Title
Smart Electric Vehicle Charging: Mitigating Supply-Demand Disparity Through User Incentives

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Smart Electric Vehicle Charging: Mitigating Supply-Demand Disparity Through User Incentives

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Mechanical Engineering

by

Tianyang Zhang
California has set the goal to source 100% of its electricity from renewable energy by 2045, up from 32% in 2017. Meanwhile, the growing mismatch between the renewable energy generation and peak demand is raising concerns on the electric grid’s stability and efficiency. At the same time, electric vehicles are expected to reach 2.3 million in sales by 2050 in the US. The escalating load of electric vehicles amplifies load peaks and may exacerbate the existing supply-demand discrepancy. However, electric vehicle drivers are typically flexible in choosing the time to charge their vehicle batteries. This flexibility allows the electric vehicle drivers to shift their charging time and power to match the supply with little sacrifice or discomfort. As a result, incentives can be utilized to guide electric vehicle user behaviors to mitigate the grid’s demand-supply discrepancy.

Today, most existing solutions for the demand-supply disparity directly control the time and power of every load in the grid. But the forced control is difficult to implement for electric vehicles due to the lack of hardware support and commercial viability. Instead, incentives can motivate voluntary user behavior changes. This approach is more practical for large-scale deployments.

This dissertation presents a smart electric vehicle charging system that incentivizes users to shift their charging time to match the renewable energy generation. The system applies non-monetary and monetary incentives by assigning charging priorities and awarding
in-system virtual currency to users based on their consumption of renewable energy. Consequently, users with higher renewable energy consumption receive more power and faster service from the charging system. The effectiveness of the non-monetary incentives is demonstrated through two experiments conducted on the UCLA campus for 15 and 14 months respectively. The first experiment with four charging plugs and one solar panel measures users’ willingness to manually change their consumption schedules to match the renewable energy generation. The results indicate that the solar consumption ratio has grown by 37% since the incentives were implemented. The second scaled-up experiment with 28 charging plugs and 2 solar panels introduced system algorithms to automatically control users’ charging schedules when they choose so. The results reveal that more than 23% of the participants use the automatic programs regularly to improve their renewable energy usages.

The incentive design and data analysis in this dissertation provide comprehensive insights on utilizing electric vehicles to mitigate demand-supply disparity through user behavior changes. Additionally, the experiment and system implementations provide practical experience on building effective interactions between the system and users.
The dissertation of Tianyang Zhang is approved.

Adrienne G Lavine

Xiaochun Li

Mario Gerla

Rajit Gadh, Committee Chair

University of California, Los Angeles

2018
To my family, colleagues and friends.
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Zhang T., Chu C., Gadh R., “A two-tier energy management system for smart electric vehicle charging in UCLA: A Solar-To-Vehicle (S2V) case study”, Innovative Smart Grid Technologies - Asia (ISGT-Asia), 2016 IEEE

CHAPTER 1

Introduction

1.1 Background

The number of electric vehicles (EVs) is rapidly growing worldwide. In the United States, the projected EV sales is expected to reach 2.3 million by 2050 [US 18], as shown in Fig. 1.1. The escalating electric energy demand puts additional stress on the power grid. Moreover, increasingly powerful Direct Current Fast Chargers (DCFC) and vehicles with larger batteries will exacerbate the problem, amplifying the load peak further and reducing system reliability and power quality [SG15, ZSB15, SRK14]. Typical peaks of EV charging load show that the most popular time for AC charging is highly skewed towards morning arrivals at work and during lunchtime [Cha18].

Figure 1.1: Sales of electric vehicle: past and future projection [US 18].
At the same time, the rising awareness of global warming and energy sustainability has led to a worldwide effort to introduce more Renewable Energy Resources (RES) into the energy mix. In 2017, California sourced 32% of its electricity from renewable energy and has set the goal to reach 100% by 2045 [Com17]. Currently, photovoltaics (PV), wind and geothermal are among the most promising and popular types of RES [Zer17, TMS17, Pam17]. However, large scale adoption of RES is raising concerns on the electric grid due to the mismatch between RES generation and peak demand. For example, PV energy has created a significant increase in daytime generation and a valley of net demand in the afternoon, followed by another net demand peak at night, most famously described by the “California Duck Curve” [DOB15] shown in Fig 1.2. Wind energy also suffers from problems such as generation curtailment from transmission and demand issues all over the world [Zer17].

![California Duck Curve](from California Independent System Operator)

Figure 1.2: California Duck Curve (from California Independent System Operator).

