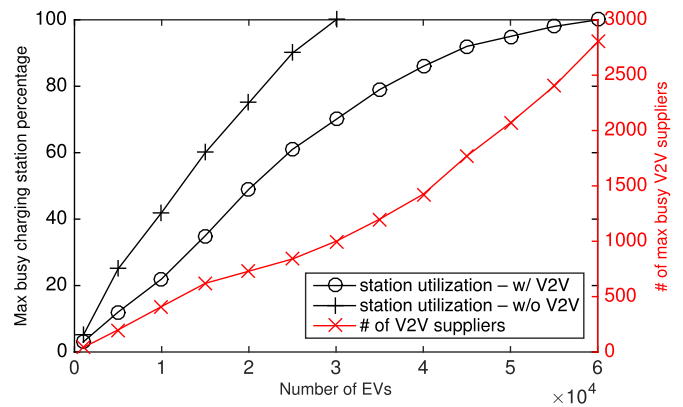


Fig. 12. The utilization of charging stations with and without V2V charging and the maximum number of V2V suppliers occupied with V2V charging (Dallas).

Fig. 11 compares charging power demand from the grid with and without V2V charging (using maximum weighted bipartite matching in Dallas). Note that the system-oriented matching gives priority to V2V suppliers only at peak times, thus, in off-peak times (e.g., 10–15), the demand from the grid decreases remarkably less compared to peak times. During peak time, V2V suppliers are prioritized but as the number of available V2V suppliers gets smaller, more charging stations are matched to demanders to satisfy all the user demands with the total minimum detour cost. V2V charging effectively reduces the peak charging load by 47% reducing the stress on the system in Dallas. We have observed similar (40–55%) reductions in other cities and slightly less reduction (35–43%) with stable matching as it only considers user preferences (based on detour costs) and do not give priority to V2V suppliers any time.

We also look at the maximum charging station utilization with and without V2V suppliers. Fig. 12 shows these values together with the number of maximum V2V suppliers used at a time with different number of EVs in the network. With V2V charging, demanders are matched to V2V suppliers if they offer lower

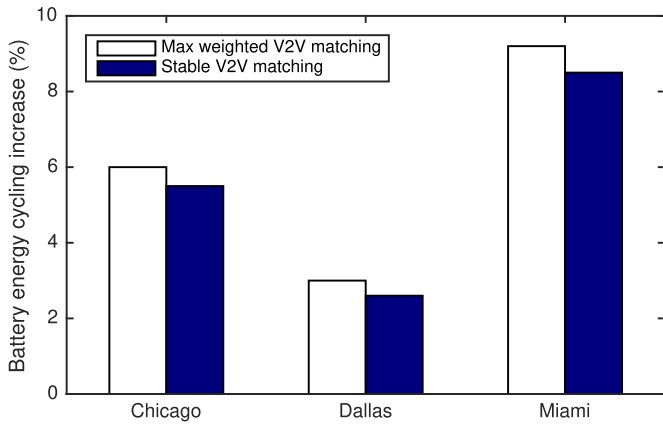


Fig. 13. Average increase in energy cycling of supplier EVs.

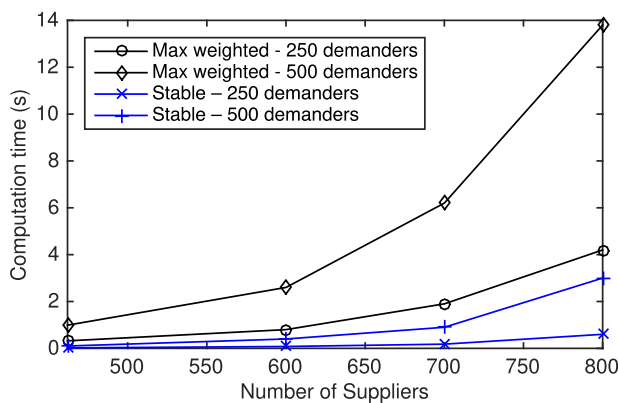


Fig. 14. Computation times of proposed algorithms with different number of demanders and suppliers (Dallas).

detour cost, but eventually all stations are used in both cases. Moreover, with V2V charging more demands could be supplied.

While V2V charge sharing increases charging opportunities for demander EVs, there will be additional deterioration on the supplier EV batteries. Assuming that battery deterioration due to discharging of batteries while transferring energy to a demander EV is same as it is due to discharging while driving, we can expect some correlation between battery deterioration and the total energy cycling on the batteries (actual deterioration will depend on several factors including battery temperature, driving style, cell type). We have quantified the ratio of additional energy cycling on the supplier EV batteries beyond their own needs. The results presented in Fig. 13 show that there is on average 3–9% increase in the total energy cycling of EVs. EVs in Miami have the highest average increase due to the highest demands. Moreover, maximum weighted bipartite matching yields more increase in all cities due to the fact that it gives preference to V2V suppliers while stable matching might select a closer station instead.

