Shared Solar-powered EV Charging Stations: Feasibility and Benefits

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***Abstract*—Electric vehicles (EV) are growing in popularity as a credible alternative to gas-powered vehicles. These vehicles require their batteries to be "fueled up" for operation. While EV charging has traditionally been grid-based, use of solar powered chargers has emerged as an interesting opportunity. These chargers provide clean electricity to electric-powered cars that are themselves pollution free resulting in positive environmental effects. In this paper, we design a solar-powered EV charging station in a parking lot of a car-share service. In such a car-share service rental pick up and drop off times are known. We formulate a Linear Programming approach to charge EVs that maximize the utilization of solar energy while maintaining similar battery levels for all cars. We evaluate the performance of our algorithm on a real-world and synthetically derived datasets to show that it *fairly* distributes the available electric charge among candidate EVs across seasons with variable demand profiles. Further, we reduce the disparity in the battery charge levels by 60% compared to best effort charging policy. Moreover, we show that 80th percentile of EVs have at least 75% battery level at the end of their charging session. Finally, we demonstrate the feasibility of our charging station and show that a solar installation proportional to the size of a parking lot adequately apportions available solar energy generated to the EVs serviced.**

I. Introduction

Over the past few years, electric vehicles (EV) have gained significant traction because of their appeal as a credible alternative to gas-powered vehicles. Since 2008, more than 4,10,000 EVs have been sold in the US alone by December 2015, representing 33% of the global sales [9]. With EVs expected to be a major source of transportation in the future, there has been meaningful discussion around their adoption including those for policymakers [16]. However, EVs require a charging station that enables them to "fuel up" its batteries similar to gasoline powered cars. While EVs are inherently pollution free, the electricity used to charge their batteries may be drawn from traditional fossil-fuelled power plants, diminishing their appeal as an environment-friendly mode of transport.

Recently, there is a move towards designing solar-powered EV charging stations that provide clean electricity. With the reduction in solar costs and improvement in solar efficiency, building solar-powered EV charging station presents an excellent opportunity to *greenify* our transportation needs, making EVs end-to-end environmentally positive. While PV systems may be installed on rooftops to build such charging stations, solar canopies installed on parking lots make an excellent choice for solar-powered EV charging stations as it not only generate clean electricity but also provide shade to the vehicle (see Figure 1).

Fig. 1. Solar canopy parking lot with EV chargers.

In our paper, we consider a solar-powered charging station for an EV car-share service (such as ZipCar, Autolib). Usually, in a vehicle-sharing service, gasoline powered vehicles are popular but with rising popularity of electric cars, these service providers may soon own more electric cars. In fact, some vehicle-sharing services already have Tesla models, cars that run solely on electricity. Typically, vehicle-sharing service leases vehicles to consumers and bill consumers using a pay-per-use model. When the cars are not in use, they may be charged from the power outlet until the start of the next lease.

Designing a solar-powered charging station for a car-share service poses interesting challenges. First, the solar canopies must be appropriately sized to deliver enough power to charge the cars. While a small PV system may not deliver enough energy, a large PV system may cause wastage of energy. Second, solar power is intermittent as the amount of power generated on any given day is dependent on ambient weather conditions such as cloud cover and temperature. Finally, vehicles must be charged such that depleted batteries have a higher priority over batteries with more charge. Obviously, a user will prefer a car with more charge over a car with less charge. Thus, to improve user satisfaction, if an electric car is 80% charged and another car is 20% charged, charging preference must be given to the car with a lower battery level. Note that the solar power in a given day is limited, thus if multiple cars are plugged in for charging, the best effort equal charge may be sub-optimal as it does not prioritize one car over the other.

Prior research work mostly focuses on sizing and placement of charging stations in a given location[12], [4], energy demand prediction of EVs [6], [11], and EV charging strategies

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Car model	Battery size (kWh)	Range (mi)	Charge rate (kW)
Tesla S (pure electric)	70	240	10
Nissan Leaf (pure electric)	30	107	6.6
Chevrolet Volt (electric+gas)	18	53	3.6
Mitsubishi i-MiEV (pure electric)	16	62	3.3
Ford Fusion (electric+gas)	7	19	3.3

TABLE I
SUMMARY OF THE ELECTRIC CARS IN THE DATASET

to reduce the impact on the power system [20]. However, they do not consider a grid-isolated solar-powered charging stations in a car-share scenario. Here, we present an approach to apportioning solar energy to cars such that it maximizes both solar utilization and user satisfaction. Our contributions are as follows:

Vehicle-sharing scenario modeling. We model - (i) the battery characteristics of cars with different charging rates and battery sizes, (ii) energy constraints in a PV system, and (iii) the availability of vehicles in a shared system. In addition, we model the *utility function* for a shared scenario such that it maximizes both solar utilization and user satisfaction.

Energy-allocation Framework. We develop an allocation framework that uses day-ahead solar energy prediction and ground truth solar energy data to first arrive at a schedule and later determines the actual allocation respectively.