This dissertation presents comprehensive efforts to provide an efficient and sustainable EV-centric local grid by utilizing user incentives and behavior changes to mitigate the demand-supply discrepancy between RES generation and grid load.
Table 1.1: Plug-in Hybrid Electric Vehicle

<table>
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<th>Characteristic</th>
<th>Value</th>
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<tr>
<td>Battery Size</td>
<td>Smaller</td>
</tr>
<tr>
<td></td>
<td>(8.8kWh-Prius, 17kWh-Volt, 18.4kWh BYD Tang)</td>
</tr>
<tr>
<td>Power Source</td>
<td>Electric motor + Internal Combustion Engine (ICE)</td>
</tr>
<tr>
<td>Type of powertrain</td>
<td>Parallel (Honda Insight), Series (Chevy Volt), Series Parallel (Prius)</td>
</tr>
<tr>
<td>Applications</td>
<td>Economy based (Prius)/Performance based (McLaren P1, BMW i8)</td>
</tr>
<tr>
<td>Typical charging amount</td>
<td>55% of capacity per session</td>
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### 1.2 Electric Vehicle

Currently, EV can be categorized into two types: Plug-in Hybrid Electric Vehicle (PHEV) and Battery Electric Vehicle (BEV). BEVs are fully electric and do not have an Internal Combustion Engine (ICE). PHEVs were created to bridge the gap between traditional ICE vehicles and BEV, addressing issues such as the high cost of batteries and insufficient infrastructure coverage. Characteristics of PHEVs and BEVs are described in Table 1.1 and 1.2 respectively.

Vehicle-to-Grid (V2G) is an upcoming technology that allows EVs to discharge electricity back to the grid [KT05]. This turns EV into a bi-directional energy storage device and makes it an extremely valuable asset to the electric grid. Yet, wide commercialization for V2G is still controversial over concerns on battery life, mileage loss and low financial return [PMM15].

With coordination and scheduling of charging time and power, EVs could still be valuable as a shiftable demand in the grid to alleviate over-generation and night peak problems [SMN11]. A typical US EV driver’s charging pattern can have remarkable flexibility. It is reported that a typical US driver spends 0.8 hours per day in the vehicle and drives an average of 37 miles per day [Tra16, AAA16]. Using a Nissan Leaf’s EV consumption rate [Wik18b], the traveled distance translates to an energy consumption of 9.8 kWh, which can be finished in less than 2 hours with a common Level-2 AC charger. With EVs being parked
23.2 hours a day on average and requiring fewer than 2 hours a day of charging, US EV users are expected to have significant flexibility in choosing their time of charging, as illustrated in Fig. 1.3. Therefore, if the coordination of an EV aggregation is coupled with the dynamics of RES generation, the effect of EVs’ load on the external grid can be minimized while offsetting the negative impact of RES on the grid. In this way, EVs can be utilized to address the grid’s disparity in demand and supply by shifting the time and power of their consumption to match the RES generation.

1.3 Electric Vehicle Supply Equipment

Electric Vehicle Supply Equipment (EVSE) refers to the hardware and equipment that provide energy to EVs. Currently, charging stations have gained the default market position, but alternatives such as battery swapping stations are also under development.

There are two main kinds of charging stations by output: AC and DC. AC charging stations are the most popular choice in the current EVSE market thanks to their simple structure and wide availability. However, because EV’s powertrain system uses DC, an on-board converter is needed to convert AC to DC. This introduces extra costs for EVs. A typical AC charging station has an overall efficiency of around 83.6% based on reported experiments [GOV15]. Fig. 1.4 shows the three AC plug standards in different regions. The
Figure 1.3: The flexibility for an average US driver to adjust their charging time window.

<table>
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<td>up to 62.5 kW</td>
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<td>J1772</td>
<td>36 kW/90 kW</td>
<td>PLC</td>
<td>BMW i3</td>
</tr>
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<td>Tesla Supercharger</td>
<td>up to 120 kW</td>
<td></td>
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The technical details of the US standard SAE J1772 is discussed in Chapter 3.

Today’s DC charging stations are mostly used for high-speed charging. While there exist multiple DC charging standards, the markets are still in lack of a dominant player. Table 1.3 shows the current existing DC standards. A CHAdeMO charging station at 50kW has an overall efficiency of around 87.2% based on experimental results [GOV15].

