Event-based Electric Vehicle Scheduling Considering Random User Behaviors

Bin Wang, Yubo Wang, Charlie Qiu, Chi-Cheng Chu, Rajit Gadh
Department of Mechanical Engineering
University of California, Los Angeles, USA
{wangbin, gadh }@ucla.edu

***Abstract*— Uncontrolled Electric Vehicle (EV) and Plug-in Hybrid Electric Vehicle (PHEV) charging within a local distribution grid may cause unexpected high load, which further results in power quality degradation. However, coordinating charging behaviors of a number of EVs is a challenging task, which involves not only the deterministic schedule computing but also nondeterministic EV driver behaviors with random arrival time and energy demands. Previous researches in this area rarely consider these random behaviors for real EV users. In this paper, an implementable event-based cost optimal scheduling algorithm (ECSA) is developed, which solves EV scheduling problem by dynamically estimating the stay duration and energy demand for each participating EV user. Datasets, including users' historical charging records and time series meter data collected from Electric Vehicle Supply Equipments (EVSEs) in UCLA campus, are utilized for feature extraction. Based on that, proper inference technique is employed to determine parameters within each charging session. In addition, solar generation integration into EVSEs is also considered in our problem formulation. The proposed approaches are tested and validated by real EV charging schedules of users in UCLA campus. The results from simulation experiment demonstrate that the proposed algorithm has a better performance in cost minimization and load shifting compared to existing equal-sharing scheduling algorithm (ESSA).**

Keywords—EV Scheduling; EV Charging Behaviors; Renewable Energy Integration; Charging Algorithm;

I. INTRODUCTION

Electric Vehicle (EV) and Plug-in Hybrid Electric Vehicle (PHEV) have acquired increasing popularity according to online sales reports[1]. The initiative from California state government plan to place 1 million zero-emission EVs on road by 2020[2]. Consequently, more Electric Vehicle Supply Equipments (EVSEs) will be installed at both home dominant areas and public places. However, as the penetration of EV increases, uncontrolled EV charging will have sever impacts on local distribution grid, which might further degrade the power quality [3]. In the foreseeable future, managing a number of EV charging will be a challenging task due to the following reasons: 1) demand side uncertainties, including start time, stay duration and requested energy from users; 2) grid side constraints, which might be reflected on real-time energy prices with different levels during the day; 3) renewable integration with charging infrastructure [4], which enables energy from PV panel to charge EVs and requires highly flexible scheduling algorithms. Therefore, an effective EV scheduling system should consider all the factors aforementioned and dynamically update energy consumption schedules based real-time monitoring data.

Researchers have proposed potentially effective approaches to solve this scheduling problem. Gan et al. [5] models aggregated EV charging as an optimal control problem, in which case, the expected stay duration and the required energy for each vehicle are assumed to be collected from EV users in advance. This is not true in real cases. Then, optimal schedules are solved in distributed fashion, based on convex optimization. Alizadeh et al. [6] proposes a stochastic model to describe the EV charging demand based on queuing theory. Vehicle arrival and energy consumption for next time slot are modeled as random variables, whose probability density distribution can be retrieved from a considerably large dataset. However, such dataset is not available due to the lack of large scale EV implementation and data collection. Authors in [7] have developed intelligent charging algorithms based on TOU price from day-ahead predictions, which shift charging loads effectively to time ranges with lower prices so that global charging cost is minimized. [8] discusses an implementation of charging system which enables to EV users to select price preference through mobile application. In addition, renewable energy, such as solar generation, is modeled into EV scheduling problem to improve the system efficiency [9]. Chung et al. [10] have developed an EVSE, which is capable of multiplexing the charging power up to 4 charging outlets/vehicles to maximize the charging service. Vehicle-to-Grid service is also supported by the hardware[13][14]. Framework that includes cloud side regulation programs and client side mobile application has been built on the mesh communication network between control center and charging infrastructures[8][9], which provides foundation work for this paper.