In Fig. 14, we provide the actual computation times of the proposed algorithms on a computer with Intel core i7 processor with speed 2.5 GHz and a 16GB of memory. We have considered different number of demanders and suppliers and used Dallas scenario; therefore, the initial number of suppliers

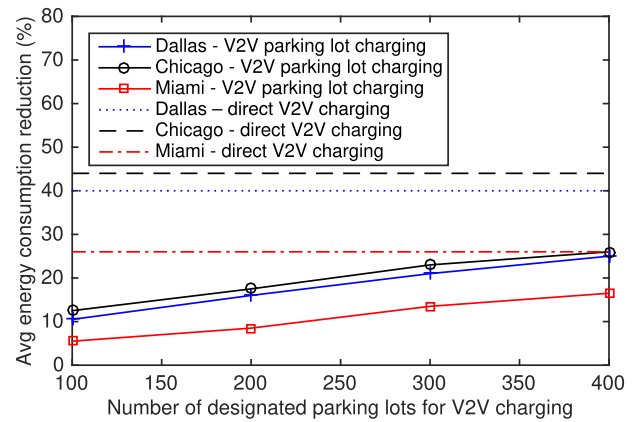


Fig. 15. Average energy consumption reduction with direct V2V charging vs. V2V charging at designated parking lots.

used is equal to the charging stations available (i.e., 462) in Dallas area. We increased the number of suppliers by adding new V2V suppliers and showed how the computation time of the algorithms increase. Note that the maximum weighted bipartite matching has an asymptotic cost of $O(V^3)$ while the stable matching has $O(V^2)$. The computation times shown in the figure however include all the other associated house keeping operations available in our code as well. In general, we observe that stable matching has lower cost than the maximum weighted matching, as expected. Moreover, we have used very large number of demanders (namely 250 and 500) in these results, but in practice the number of demanders at a single decision time frame (e.g., every 1 min or less) may not reach that large numbers. The proposed algorithms can however obtain the matching very quickly even with large number of demanders and suppliers.

Finally, we compare the proposed direct V2V charge sharing system with the literature that use V2V charging at designated parking lots [13], [23]. To this end, we distribute different number of parking lots in each city proportional to the population densities and obtain the average daily energy consumption reduction ratios in both cases. Here, we use maximum weighted bipartite matching only as stable matching results are similar. Fig. 15 shows the results for each city with parking lots between 100 and 400. Note that the results with direct V2V charging proposed in this paper are the average values from Fig. 10 and do not change with different parking lot counts as they are not used. With increasing parking lot counts, V2V parking lot charging offers more reduction in energy consumption as closer charging opportunities are found. However, the proposed direct V2V charging system offers 80–90% more reduction compared to V2V charging at parking lots and it does not require an upfront cost of building those charging lots. Moreover, the parking lot scenario is intrusive to the supplier EV drivers and requires them to drive to these parking lots, yielding unnecessary consumption. On the other hand, the proposed scheme aims to utilize supplier EVs non-intrusively without changing their daily life. Thus, the charging service cost will also be less as the drivers will require less incentive.

V. CONCLUSION

In this paper, we study charge sharing coordination among the suppliers and demanders in a direct V2V charge sharing system. We introduce two different matching algorithms that approach the problem from system and individual EV's point of view. We evaluate the performance of the system in three metro areas with realistic commuting patterns and current charging station infrastructure. EV models and specifications are determined based on current EVs in the market. Simulation results show that the proposed direct V2V charge sharing algorithm can reduce the energy consumption of EVs due to less energy spent to reach a charging point, offload grid charging power in peak times by 35-55%, and can help supply more EV charging requests without building new charging stations or designated parking lots for V2V charging. On the other hand V2V charging only causes slight (i.e., <10%) increase in the energy cycling of supplier EVs. The proposed matching algorithms also show different performance with respect to different performance metrics (e.g., individual-oriented stable matching provides more average energy consumption reduction while system-oriented bipartite matching provides more peak charging load reduction), thus either one could be preferable depending on the network optimization goals. As a future work, we plan to study the pricing with the proposed V2V charging system through different market mechanisms and investigate fair matching algorithms when demands are more than supplies.