Most of the current installed charging stations simply charge EVs when they are plugged in and do not support advanced control of the charging time and power [Cha18]. Instead, technologies such as smart EV charging enable modern EVs to change the time and power of their charging while plugged in and serve as a temporary controllable load [Std01]. Therefore, in order to utilize EVs to mitigate demand-supply disparity, the smart EV charging technology is fundamental.
1.4 State-of-Art

To solve the discrepancy problem between supply and demand, an effective system to manage customers’ consumption and RES generation is needed. Moreover, the system should be practical enough to consider real-life implementation and commercialization constraints.

1.4.1 Smart Electric Vehicle Charging

To understand how EV charging will impact the power distribution grid, Mozafar [MAM18] studies the effects of EVs on power system demand, stability and reliability. Kheradmand [KG18] evaluates the distribution grid’s well-being and reliability in the presence of EVs. Amini [AMK17] proposes a two-stage approach to allocate EV charging lots and RES in the distribution network. Mohammadi [MMK18] presents a decentralized decision-making algorithm for collaborative optimal power flow in the transmission and distribution networks. Nienhueser [NQ16] and Schuller [SFG15] discuss the impact and future of RES integration with EVs considering EVs’ economic and environmental impacts and load flexibility.

Smart EV charging algorithm with various optimization approaches are widely proposed as well [XMC16, JZX15, IMM14, DMB18]. Infrastructures such as military bases have been especially devoted to using smart charging algorithms to improve resilience, efficiency and re-
Several real-time smart charging algorithms are designed based on user priorities. Many minimize energy costs for drivers and aggregators assuming a dynamic or Time-of-Use (TOU) pricing scheme. While this is an effective approach, flat-rate pricing is still dominant in the real world and there remain many obstacles for full implementation of dynamic pricing. Without dynamic pricing, the algorithms’ performance would be limited. Moreover, most of the studies assume complete information on user behavior and full control of each EV, which is rarely available for consumer markets because of limitations on hardware support and commercial viability.

To manage users’ behaviors, many works use incentives, demand response and dispatch control. Valles, Eissa and Yu model incentive programs by considering user responsiveness, multiple resources’ coordination and hierarchical electricity markets. Zhang, Haghi and Zhao provide market investigation, benefit analysis and execution experience of providing incentives. Rubino, Mortaz and Lu review and propose microgrid scheduling and dispatch algorithms with EV smart charging. Nonetheless, few incentive programs in the current market focus on EV users’ behavior changes.

### 1.4.2 Renewable Energy Resources Integration

The RES integration issues have been addressed by extensive efforts. Dawound reviews common optimization techniques for microgrid with RES. Mehdizadeh, Javidsharif and Lorenzo use information gap decision theory, multi-objective optimization and model predictive control to schedule RES-based microgrid.

Furthermore, solutions based on EV charging to increase RES utilization are widely investigated. Mouli designs a solar harvesting system to charge EVs. Many consider EV as a controllable load and use linear programming, convex programming, mixed-integer programming and semi-Markov decision process to maximize
RES utilization. Yet, most of the optimization algorithms either involve V2G capability or placement of energy storage. As discussed in Section 1.3, current V2G technology is still far from wide commercialization and most energy storage systems are expensive to purchase and install [FMM15].

Experiments and implementation experience in RES-based grids are also reported [PW17, LDG17, QMB18, APG17]. Peng [PW17] and Lopez [LDG17] summarize deployment experience of renewable microgrid in Singapore and Andean countries. Quashie [QMB18] and Arcos [APG17] verify the effectiveness of their proposed control algorithms through experiments conducted in Canada and Spain. Zhang [ZCG16] reports an Energy Management System (EMS) with load curtailment experiments based on real-time RES generation. While the reported systems provide valuable insights on practical implementations, they are mostly large scale multi-resource projects without particular focus on using EVs and driver behaviors to mitigate the demand-supply disparity.

1.4.3 User Demand

The information on users’ energy demand is important and foundational to effective demand control. However, current charging standards do not collect propriety vehicle information, such as battery State of Charge (SOC), to reveal the true user demand [Std01].

There are prediction algorithms for different energy resources [KLC11], such as photovoltaic systems [SWL13], smart buildings [BMC13], and wind turbines [SM13], but few focus on EV consumption due to the lack of user behavior data. Aabrandt and Ashtari convert driving habits and cycles into energy consumption to predict EV energy demand [AAP12, ABS12]. This approach is impractical for user management because they consider each individual driver identical and study them in an aggregated fashion. Alizadeh [ASD14] predicts EV chargers’ demand profiles with data collected from on-board devices, which require additional hardware and communication services and increase cost of vehicle significantly. Majidpour [MQC15] uses time-series analysis to predict aggregated EV load based on charging station power data. Although time-series prediction can be useful for
general aggregated loads, EV’s consumption rate is mostly constant and predictable, so the
time-series method is not suitable for predicting EV load.