In this paper, we focus on the implementable solutions to handle the random charging behaviors. The objective is to minimize the operational cost for providing charging services and satisfy charging demands to maximum extent. Photovoltaics(PV) generations are modeled as the potential power supply for existing EVSEs. The scheduling algorithms will be triggered once pre-defined events are detected by monitoring program. The contributions of this paper can be summarized as: 1) Proper inference is utilized to determine parameters for EV charging sessions， based on the real time usage data collected in more than 50 EVSEs with around 200 charging outlets in UCLA campus; 2) We consider the EV charging schedules from real users in UCLA campus and develop estimation algorithms to adaptively determine charging session parameters, such as energy consumption and stay

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duration. 3)Event-based scheduling algorithm is developed to handle random EV charging behaviors by analyzing users' historical records and then adaptively update schedules to minimize the operational cost and maximize the utilization of renewable energy.

The rest of this paper is organized as follows: Section II discusses the operating framework to support this scheduling system and the existing algorithms. Section III introduces the data models and feature extraction procedures. Session IV discusses the details of Event-based Cost Optimal Scheduling Algorithm(ECSA). Finally, we evaluate the results from ECSA and discuss the potential improvements in section V.

II. SYSTEM OVERVIEW

A. System Architecture

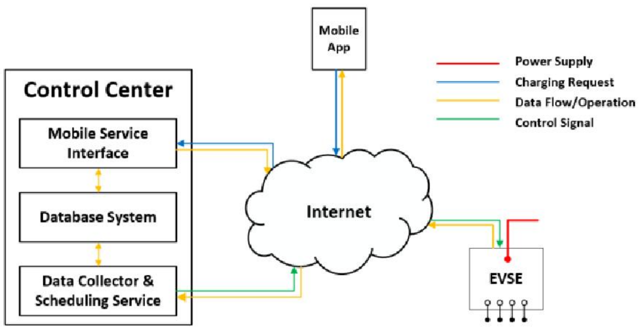

Fig. 1 System Overview

System architecture and functioning components are displayed in Fig.1. Charging services on software side are built on top of the complex communication network[11] among numerous components in the system, including EVSE, EV users and cloud side services. On client side, EV users are able to initiate a charging session by sending charging requests through their mobile applications. Immediately, the corresponding EVSE information and user account ID will be pushed to mobile service interface on control center via secured HTTP message. Meanwhile, another service with both data collection and scheduling modules are running on control center, which periodically retrieves real-time data from meters in each EVSE. Once pre-defined events are detected by the monitoring program, corresponding scheduling algorithm will be initiated to handle the charging sessions on that specific EVSE. All the monitoring data in time series for each EVSE and records for all charging requests associated with user information are stored in database system, which can be later accessed by other services, such as feature extraction service. As a possible implementation in the future, the power source for each EVSE can be connected to both grid and renewable generations, e.g. solar panels, in stand-alone mode.

B. EVSE with Current Multiplexing

The EVSE developed by UCLA Smart Grid Energy Research Center (SMERC) has one distinguished feature with current multiplexing, i.e. split the power supply from single source to multiple charging outlets within a preset range [11]. That charging duty-cycle can be modified from 0 to 50% for each outlet, i.e. *0A* to *30A*, which provides possibilities for scheduling algorithm to allocate different ratio of power supply to different vehicles connected according to their varied demand and availabilities. In addition, a status indicating whether or not a vehicle is plugged can be retrieved in real-time, which enables monitoring program on control center to obtain the leave time for each vehicle. We will discuss the inference process in later section.

C. Existing Scheduling Algorithm

In our system, a number of scheduling algorithms have been developed and implemented. Some of them require users to input their energy demand and preferences [8], while others, e.g. Equal-Sharing Scheduling Algorithm(ESSA), serves only for data collection purpose and just requires a simple click on mobile application to submit a charging request. In this case, least user interactions is needed and most original information for user behavior can be preserved. Charging session will start right after request is submitted. When more than one vehicles are plugged-in, the power supply will be shared equally among them by ESSA. The details are displayed Fig. 2:

Algorithm 1: Equal Sharing Scheduling Algorithm (ESSA)

***Event e*:**
$V \leftarrow$ connected vehicles
$n \leftarrow$number of active vehicles
$DC \leftarrow \frac{maxDC}{n} \cdot \eta \cdot 100\%$
for i $\in$ [1,2, … , n]
set duty-cycle to DC for i^{th} vehicle in V
wait for current to stabilize
end

Fig. 2 Pseudocode of ESSA

$maxDC$ denotes the maximum duty-cycle for each power source and η is a safety coefficient. In this algorithm, each vehicle will be assigned a percentage of circuit duty-cycle and continues charging until current drops below a pre-defined threshold, which is also an indicator for scheduling algorithm to close charging sessions. Accordingly, the start time, finish time and accumulated meter data are collected to calculate the final energy consumption.