Implementation and Evaluation. We implement our algorithm and simulate the solar-power charging station using an extensive real-world EV charging trace extracted from the Dataport dataset [15] to evaluate our approach. We show that our approach prioritizes depleted batteries over batteries with more charge so as to maximize user satisfaction level. In addition, we show that it is feasible to build grid-isolated solar-powered charging stations.

II. BACKGROUND

In this section, we present an overview on EVs and solar-powered charging stations. We also present our assumptions and charging metrics used for solar energy allocation.

Overview. Electric Vehicles such as electric cars or electric scooters have an electric engine that is powered using onboard batteries. EVs need to be plugged into power outlets for charging when its batteries are depleted. Electric cars are growing in popularity and many cars such as Tesla S, Chevy Spark and Nissan Leaf are available in the market. In countries such as China, electric two-wheelers (e.g. scooters, mopeds) are more common. The driving range of an electric car depends on the size of its battery capacity (see Table I).

Electric vehicles need a charging station — similar to gas station — where they can be charged whenever their battery run low. Such an EV charging station is now being deployed at various locations such as highway rest stops, parking lots and pay garages. Residential owners of EVs can install a charging station in their garages too. Typically, EV charging stations draw power from the grid and use this electricity to charge EV batteries. Thus, even though EV engines are pollution free, charging of batteries is not — since electricity used to charge them may have been produced using traditional fossil fuels. To achieve a net end-to-end carbon-free footprint for EVs, many charging stations are beginning to adopt solar power. A residential owner can install solar panels on rooftops to charge the EV batteries. Many parking lots are beginning to install solar canopies to produce solar energy and can additionally employ chargers to power EVs. Figure 1 shows a deployed solar canopy that is also equipped with a solar EV charger.

Vehicle charging objectives. Solar-powered EV chargers such as EV arc are completely powered by solar energy [7]. In such cases, the rate of charging of EV batteries is constrained by the electricity generated by solar panels. Furthermore, if multiple EV cars are plugged into one charging stations and solar electricity is constrained (i.e. sum of charging rate of all EVs is greater than current solar output), then charging station needs to determine how to apportion the solar energy across cars. Cars may be heterogeneous, and may have different charge levels. A simple best effort charging policy that equally divides energy may not be the best strategy since maximize user satisfaction is an important goal in a car-share service.

We consider two objectives — *utilization* and *fairness* — in allocating solar energy to EVs in a car-share service. Maximizing solar *utilization* ensures the algorithm generates allocation schedule such that charging stations deliver as much solar energy as possible and avoids waste. *Fairness* ensures charging station allocates energy to maximize user satisfaction i.e. users drive off cars with sufficiently charged batteries.

Key Assumptions. We assume that users use a reservation system to check out and return the cars — so arrival and departure times of all EVs are known. In addition, cars are plugged into the charging station when parked at the car-share service station. We also assume that the EV charging stations do not have batteries to store the excess solar energy, and excess energy is not utilized. Although storing the energy may be a better alternative, in our study, we focus on the feasibility of running a charging station using solar power only. In future, we plan to study the addition of batteries in a solar-powered charging station. Note that while we evaluate our approach using electric car datasets, our approach is also applicable to sharing schemes where electric bikes, Segways etc. are used. Although this work is primarily motivated by the car-share service, the objectives described above are applicable in any shared environment where arrival and departure times are known beforehand. For example, in a workplace parking lot, the arrival and departure times can be estimated due to fixed working hours.

III. PROBLEM FORMULATION AND SYSTEM DESIGN

We first introduce the solar-charge allocation problem in a car-share service and formally derive the algorithm that maximizes solar energy *utilization* and delivers energy to electric vehicles in a *fair* manner. Essentially, the problem requires maximizing the total power supplied to EVs, and ensures *fair* energy allocation i.e. giving priority to depleted batteries over the ones with relatively higher charge. Formally, for a duration of T slots, given a solar energy generation

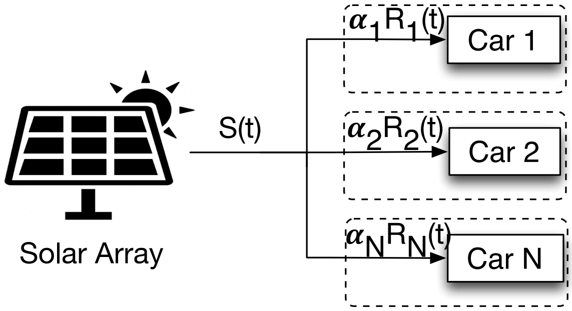


Fig. 2. Basic block diagram of a solar-powered EV charging station.