Therefore, the fundamental task for accurate user demand prediction is to find each user’s
arrival and departure time and his/her energy demand.

### 1.5 Organization and Contribution

The dissertation discusses smart charging system design by leveraging user incentives, system
optimization and user behavior analysis. The rest of the dissertation is organized as the
following:

Chapter 2 presents the smart EV charging system with user incentives to address the time
and power discrepancy between local RES supply and demand. A priority-based system is
designed and implemented on campus to examine its effectiveness among long-term UCLA employees with personal vehicles. A monetary incentive system is added to improve the system effectiveness.

Chapter 3 presents the efforts made to modernize basic EV charging equipment to in-
tegrate with smart phone applications and advanced connectivity. Pilot projects using the technologies are also presented.

Chapter 4 presents a two-level Energy Management System to address the multitude of distributed controllers and the need to effectively control them. This chapter shows detailed designs, algorithms and experimental results for the upper level controller called Super Control Center.

Chapter 5 presents the analysis of user behavior data in order to determine the ideal model to formulate an EV user’s consumption pattern.

Chapter 6 presents a large scale stochastic model for the interactions between EV drivers and EVSE service providers.

Chapter 7 discusses the future research and development trend on vehicle-grid integra-
tion and Chapter 8 concludes the dissertation. The contribution of the dissertation can be
summarized as following:

1. An incentive system integrated with priority-based ranking system is proposed, studied and verified. The system is designed with realistic considerations on implementation and commercialization constraints. Experiments conducted for 15 months and 14 months on the UCLA campus have shown that using the priority ranking system, user behaviors have improved on renewable energy usage and the solar consumption rate are increased by 37% over time. More than 23% of users are explicitly committed to changing their consumption patterns by signing up for the automatic improvement program. The system has proven its effectiveness in promoting the value of priority and renewable energy amongst users. An unique blockchain cryptocurrency system design has also been added to the system.

2. Extensive hardware and software optimization has been designed and implemented on the UCLA campus. The system components are modernized to incorporate cloud infrastructure and advanced connectivity.

3. A new two-level EMS is proposed, designed and implemented to manage energy resources on campus and device levels. The EMS procures local demand-supply balancing and sustains reliable service through experiments over years across different locations.

4. User consumption data of 18,599 sessions and 340 users have been analyzed to find the best method to characterize the energy demand of a typical campus EV user.

5. A stochastic model is proposed to model the stochastic interaction between EV drivers with individual operations and EVSE service providers. The model is evaluated by Monte-Carlo simulation and analytic solution.
CHAPTER 2

EV Charging Incentives with Prioritization and Cryptocurrency

2.1 Introduction

Smart EV charging is the technology that enables modern EVs to change the time and power of their charging while plugged. In this chapter, a smart EV charging system is proposed to motivate and incentivize users to use more Renewable Energy Resources (RES) collectively even on a flat-rate pricing system. The market design can provide monetary and non-monetary incentives while reducing operating and energy cost for aggregators. The system does not require energy storage and is suitable for large-scale adoption. The system is online and designed with consideration of practical implementation issues, setting itself apart from other advanced yet nearly impossible to implement algorithms. The algorithm is implemented on the campus of the University of California, Los Angeles (UCLA) to evaluate its effectiveness. The contributions and novelties of this work are as following:

1. Overall, this chapter proposes a novel system design that provides incentives to EV users to alleviate the problems of RES over-generation and mismatch between RES supply and demand. Real-time control algorithms for EV charging stations and optimal strategies for users to reach a Nash equilibrium local optima are also proposed. The algorithms incorporate considerations of real EV charging station implementation and are verified with experiments of 15 months and 14 months.