III. DATA ANALYSIS FOR EV CHARGING BEHAVIORS

Data in time series for each meter mounted in EVSEs are collected periodically and then stored in a relational database on control center. After a brief exploratory analysis of user behaviors, typical patterns can be identified, which gives us an incentive to design scheduling algorithms based on user energy consumption patterns. In this section, we briefly introduce the methods we use to extract important features from raw data and further estimate schedule parameters given start time and user index. The dataset that is used in this paper contains more than 10000 valid charging session records since 2013 Jan. 1st. There are more than 200 active users, more than 50 EVSEs and 200 charging outlets in this system.

A. Parameters to Describe a Charging Session

To evaluate impacts on electric grid from EV charging behaviors, the following parameters can be defined to describe EV charging sessions. Fig. 3 illustrates sequence of parameters in time series.

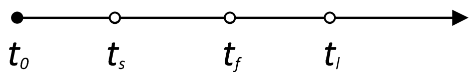

Fig. 3 Charging session Parameters

- *Start Time*: t_s, represents the time when vehicle arrives at certain EVSE and submits a charging request.
- *Finish Time*: t_f, denotes the time when this charging session is terminated due to low charging current, which might be caused by fully charged battery or disconnected vehicle.
- *Leave Time:* t_l, is the time when the user unplugs her vehicle and leaves charging infrastructure directly.
- *Charging Power*: $r_n = \{r_{t_s}, r_{t_s+\Delta t}, r_{t_s+2\cdot\Delta t}, \dots, r_{t_f}\}$ is an array of power consumption rate at each time interval between t_s and t_f. Δt is time interval at which data collector service and scheduling service is working.
- Energy Consumption for vehicle n: E_n, denotes the energy consumed within each charging session. E_n can be computed as:

$$E_n = e_{tf} - e_{ts} \tag{1}$$

where e_{tf} and e_{ts} are accumulated energy consumption value read from meter at session start time and finish time, respectively.

Note that $t_f \leq t_l$ holds by the definition, which is obvious when vehicle is fully charged before departure. If vehicle leaves unexpectedly before battery is full, the charging session will be terminated by scheduling algorithm automatically and $t_f = t_l$ in this case. Another important parameter, stay duration d_n can be obtained by $t_l - t_s$. In later section, r_t will be the decision variable in our problem formulation.

B. *Inference for EV Charging Parameters*

Decisions made by scheduling algorithms are based on the real-time data collected from EVSEs in time series. Unfortunately, there does not exist explicit signals from EVSEs, indicating termination of a charging session. Thus, proper inference is needed to determine some of the aforementioned parameters, such as leave time.

1) Determine when to close a charging session

Scheduling algorithm must adaptively check if power consumption rate falls below a threshold. However, at the end of charging sessions, power drawn by some types of EVs is not stable, which might be caused by different designs of internal Battery Management System (BMS). Therefore, we employ a method based on moving average to adaptively evaluate the power consumption rate.

Assume the real-time power data for each meter at time t is denoted by y_t. The action to close a charging session is determined by a parameter for the averaged power consumption level, denoted by c_t, which can be calculated by:

$$c_t = \frac{1}{H} \cdot \sum_{i=1}^{i=H} y_{t-i-1} \tag{2}$$

where H is the length of moving window, 10 in our case. When the average power consumption level c_t drops below a pre-defined threshold $\underline{c}$, 0.1 kW in our case, the close charging decision will be made. Fig. 4 illustrates this inference process:

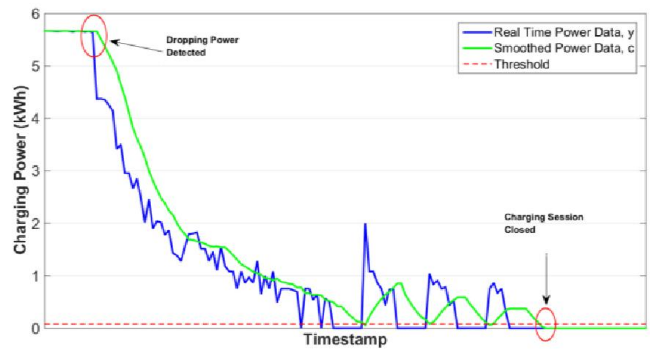

Fig. 4 Inference Process to Close Charging Sessions

In addition, by evaluating the latest power data before closing the charging session, one can infer whether or not EV is fully charged. If the power value is still higher than the threshold, the plug is believed to be disconnected by the user when the charging is still in process.

2) Determine leave time

Leave time can also be inferred from time series data by detecting the earliest time when plug-in status changes to negative. The inference is illustrated below:

$$t_l = \begin{cases} t_f, & c_{tf} > \underline{c} \\ min(t), & c_{tf} \leq \underline{c}, t > t_f \; where \; pl(t) = 0 \end{cases} \tag{3}$$

If the power consumption rate when charging session is being close, c_{tf} is larger than the threshold, $\underline{c}$, the time to close charging session is exactly the leave time because the vehicle is believed to be manually un-plugged. On the other hand, when power consumption is lower than threshold, the leave time can only be inferred from the time when plug-in status changes from 1 to 0. $pl(t)$ denotes the plug-in status at time t.

C. *Parameter Estimation based on Historical Records*

Based on the existing dataset, the objective is to extract features of EV energy consumption patterns and then apply it into scheduling algorithms. According to the observations, we find the charging behaviors, especially the parameters aforementioned have strong user dependence. A typical user's schedules are illustrated in Fig. 5.

According to the visualizations above, leave time generally follows a linear relation with start time for this specific user. Similarly, the longer this user stays, the larger portion of energy can be consumed. This behavioral pattern represents a category of users, whose charging session parameters can be estimated using similar methods. We only display one typical user category, because the following estimation algorithm can also be applied to other categories.

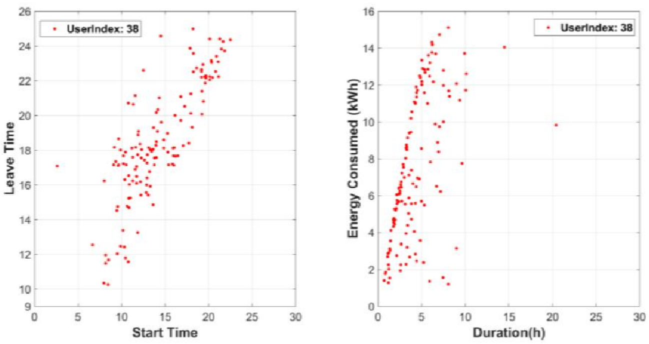

Fig. 5 Charging Patterns for a Typical User

At each time interval, after scheduling algorithm initiates, the estimation of stay duration and expected energy consumption are needed. A simple estimation method is utilized, which searches similar historical charging sessions for specific user index and calculate the average energy consumption and stay duration. For the purpose to extract features for historical charging sessions, the data structure we use to describe one charging session is a 5-tuple, which is defined as:

$$s := (u, t_s, t_f, t_l, e)$$

where u is the user index to which this session belongs; e is the energy consumption calculated by (1).

The expected energy consumption and expected stay duration can be estimated by

$$\hat{e} = \frac{1}{M} \cdot \sum_{i \in M} S[i].e \tag{4}$$

$$\hat{d} = \frac{1}{M} \cdot \sum_{i \in M} S[i].t_l - S[i].t_s \tag{5}$$

where $S[i].t_s \in [t_{s0} - \Delta t, t_{s0} + \Delta t]$, $(S[i].t_l - S[i].t_s) > t - t_{s0}$ and M denotes the count (length) of qualified sessions. The detailed method to implement this function is shown in Fig. 6.