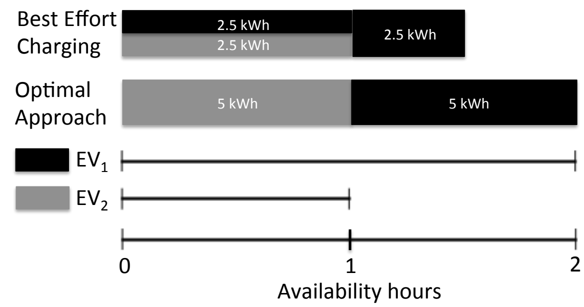


Fig. 3. An illustrative comparison between best effort equal charging policy and an optimal approach. While best effort equal charging policy allocates 7.5 kWh of solar energy, an optimal approach allocates 10 kWh.

sequence $\langle S_t \rangle$, $\forall t \in [1, .., T]$, N vehicles with energy demand D_i, battery efficiencies α_i $\forall i \in [1, .., N]$, and the availability of vehicles $A_i(t) \in [0, 1]$ $\forall i, t$, a charge allocation algorithm generates a *fair* charging sequence schedule $\langle R_i(t) \rangle$, where $R_i(t)$ is the amount of energy delivered to vehicle i at time slot t.

Figure 2 shows the charging station model of a solar-powered EV charging station. Specifically, there are k power outlets in the charging station that can be used to charge the EV. The solar power generated, at any given time t, is distributed to the EVs and any excess power is unused. Although the amount of solar power generated is not known in advance, the day-ahead solar power predictions can be precomputed. In our approach, the algorithm uses the predicted solar energy as an input to generate the charging schedule. Since the actual charging schedule may differ based on the actual solar energy generated, we later discuss how we manage the charging in practice.

A. EV Charging policy

Below, we describe our utility function that meets our dual objective of — *utilization* and *fairness*. Later, we discuss a simple best-effort charging policy that may be used but does not meet the dual objectives of a car-share scenario.

1) Utility function for charging: We associate a utility function U_i i.e. *dissatisfaction level* the user perceives when it receives an EV with a given battery level. Clearly, a higher battery level translates to lower dissatisfaction level and vice-versa. Utility function formulation helps minimize the dissatisfaction level and ensure the vehicles are fairly charged. Figure 4 shows a sample utility function for a user at a given battery level. This function is convex and it provides diminishing returns at the tail-end with smaller dissatisfaction as battery level increases. Intuitively, the dissatisfaction gap is much higher among users who receive vehicles with a low and a high battery level. Whereas, the dissatisfaction gap is lesser when users receive vehicles with moderate or high battery level.

2) Best-effort charging: In a best-effort charging policy, the power generated per unit time can be divided equally or proportionally to the available EVs. However, such a policy may not guarantee maximum solar utilization over the day. For illustration, let us consider two EVs (EV_1 and EV_2) available in the charging station for 1 & 2 hours respectively, and each arrives with an initial battery capacity of 0% and requires 5 kWh of energy to reach 100% battery level (see Figure 3). For simplicity, let us assume the solar energy available per hour is 5 kWh. A best effort equal charge policy divides the charge equally among available EVs. Thus, in the best effort policy, both EV_1 and EV_2 receives 2.5 kWh in the first hour and EV_2 receives 2.5 kWh in the second hour. The policy neither maximizes *utilization* nor *fairness*, as total solar energy allocated is 7.5 kWh out of 10 kWh of available solar energy (lower utilization) and disparate battery levels of 50% and 100% (less fairness). However, an optimal strategy distributes 5 kWh to EV_1 in the first hour and 5 kWh to EV_2 in the second hour. Since both EVs receive 5 kWh of solar energy and all the available solar energy is utilized, the optimal strategy maximizes both *utilization* and *fairness*.

Usually, best effort charging policy work in scenarios where arrival and departure times of EVs, or solar energy generated is unknown. However, in a car-share scenario, the availability of EVs is known with arrival and departure times. This information can be leveraged to derive charging schedules that best utilizes the available solar energy and divides the solar energy fairly. Below, we describe our approach to allocate solar energy fairly while maximizing utilization.

B. A LP approach to Solar-Charge Allocation

We provide a linear programming (LP) framework to solve the offline allocation problem. The linear program takes into account the solar energy generated, the energy demand for each vehicle i, availability and battery level of each vehicle, to determine the *fair* allocation while maximizing the total solar energy delivered to the vehicles. First, we define our model. The sum total solar energy delivered to each vehicle i in time slot t cannot exceed the total solar energy $S(t)$ generated by the PV panels in time slot t.

$$\sum_i R_i(t) \leq S(t) \quad \forall t \tag{1}$$

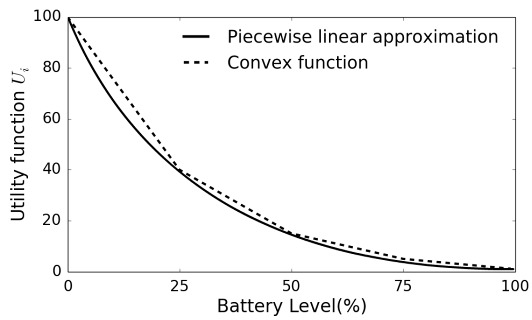


Fig. 4. Sample utility function to associate user dissatisfaction for a given battery level. While low battery level gives higher dissatisfaction, higher battery level provides lower dissatisfaction.

where, $0 \leq R_i(t) \leq R_i^{max}$ and R_i^{max} is the maximum charge rate of vehicle i.