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REFERENCES

- [1] "Electric vehicle outlook 2017," Bloomberg New Energy Finance, New York, NY, USA, Tech. Rep., 2017. [Online]. Available: https://data.bloomberglp.com/bnef/sites/14/2017/07/BNEF_EVO_2017_Executive_Summary.pdf. Accessed on: Aug. 8, 2017.
- [2] "Plugged in: How americans charge their electric vehicles," Idaho National Laboratory, Idaho Falls, ID, USA, Tech. Rep., 2015. [Online]. Available: <https://avt.inl.gov/sites/default/files/pdf/arra/PluggedInSummaryReport.pdf>. Accessed on: Nov. 3, 2018.
- [3] S. D. Manshadi, M. E. Khodayar, K. Abdelghany, and H. Üster, "Wireless charging of electric vehicles in electricity and transportation networks," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4503–4512, Sep. 2018.
- [4] C. Liu, K. Chau, D. Wu, and S. Gao, "Opportunities and challenges of vehicle-to-home, vehicle-to-vehicle, and vehicle-to-grid technologies," *Proc. IEEE*, vol. 101, no. 11, pp. 2409–2427, Nov. 2013.
- [5] "AAA unveils North America's first roadside assistance truck capable of charging electric vehicles," AAA, Heathrow, FL, USA, Jul. 2011. [Online]. Available: <http://newsroom.aaa.com/2011/07/ev-charging-station>. Accessed on: Nov. 3, 2018.
- [6] Andromeda Power, 2018. [Online]. Available: www.andromedapower.com
- [7] T. J. C. Sousa, V. Monteiro, J. C. A. Fernandes, C. Couto, A. A. N. Melendez, and J. L. Afonso, "New perspectives for vehicle-to-vehicle (V2V) power transfer," in *Proc. 44th Annu. Conf. IEEE Ind. Electron. Soc.*, Oct. 2018, pp. 5183–5188.
- [8] M. C. Kisacikoglu, F. Erden, and N. Erdogan, "Distributed control of PEV charging based on energy demand forecast," *IEEE Trans. Ind. Inform.*, vol. 14, no. 1, pp. 332–341, Jan. 2018.
- [9] P. You and Z. Yang, "Efficient optimal scheduling of charging station with multiple electric vehicles via V2V," in *Proc. IEEE Int. Conf. Smart Grid Commun.*, 2014, pp. 716–721.
- [10] P. You, Z. Yang, M.-Y. Chow, and Y. Sun, "Optimal cooperative charging strategy for a smart charging station of electric vehicles," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2946–2956, Jul. 2016.
- [11] A.-M. Koufakis, E. S. Rigas, N. Bassiliades, and S. D. Ramchurn, "Towards an optimal EV charging scheduling scheme with V2G and V2V energy transfer," in *Proc. IEEE Int. Conf. Smart Grid Commun.*, 2016, pp. 302–307.
- [12] R. Alvaro-Hermana, J. Fraile-Ardanuy, P. J. Zufiria, L. Knapen, and D. Janssens, "Peer to peer energy trading with electric vehicles," *IEEE Intell. Transp. Syst. Mag.*, vol. 8, no. 3, pp. 33–44, Fall 2016.
- [13] R. Zhang, X. Cheng, and L. Yang, "Flexible energy management protocol for cooperative EV-to-EV charging," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 1, pp. 172–184, Jan. 2019.
- [14] M. Wang, M. Ismail, R. Zhang, X. Shen, E. Serpedin, and K. Qaraqe, "Spatio-temporal coordinated V2V energy swapping strategy for mobile PEVs," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1566–1579, May 2018.
- [15] I. Frade, A. Ribeiro, G. Gonçalves, and A. Antunes, "Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal," *Transp. Res. Record, J. Transp. Res. Board*, vol. 2252, pp. 91–98, 2011.
- [16] A. Hecker and R. Wies, "Charging infrastructure for EVs in Beijing: A spatial analysis from real customer data at two districts," in *Proc. Int. Conf. Connected Vehicles Expo*, IEEE, 2015, pp. 336–341.
- [17] E. Bulut and M. C. Kisacikoglu, "Mitigating range anxiety via vehicle-to-vehicle social charging system," in *Proc. IEEE 85th Veh. Tech. Conf.*, Jun. 2017, pp. 1–5.
- [18] M. Kane, "Here is how Nissan leaf can rescue stranded Tesla model S," 2017. [Online]. Available: <https://insideevs.com/here-is-how-nissan-leaf-can-rescue-stranded-tesla-model-s/>. Accessed on: Nov. 3, 2018.
- [19] K. Zhang *et al.*, "Incentive-driven energy trading in the smart grid," *IEEE Access*, vol. 4, pp. 1243–1257, 2016.
- [20] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains," *IEEE Trans. Ind. Inform.*, vol. 13, no. 6, pp. 3154–3164, Dec. 2017.
- [21] R. Zhang, X. Cheng, and L. Yang, "Stable matching based cooperative V2V charging mechanism for electric vehicles," in *Proc. IEEE Veh. Tech. Conf.*, 2017, pp. 1–6.
- [22] R. Zhang, X. Cheng, and L. Yang, "Flexible energy management protocol for cooperative EV-to-EV charging," in *Proc. IEEE Global Commun. Conf.*, 2016, pp. 1–6.
- [23] G. Li, L. Boukhatem, L. Zhao, and J. Wu, "Direct vehicle-to-vehicle charging strategy in vehicular ad-hoc networks," in *Proc. IEEE Int. Conf. New Tech. Mobility Secur.*, 2018, pp. 1–5.
- [24] E. Ucer, M. Kisacikoglu, E. Bulut, M. Guven, Y. Sozer, and L. Giubolini, "A flexible V2V charger as a new layer of vehicle-grid integration framework," in *Proc. IEEE Transp. Electrific. Conf.*, 2019.
- [25] R. K. Daley, J. Nangle, G. Boeckman, and M. Miller, "Refueling behavior of flexible fuel vehicle drivers in the federal fleet," Nat. Renewable Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-5400-61777, 2014.
- [26] R. Kitamura and D. Sperling, "Refueling behavior of automobile drivers," *Transp. Res. Part A, General*, vol. 21, no. 3, pp. 235–245, 1987.
- [27] K. Li, M. Lu, F. Lu, Q. Lv, L. Shang, and D. Maksimovic, "Personalized driving behavior monitoring and analysis for emerging hybrid vehicles," in *Proc. Int. Conf. Pervasive Comput.*, 2012, pp. 1–19.
- [28] S. Gao, K. Chau, C. Liu, D. Wu, and C. C. Chan, "Integrated energy management of plug-in electric vehicles in power grid with renewables," *IEEE Trans. Veh. Technol.*, vol. 63, no. 7, pp. 3019–3027, Sep. 2014.
- [29] E. Ucer, I. Koyuncu, M. C. Kisacikoglu, M. Yavuz, A. Meintz, and C. Rames, "Modeling and analysis of a fast charging station and evaluation of service quality for electric vehicles," *IEEE Trans. Transp. Electrific.*, vol. 5, no. 1, pp. 215–225, Mar. 2019.
- [30] Charging with a BMW i3, 2019. [Online]. Available: <https://support.fastned.nl/hc/en-gb/articles/204784718-Charging-with-a-BMW-i3>
- [31] Y. Cao and N. Wang, "Toward efficient electric-vehicle charging using VANET-based information dissemination," *IEEE Trans. Veh. Technol.*, vol. 66, no. 4, pp. 2886–2901, Apr. 2017.
- [32] E. S. Rigas, S. D. Ramchurn, N. Bassiliades, and G. Koutitas, "Congestion management for urban EV charging systems," in *Proc. IEEE Int. Conf. Smart Grid Commun.*, 2013, pp. 121–126.
- [33] H. W. Kuhn, "The hungarian method for the assignment problem," in *50 Years of Integer Programming 1958-2008 - From the Early Years to the State-of-the-Art*, 2010, pp. 29–47. [Online]. Available: https://doi.org/10.1007/978-3-540-68279-0_2