Algorithm 2: Estimate Energy Consumption and Stay Duration

Input: $t, t_{s0}, UserIndex$
Output: $\hat{e}, \hat{d}$
Extract historical sessions: S, where $S.t_s \in [t_{s0} - \Delta t, t_{s0} + \Delta t]$ and $(S.t_l - S.t_s) \geq t - t_{s0}$ and $S.u = UserIndex$
if $S.length \geq 0$
estimate energy consumption $\hat{e}$ and stay duration $\hat{d}$ by calculating (4), (5)
else
$\hat{e} \leftarrow e + \Delta e$
$\hat{d} \leftarrow d + \Delta d$
end

Fig. 6 Estimation Algorithm Energy Consumption and Stay Duration

The estimation request time t, user index and the start time for current charging session t_{s0} are sent to estimation function as inputs. The estimated stay duration $\hat{d}$ and energy consumption $\hat{e}$ are the results as output. First, the algorithm will search neighbor sessions in terms of start time and duration. Then average value for the neighbors will be used as estimation for current session. However, if it does not have such neighbors, it is believed that current session belongs to a relatively new user in the system. Thus, preset value Δe and Δt_d will be used as short term estimations so that scheduling algorithm can frequently check this charging session.

IV. Event-based cost-optimal Charging Algorithm

ECSA is designed to dynamically compute EV schedules according to the random user behaviors. As an EV scheduling algorithm, it aims to achieve better energy delivery efficiency and minimize the operational cost for system administrator, meanwhile satisfying EV charging demand from users. Our implementation assigns each thread to each EVSE, hence our scheduling algorithm works at EVSE level. In this case, we assume there exists a selfish operator, who wants to minimize operational cost in monetary terms by shifting charging load to time zones where energy price is lower and maximizing the usage of renewable energy. [11] have demonstrated the idea for standalone EVSE with several solar panels, but the details of solar energy integration into local distribution system is not within scope of this paper. Thus, for simulation purpose, we assume there exist several PV panels connecting to our EVSE.

A. Problem Formulation

1) User Model

As discussed above, each charging session for user n can be described by the aforementioned parameters defined in the tuple $s_n := (u_n, t_{n,s}, t_{n,f}, t_{n,l}, e_n)$. Thus, the ideal scenario is that scheduling algorithm allocates more energy than expected, i.e. $e_n > \hat{e}_n$, before user n leaves. e_n increases as the charging process goes on.

$$e_n(t) = e_n(t - \Delta t) + r_n(t) \cdot \Delta t, \qquad \forall t \in [t_{n,s}, \hat{t}_{n,f}] \tag{6}$$

$$e_n(t_{n,f}) \geq \hat{e}_n \tag{7}$$

2) EVSE Model

Since the EVSE in this paper can be equipped with multiple power sources and certain outlets may share the same power source, which adds one more constraint that total power drawn from each power source cannot exceed its upper limit. In addition, power consumption rate at each outlet cannot exceed the maximum value for that power source:

$$0 \leq r_n(t) \leq r_k^{max} \cdot \eta, \qquad \forall t \in [t_{n,s}, \hat{t}_{n,f}] \tag{8}$$

Where r_k^{max} denotes the limitation from for power source k. Let $k =: \{1,2, \ldots, K\}$ denote the order of power source number in one EVSE. For each power source k in the EVSE, we have:

$$0 \leq \sum_{n \in N_k} r_n^k(t) \leq r_k^{max} \cdot \eta, \qquad \forall t \in [t_{n,s}, \hat{t}_{n,f}] \tag{9}$$

where N_k denotes the charging sessions for power source k.

3) Energy Price and Solar Generation

Energy price represents cost for unit energy consumption at different time instant. Real-time pricing have been proposed and implemented in several regions within United States. The price list similar as that in [12] is virtually created for simulation. Numerous researches on solar energy prediction have been conducted. The detailed approaches for solar generation prediction are out of scope of this paper. We simply apply day-ahead prediction and use that to make charging decisions. According to the observation from integration project at UCLA [15], each panel has an approximate 0.28 kW peak power output and we assume 10 panels are connected to support one EVSE.