We assume access to the charging station is reservation based and the arrival and departure of each vehicle are known. In each time slot t, $R_i(t) = 0$ when vehicle i is not available for charging. When vehicle i is available, its charging is determined by the availability of power outlets. Let O^{max} denote the max. number of power outlets in the station. The number of vehicles charging at any given time t is given by,

$$\sum_i x_i(t) \leq O^{max} \quad \forall t \tag{2}$$

where, $x_i(t) \in [0, 1]$, denotes whether vehicle i is plugged in for charging in time slot t. Since vehicles are charged only when plugged in, we must have

$$R_i(t) \leq x_i(t) * R_i^{max} \quad \forall i, t \tag{3}$$

Next, the energy stored in the battery at vehicle i at slot $t + 1$ must satisfy energy conservation constraint. Let $Y_i(t)$ denote the amount of energy stored in the battery at vehicle i at slot t. We have

$$Y_i(t + 1) = Y_i(t) + \alpha_i R_i(t) \quad \forall i, t \tag{4}$$

where, $0 \leq \alpha_i \leq 1$ denotes the efficiency of the battery for the i^{th} vehicle. Energy stored in the battery at vehicle i cannot exceed its max capacity Y_i^{max} or underflow. We must have

$$0 \leq Y_i(t) \leq Y_i^{max} \quad \forall i, t \tag{5}$$

Let, $B_i(T_{dep})$ denote the battery level of the vehicle i when it leaves at time slot T_{dep}. The objective is defined as a piecewise linear function (as shown in Figure 4) of a convex function that aims to maximize the battery level for each vehicle i while prioritizing depleted batteries over charged batteries and is defined as

$$\min \sum_i U_i(B_i(T_{dep})) \tag{6}$$

where $U_i(.)$ is the utility function and defined as a piecewise linear approximation of a convex function (see Figure 4). Intuitively, the objective function maximizes the battery level by minimizing the utility function $U_i(.)$ associated with battery level B_i. In addition, the utility function is *fair* as lower charged batteries have a higher dissatisfaction compared to higher charged batteries.

C. Online Charging Algorithm

Based on availability of the EV, the above offline LP produces a charging sequence schedule $\langle R_i(t) \rangle, \forall i, t$. Depending on factors such as weather conditions, the actual solar energy generated may be greater or less than the predicted value. Thus, the actual solar energy $S_{actual}(t)$ generated may be more/less from the predicted value $S_{predicted}(t)$. We adjust the charging sequence proportionally by increasing/decreasing the $R_i(t)$ values. Thus, at any given time t, the charging algorithm has the following cases:

1) If $S_{actual}(t) == S_{predicted}(t)$, then do not modify the $R_i(t)$ values.
2) If $S_{actual}(t) < S_{predicted}(t)$, then divide the energy proportionally by $R_k^{new}(t) = S_{actual}(t) * R_k(t)/\sum_{k \in A(t)} R_k(t)$, where $A(t) = \{k | (R_k(t) > 0) \wedge (k \in N)\}$ is the set of available vehicles to allocate energy.
3) If $S_{actual}(t) > S_{predicted}(t)$, then we take the following steps to proportionally divide the available energy:
Step 1. Compute the excess energy available for allocation. $excess\_energy = S_{actual}(t) - \sum R_i(t)$
Step 2. Divide the energy proportionally based on current allocation to available vehicles. $R_k^{new}(t) = R_k(t) + excess\_energy * R_k(t)/\sum_{k \in A(t)} R_k(t)$,
where $A(t) = \{k | (R_k(t) > 0) \wedge (R_k(t) < R_i^{max}) \wedge ((Y_k(t) + R_k(t)) < Y_k^{max}) \wedge (k \in N)\}$ is the set of available vehicles to allocate energy such that its constraints are not violated.
Step 3. Ensure the capacity constraints and charging constraints are not violated. $R_k^{actual}(t) = \min(R_k^{new}(t), R_k^{max}, Y_k^{max} - Y_k(t))$
Step 4. Update $excess\_energy = \sum R_k^{new}(t) - \sum R_k^{actual}(t)$
Step 5. Repeat step 2 until excess energy is zero or no vehicles left to allocate the excess energy to. i.e. $excess\_energy == 0$ or $|A(t)| == 0$
In other words, at each iteration, the algorithm distributes the excess energy to available vehicles and repeats until no energy is left to distribute or all the vehicle constraints are met.