- [34] D. Gusfield and R. W. Irving, *The Stable Marriage Problem: Structure and Algorithms*. Cambridge, MA, USA: MIT Press, 1989.
- [35] D. McVitie and L. B. Wilson, "Stable marriage assignment for unequal sets," *BIT Numer. Math.*, vol. 10, no. 3, pp. 295–309, 1970.
- [36] D. Gale and L. S. Shapley, "College admissions and the stability of marriage," *Amer. Math. Monthly*, vol. 69, no. 1, pp. 9–15, 1962.
- [37] M. Fiore and J. Häri, "The networking shape of vehicular mobility," in *Proc. Int. Symp. Mobile ad hoc Netw. Comput.* ACM, 2008, pp. 261–272.
- [38] I. Stepanov, J. Hahner, C. Becker, J. Tian, and K. Rothermel, "A meta-model and framework for user mobility in mobile networks," in *Proc. IEEE Int. Conf. Netw.*, 2003, pp. 231–238.
- [39] National Household Travel Survey, 2017. [Online]. Available: <http://nhts.ornl.gov/>. Accessed on: Nov. 3, 2018.
- [40] R. Smith, S. Shahidinejad, D. Blair, and E. Bibeau, "Characterization of urban commuter driving profiles to optimize battery size in light-duty plug-in electric vehicles," *Transp. Res. Part D, Transp. Environ.*, vol. 16, no. 3, pp. 218–224, 2011.
- [41] CMAP, "Chicago regional household travel inventory," 2015. [Online]. Available: <https://www.cmap.illinois.gov/data/transportation/travel-tracker-survey>
- [42] "Officeteam report," Sep. 2018. [Online]. Available: <http://rh-us.media room.com/2018-09-10-More-Than-Half-Of-Workers-Take-30-Minutes-Or-Less-For-Lunch-Says>. Accessed on: Jan. 10, 2019.
- [43] Charge Point Stations, Accessed on: Nov. 3, 2018. [Online]. Available: https://na.chargepoint.com/charge_point



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