Global objective function for each EVSE is defined by:

$$min \sum_{t\in T} \max\{\sum_{n\in N} r_n(t) - PV(t), 0\} \cdot P(t) \cdot \Delta t \tag{10}$$

s.t. (6), (7), (8), (9)

where $PV(t)$ denotes solar output at time t, and $p(t)$ denotes the energy price. When total power consumption is larger than the renewable generation, system operator has to buy additional power from electric grid to satisfy charging. Note that $\hat{e}_n$, $\hat{t}_{n,f}$ are both conditional estimations in (6), (7), (8) and (9) based on users' historical records, which are computed every time as the scheduling algorithm is triggered by pre-defined events. The schedules for next time interval will be updated based on computation results until new event is detected.

B. Implementation of Event-based Scheduling Algorithms

1) Event Definition

The implementation is based on events defined in advanced to describe a significant change of scheduling variables, which makes it necessary to re-initiate the schedule computation. The following types of events are tentatively designed for triggers.

Event 1: New vehicle arrives with charging request.

Event 2: Vehicle leaves from EVSEs or finishes charging

Event 3: Energy already consumed exceeds the estimated one, which is believed as an abnormal behavior and we infer that this user needs more energy than consumed.

Event 4: Leave time exceeds the estimated one, which might indicate the extended stay duration for this user.

2) Scheduling Algorithm

Algorithm 3: Event-based Cost Scheduling Algorithm (ECSA)

```
Event Trigger:
  for each power source k ∈ K
      N_k ←extract charging sessions at power source k
      for each session n ∈ N_k
          evaluate and estimate ê_n, d̂_n from Algorithm 2
      end
      Compute schedules by (10), subject to (6), (7), (8), (9)
      update schedules for each charging session
  end
```

Fig. 7 Pseudocode for ECSA

Once any of the above events is detected by monitoring program on cloud-side, scheduling computation will be triggered for that EVSE, in Fig.7. Hereby, all charging sessions will be re-evaluated as indicated by *Algorithm 2*, considering the current check time. The last step is to solve optimization problem given the parameters of all charging sessions. The new schedules will be updated for the following time intervals.

V. Results and Discussion

In this section, results from ECSA algorithm will be discussed, based on comparison with the original ESSA. We will show the performance of cost saving, load shifting and also the error rate, which is inevitable if we consider random behaviors. Finally, we will discuss potential methods to improve the scheduling accuracy and the trade-offs in implementation.

A. Experiment setup

To set up simulation experiment, we randomly select 10 continuous days and extract the real charging sessions submitted on one particular EVSE in UCLA campus. The extracted charging sessions are ordered by the start time and labeled with power source number so that real charging events can be reproduced exactly. We use dataset for the past year as the base dataset, from which we can extract user historical behaviors and estimate energy consumption and stay duration. Δt, i.e. time interval for scheduling algorithm is set to *15* min.

B. Cost Saving and Load Shifting

As the primary objective, cost saved will be an important criteria comparing to original ESSA. Time-variant price curve and predicted solar generation are set as inputs for scheduling algorithm. Fig.8 shows scheduling results for 2015 Mar. 17th. Blue curve indicates the new load curve from ECSA.

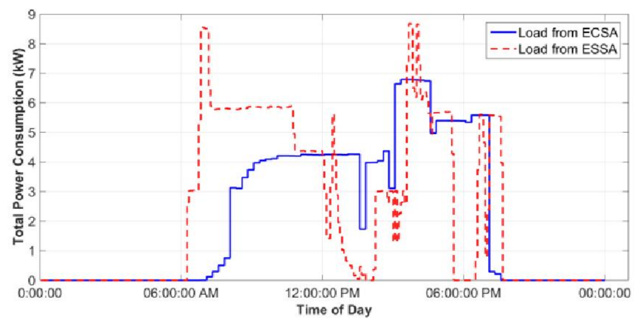

Fig. 8. EV Power Consumption from ESSA and ECSA

It can be easily identified from Fig.8 that ECSA can shift load to region with abundant solar energy and lower energy prices so that overall energy cost will be reduced. However, careful readers may notice that the area below blue line in Fig. 8 is slightly smaller than that of red, i.e. less total energy from ECSA is consumed compared to ESSA. That is because exceptions, i.e. estimation errors, exist during the scheduling process. As the first vehicle arrives, the scheduling algorithm cannot predict behaviors information for other users, who might come later to share the same power source with current user. Thus, ECSA naively schedules higher power consumption to preferable time range. With the realization of new charging sessions with the same power source, ECSA starts to consider power source limitation and update charging schedules for previous user as soon as possible.