IV. Evaluation Methodology

We evaluate our solar-charge allocation algorithm using both synthetically generated data and the Dataport dataset[1] — a real-world trace comprising, in part, power consumption of EVs and power generation of solar panels located in Austin, Texas. The dataset includes detailed information such as the amount of energy used to charge the battery, the time of the

[1] http://dataport.pecanstreet.org/

Number of Cars	97
Car Sessions used	9083 out of 12123
Median Charging Session	65 minutes
Median Car's Energy Demand	3.31 kWh
Median Daily Energy Demand	104.8 kWh
Solar panel Size	18 kW
Median Daily Solar Energy	74.5 kWh

TABLE II
SUMMARY OF CARS AND SOLAR INSTALLATION IN EV DATASET

day and the duration a car is connected to a power outlet. It also contains solar power generation traces from multiple residential buildings. Further, our dataset is at a minute level granularity collected for a three-year period.

To simulate the charging operations of a car-share service with a solar-power charging station, we construct an EV dataset combining the EV and solar data described above. First, we assume that the solar-powered EV charging station has 5 power outlets. Since the charging station can service a maximum of five vehicles at any given time slot, we construct our EV charging dataset by making a simplifying assumption that the vehicles are selected from the dataset on a first-come-first-serve (FCFS) basis until all power outlets are occupied for any given time slot. We refer each contiguous interval of charging by a vehicle in the dataset as a *charging session*. Since the vehicles can be charged only when solar energy is available, we consider only those charging sessions that charge after sunrise and before sunset (see Table II). Collectively, the dataset contains 9083 charging sessions. Further, we assume that the amount of charge drawn during a given charging session is the amount needed to fully charge its battery.

PV system sizing: We first determine the size of the solar panel needed to cover a single car in a parking lot. The dimension of a single parking lot for a car in the US is around 9 ft. X 18 ft — a total area of 162 sq.ft. A typical solar panel of size 17.57 sq. ft. produces 345 watts[2]. Thus, the amount of solar power generated from a single parking lot is around 3.2 kW. and a parking lot with 5 vehicles can generate around 18 kW. Unless stated otherwise, we use a 18 kW PV system from the dataset for our evaluation. We select a residential rooftop installation from the Dataport dataset that has a solar generation capacity of 18 kW. We use this as the ground truth for actual solar power generated. Our algorithm requires the predicted solar energy values to initially schedule the charging and later uses the actual solar energy trace for allocating charge to the EVs. We employ the methodology described in [10] that uses the solar panel's characteristics and day-ahead weather forecasts to compute the predicted solar power. We train the model using the dataset available for the previous year (2014) and predict the solar power generated for the year (2015). For our evaluation, we assume there is no loss in delivering solar energy to the cars i.e $\alpha = 1$. In addition, we evaluate at 5 minutes granularity as we wanted to ensure 5 minutes of uninterrupted charging of batteries.

Utility function: In our LP formulation, to improve the runtime, we assume a piecewise linear approximation of the convex function as shown in Figure 4. We define the piecewise linear approximation as follows:

$$U_i(x) = \begin{cases} 100 - 2.4x, & 0 \le x < 25 \\ 65 - 1.0x, & 25 \le x < 50 \\ 35 - 0.4x, & 50 \le x < 75 \\ 17 - 0.16x, & \text{otherwise.} \end{cases}$$

The utility function $U_i(.)$ is chosen such that for a given battery level range (e.g. 0% to 25%), the LP may choose to distribute energy to any EV having battery level within the range. However, between the different battery level ranges, the LP priorities lower battery such that $U_i(B_i([0,25))) > U_i(B_i([25,50))) > U_i(B_i[50,75))) > U_i(B_i[75,100)))$. In other words, cars with battery level between [0% to 25%] has a higher dissatisfaction than cars with battery level greater than 25%. Note while we select a linear approximation for our evaluation, other linear approximation of a decreasing convex function may be used.

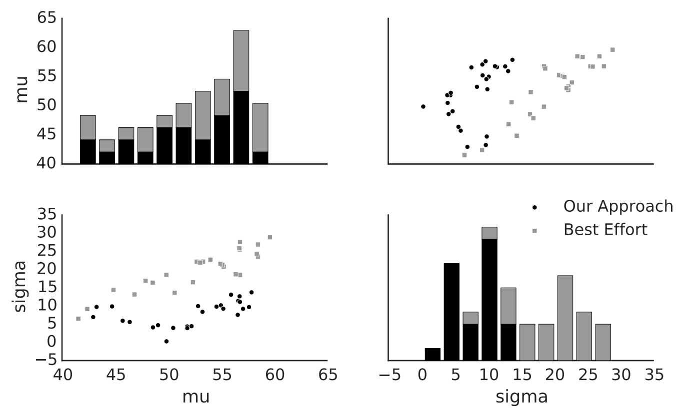


Fig. 5. Mean and standard deviation of the battery levels. Our approach show a 60% lower std. deviation compared to best effort indicating *fairer* allocation.