Fig.9 is the comparison of operational costs from 3 scheduling algorithms, ESSA, ESSA with solar integration and ECSA. Solar integration reduces the cost for both ESSA and ECSA. For ECSA, the cost decreases because of two reasons: 1) delayed energy consumption at the early stage of charging session 2) charging load shifted from regions with higher price and abundant solar energy, to regions with higher energy price and less solar energy. Suppose the energy consumptions are the same from ESSA and ECSA, there will still be larger portion of load in regions with lower price and ample solar energy, which can be observed from Fig. 8. Thus, 1) is not dominant reason for cost reduction. The effectiveness of ECSA for cost minimization is demonstrated.

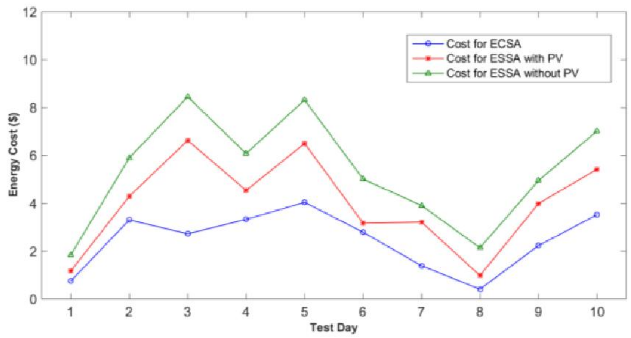

Fig. 9. Operational Cost from EV Scheduling Algorithms

The other criteria is the deviation between actual energy consumption for each vehicle and that obtained from ECSA. A metric named Average Schedule Error Rate (ASER) is defined to represent this deviation:

$$ASER = \frac{1}{L} \cdot \sum_{i}^{L} \frac{e_i - e_{i,c}}{e_i} \cdot 100\% \qquad (11)$$

where e_i is the actual energy consumption from ESSA for one charging session on a particular day. $e_{i,c}$ is the energy consumption from ECSA. L denotes the number of charging sessions on a particular test day. Smaller ASER value corresponds to less deviations. ASER values for the test days are generally acceptable considering the randomness of EV charging sessions. The energy consumption from ECSA, ESSA and ASER values are shown in Fig. 10.

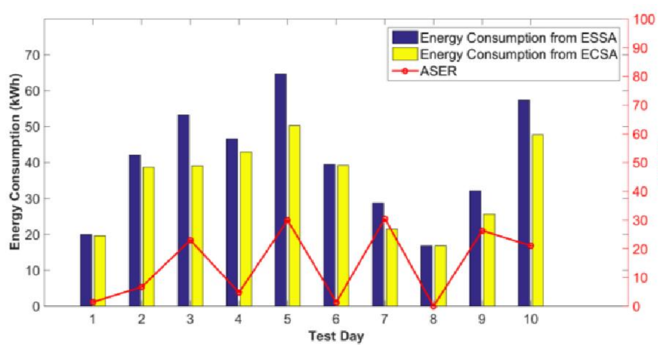

Fig. 10. Energy Consumption and Error Rate

To achieve smaller ASER values, scheduling algorithm needs to deliver as much energy as the ESSA does before each session ends. There exist trade-offs between cost minimization and error rate minimization. Being greedy for energy cannot guarantee optimal cost and vice versa. A possible modification to current ECSA is to increase the greediness for charging sessions that start not long ago and then perform optimal scheduling after energy consumption reaches certain level. Hereby, cost saving performance can be preserved while global *ASER* values can also be improved.

VI. CONCLUSION AND FUTURE WORK

In this paper, we develop an event-based EV scheduling algorithm which considers the random EV charging behaviors by adaptively estimating energy consumption and stay duration. The proposed ECSA has a better performance for cost saving by effective load shifting and maximization of renewable generation usage. However, trade-offs between scheduling accuracy and cost minimization need to be considered in implementation, which will be considered in future work.

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