V. EXPERIMENTAL RESULTS

A. Utilization and Fairness analysis

We compare the *fairness* and *utilization* of our approach to the best effort equal charging policy. As discussed earlier, the best effort charging policy distributes the available solar energy equally among the cars available. As different EVs have varying charging rate and battery capacity, the best effort charging policy may not maintain similar battery levels. In the trivial case, where solar energy available is more than the overall EV demand, the performance of our approach and the best effort charging policy would be similar, as all the energy demand can be easily met. However, for a more pertinent evaluation, we consider the case where demand is more than the overall solar energy available. In particular, we consider 5 cars from the EV dataset having a median charging rate of 3.3 kW. We assume the cars are available for the entire day with aggregate energy demand from EVs to be 3 times that of the solar energy available. In addition, we uniformly assign an initial battery level between 0% to 60% to the 5 EVs for

[2]SunPower X21 panel

the solar trace of August 2^{nd} 2015 and repeat this experiment 25 times. We compute the mean and standard deviation of the battery levels for each run.

Figure 5 shows the comparison of our approach with the best effort equal charging policy. Note that distribution of the mean battery level for both the methods across different runs is similar. In particular, the average value of the mean battery level for both the approaches is $\approx$52% suggesting both methods deliver an equal amount of solar energy to the vehicles. However, the distribution of the standard deviation of the battery levels for our approach is tighter with a lower average value compared to those of the best effort charging policy. Clearly, a *fair* allocation will ensure cars depart at similar battery levels and will have lower standard deviation. In particular, we observe that using our approach the average value of the standard deviation is $\approx$8%, whereas using the best effort charging policy the standard deviation is $\approx$20%. Thus, our approach is more *fair* compared to the best effort charging policy as the average value of the standard deviation of our approach is lower by $\approx$60%.

B. Battery level analysis

We empirically analyze the utilization of solar energy using the EV dataset for the entire year. Charging sessions in the EV dataset is used to simulate the arrival and departure times along with energy demands for EVs serviced in a car-share charging station. Solar energy is allocated using our approach, and we compute the battery level of each car at the end of the charging session. Figure 6 shows the frequency distribution of the initial and final battery level of cars charged over the entire year. As expected, we observe an increase in the number of cars leaving the charging station with a higher battery level. We observe that the 80^{th} percentile of the cars have at least 75.08% battery level at the time of departure. Among these cars, some had an initial charge as low as 1.79%.

C. Impact of solar power intermittency in charge allocation

As discussed earlier, the offline LP algorithm uses the day-ahead solar energy predictions to generate the charge allocation schedule, and the online algorithm uses the ground truth solar trace to allocate the charge. Due to solar energy prediction errors, the charge allocation schedule generated by the offline algorithm differs from the online algorithm. Here, we analyze the mismatch in the charge allocation schedule generated by the offline and the online algorithm.

1) Synthetic dataset with poisson arrivals: We use the car's charging session and other attributes from the real-world dataset to construct the synthetic dataset. However, we ignore its original arrival time and assume it to be generated from a Poisson process with a fixed rate. First, we run our offline LP approach and then the online algorithm to compute the overall energy delivered in a given day. We run our simulation for a week in each season. Figure 7 shows the difference in energy estimated by the offline LP approach and the energy delivered by the online algorithm with an arrival rate of 2 cars per hour ($\lambda = 2$). As shown in the graph, our offline algorithm estimate

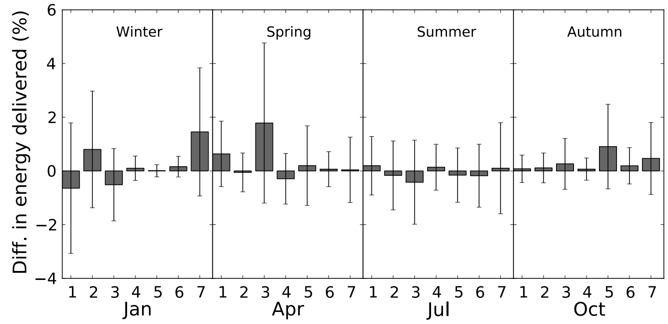


Fig. 7. Difference in overall energy estimated by the offline and the energy delivered by the online approach to the cars with poisson arrival rate of 2 cars per hour

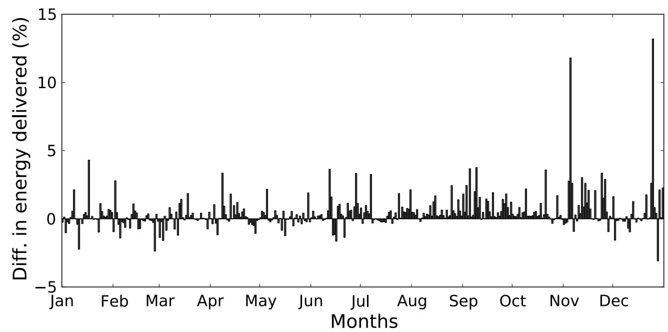


Fig. 8. Difference in overall energy estimated by the offline and the energy delivered by the online approach to the cars using real-world dataset for the entire year

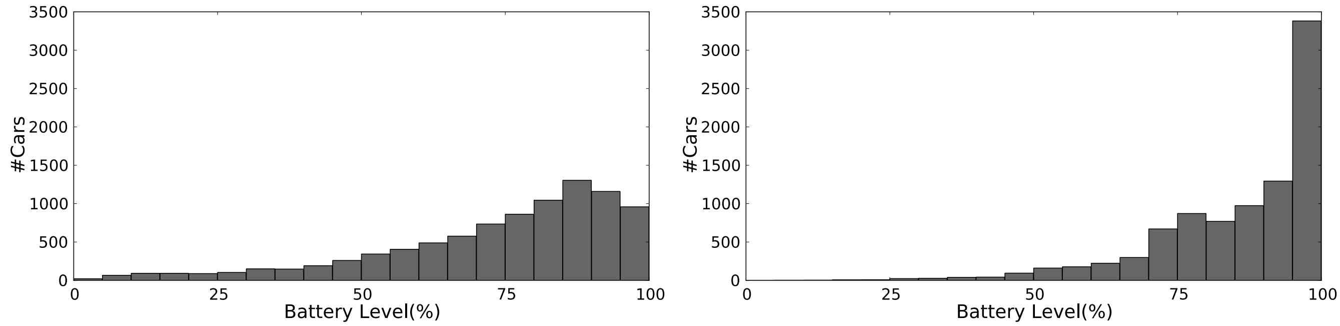
is between -4% to 4% on most days. Since the solar prediction works considerably well during summer days, we notice that the mismatch in summer is smaller compared to other seasons.

2) Real-world dataset: Unlike the previous evaluation, we use the arrival times in addition to other car attributes available in the dataset. Figure 8 shows the difference in energy estimated by the offline LP approach and the energy delivered by the online algorithm for the entire year. As the figure shows, the mismatch is less than 5% for all but 2 days, and less than 1% for 287 days. Moreover, the mismatch is negative for some days i.e. more energy is given to the cars than offline algorithm had estimated. Since the solar model may predict a lower solar energy value for the day-ahead, the actual energy allocated to the cars by the online algorithm can be higher than the offline approach.

D. Feasibility analysis of solar-powered charging station

Evaluating the feasibility of our solar-powered charging station requires us - (i) to validate the sizing of the PV system installed, (ii) demonstrate the utilization of solar energy available, and (iii) exhibit fulfillment of EVs charge demand. In this section, we assess the performance of our approach on these parameters. Similar to the earlier evaluation, we test our algorithm on both synthetic and real-world traces.

1) Synthetic dataset: To construct the synthetic dataset we consider the following scenario. We assume the car-share



(a) Initial battery level of cars at arrival

(b) Final battery level of cars at departure

Fig. 6. Battery levels of cars before/after charging at the charging station for the entire year.

service operates 5 Chevrolet Volt cars. With a maximum charge rate of 3.6 kW and battery size of 18 kWh, starting with an empty battery these cars take typically 5 hours to charge to full capacity (see Table I). For our evaluation, we assume the cars are available for the 5-hour duration to charge their batteries. In addition, we uniformly choose the arrival time for the five EVs between 9 a.m. to noon to ensure that the solar energy is available when they are plugged in. We select the solar trace of August 2^{nd} 2015 and vary the solar installation size to compute the overall EV demand fulfilled and the solar energy utilized by the charging station. To reduce specificity to a random sample, we repeat the experiment 25 times and take its average value.

Figure 9 shows the average demand fulfilled and solar energy utilized over several runs when solar installation size is varied between 2 to 36 kW. As expected, smaller sized PV system has a higher solar utilization whereas the demand fulfilled is lower, as most of the solar energy generated is delivered to the cars. As we increase the solar installation size, we notice diminishing returns in terms of demand fulfilled. This is due to lower power generation by the solar installation during morning and evening period. Even with increased solar capacity, the gap between the energy demand from EVs and the available solar energy does not decrease rapidly. The shaded region in the figure highlights a reasonable PV installation size (13.5-22.5 kW) that maximizes both demand fulfillment and solar utilization. Further, we observe that with PV installation size of 18 kW, the solar utilization is as high as 67% and energy demand fulfilled is around 68%.

2) Real-world dataset: We now evaluate the feasibility of solar-powered charging station for the real-world dataset. Similar to the previous evaluation, we vary the solar installation size to compute the overall EV demand fulfilled and the solar energy utilized for the entire year. Similar to the synthetic dataset evaluation, we observe that smaller PV installations tend to have higher solar utilization but lower demand fulfillment. It is interesting to note that the *knee point* is around 18 kW, the energy generated by the size of a parking lot that we had estimated earlier. In addition, the highlighted region around the *knee point* is the typical range of a PV system size that can be installed in a parking lot.

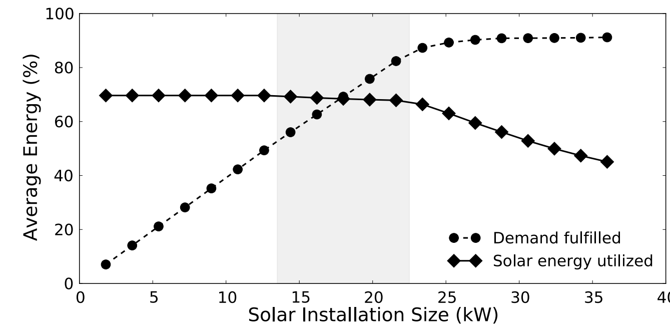


Fig. 9. Variable solar installation size with average solar utilization and demand fulfillment using the synthetically constructed dataset.

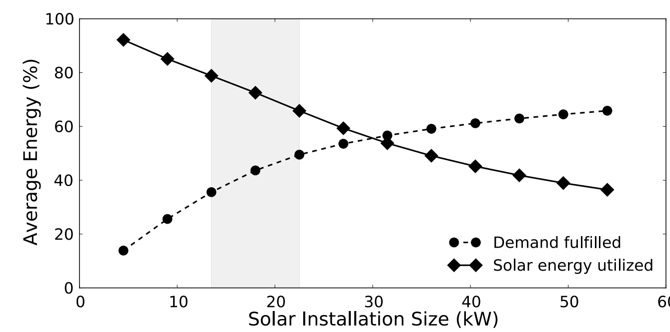


Fig. 10. Energy demand fulfilled and solar utilized using the real-world dataset for the entire year. The highlighted region shows the typical PV systems size that can be installed in a parking lot for 5 cars.

VI. Related Work

The increasing popularity of EVs raises a myriad of challenges. In this section, we provide a brief overview of research focussed on resolving such challenges. The impact of integrating EVs into the grid has been well studied. Li et. al. introduces a conceptual framework for integrating EVs into the grid and discusses its impacts and benefits [13]. Taylor et. al. presents an analysis by accounting the impact of for spatial and temporal diversities in EVs on the distribution feeders of varying characteristics [18], and Foley et.al. discusses the impact of EVs charging on electricity markets [8].

An important aspect in evaluating the EVs demand is rightsizing and placement of charging stations. Chen et. al. presents a city-wide study to find constrained number of optimal charging station locations by minimizing the cost of accessing them by EV users [4]. Liu et. al. introduces a two-step approach where initially candidate sites are initially selected based on environmental factors and the service radius of EV charging stations [12]. Also, a mathematical model is presented that calculates an optimal sizing of EV charging stations. Sweda et. al. discusses an agent-based decision support system for identifying patterns in residential EV ownership and driving activities for setting up charging station infrastructure [17]. However, our work is complementary as we consider charge allocation in a shared charging station and not setting up of charging station infrastructure in different locations. Moreover, one-time planning of locating the stations does not completely guarantee the operational challenges of charging individual EVs to maintain customer satisfaction. Thus, a reasonable charging strategy is required for optimizing operational needs.

Prior works have also examined various charging strategies that satisfy different objectives. These objectives include - (i) leveraging ToU pricing to optimize costs [2] [20], (ii) improving voltage profile [5], (iii) flatten grid electricity profile [21], and (iv) flatten residential electricity profile [14]. In addition, previous works have used EV batteries as a source to power residential homes to get a grid friendly load profile [1]. This work addresses the problem of a grid-isolated solar-power charging station in a car-share service, which differs from previous work discussed above. Further, in a car-share service, the flexibility in scheduling cars may not be present to leverage some of the strategies presented above.

Co-benefits of renewable integration with EVs have been studied in the literature. However, these studies focus either on reducing intermittency of renewable sources of energy [3] [19] or on large-scale aggregated energy demand placed by EVs and the potential renewable energy available (wind and solar) [6], [11]. However, these work do not present actionable charging strategies that we address in this paper.

VII. Conclusion

In this paper, we explored the benefits of integrating renewable solar energy with EV charging infrastructure placed at car-sharing service's parking lot. We formulated a Linear Programming approach that maximized both solar energy utilization and customer satisfaction. Comprehensive evaluation of our algorithm was performed using real-world EV charging traces. We show that our algorithm *fairly* distributes the charge among candidate EVs and improves the disparity in battery charge levels by 60% compared to the best effort charging policy. Our results indicate that the 80^{th} percentile of the EVs have at least 75% charge at the end of their charging session. Further, we assessed the performance of our approach across different seasons with variable demand profile. Finally, we demonstrated the feasibility of a grid-isolated solar-powered charging station and show that a PV system proportional to the size of a parking lot adequately apportions available solar energy generated to the EVs serviced.

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