2. A scalable incentive design is proposed to guide user behaviors. The system implements the incentives without imposing Time-of-Use (TOU) pricing and using energy storage.
Table 2.1: List of Notations

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>Rate of issuing SMERCOIN for each aggregator per kWh of RES consumption</td>
</tr>
<tr>
<td>$b$</td>
<td>Base aggregator conversion rate from SMERCOIN to fiat money</td>
</tr>
<tr>
<td>$v, e, y$</td>
<td>Total, additional exchange and utility values of SMERCOIN</td>
</tr>
<tr>
<td>$\mathcal{D}, \mathcal{S}$</td>
<td>Demand and supply of SMERCOIN in the user-level exchange.</td>
</tr>
<tr>
<td>$\mathcal{D}(v, y), \mathcal{S}(v, y)$</td>
<td>Demand and supply as function of price and utility value.</td>
</tr>
<tr>
<td>$\mathbf{B}_i$</td>
<td>SMERCOIN compensation per minute for boosting</td>
</tr>
<tr>
<td>$g_i$</td>
<td>Time delayed for providing boosting to user $i$</td>
</tr>
<tr>
<td>$c_i$</td>
<td>Total SMERCOIN price for boosting for user $i$</td>
</tr>
<tr>
<td>$u$</td>
<td>Overall RES consumption rate by EV</td>
</tr>
<tr>
<td>$a_{p,t,\text{raw}}$</td>
<td>Raw data reading from RES generation meter at time $t$</td>
</tr>
<tr>
<td>$a_{p,t}, a_{s,t}, a_{v,t}$</td>
<td>RES generation, power of charging box, power of charging station $v$ at time $t$</td>
</tr>
<tr>
<td>$a_{i,t}, a_{p,i,t}$</td>
<td>Power consumption of user $i$ at time $t$ and that in priority charging system.</td>
</tr>
<tr>
<td>$\mathbf{I}<em>i, \mathbf{I}</em>{t,i}, \mathbf{I}_{s,t}$</td>
<td>Set of users, higher priority users and lower priority users in a charging box at time $t$.</td>
</tr>
<tr>
<td>$u_{i,n}$</td>
<td>RES consumption for the $n$-th session of user $i$</td>
</tr>
<tr>
<td>$t_{n,s}, t_{n,e}$</td>
<td>Start and end time of $n$-th session</td>
</tr>
<tr>
<td>$s_i$</td>
<td>Solar score of user $i$</td>
</tr>
<tr>
<td>$\vec{k}_i$</td>
<td>User $i$ profile features other than solar score</td>
</tr>
<tr>
<td>$w(s_i, \vec{k}_i)$</td>
<td>Weight function to calculate user priority</td>
</tr>
<tr>
<td>$a_{\text{max}}$</td>
<td>Maximum rate a charging box can provide (hardware configuration)</td>
</tr>
<tr>
<td>$\vec{s}, \vec{K}, \vec{a}$</td>
<td>Set of solar score, user feature and power provided</td>
</tr>
<tr>
<td>$\tilde{E}, E$</td>
<td>Energy allowance per cycle and the set of energy tracker in Priority Round Robin</td>
</tr>
<tr>
<td>$\mathbf{R}, \mathbf{P}, \mathbf{D}$</td>
<td>Set of user starting time, stop time and energy demand</td>
</tr>
<tr>
<td>$R_i, \mathbf{P}_i, D_i$</td>
<td>Starting time, stop time and energy demand of user $i$</td>
</tr>
<tr>
<td>$R_{i}^f, P_{i}^f, D_{i}^f$</td>
<td>Starting time, stop time and energy received of user $i$ in fair sharing system</td>
</tr>
<tr>
<td>$a, a_i$</td>
<td>Charging strategy for charging box and user $i$</td>
</tr>
<tr>
<td>$\mathbf{F}, \mathbf{F}_i$</td>
<td>Feasible set for charging box and user</td>
</tr>
<tr>
<td>$\mathbf{T}<em>i, \mathbf{T}</em>{i'}$</td>
<td>Open time slots for user $i$ from server and combined with user’s own open time plan.</td>
</tr>
<tr>
<td>$\rho, \lambda_i$</td>
<td>The scaling factors for user level optimization</td>
</tr>
<tr>
<td>$r_{io}, p_{io}, d_{io}$</td>
<td>User’s original request parameters</td>
</tr>
<tr>
<td>$l_i(r_{io}, p_{io}, d_{io})$</td>
<td>Loss function of user $i$ considering change of original plan</td>
</tr>
<tr>
<td>$\tilde{D}$</td>
<td>The system estimated user demand</td>
</tr>
<tr>
<td>$\mathcal{T}_i, j$</td>
<td>Set of available slots for user $i$ for multi-boxes, chosen box index</td>
</tr>
<tr>
<td>$u_c$</td>
<td>Solar consumption ratio</td>
</tr>
</tbody>
</table>
The system incorporates non-monetary incentives (priority) and monetary incentives (blockchain-based cryptocurrency).

3. Online priority ranking algorithms, such as Priority Sharing and Priority Round Robin, are proposed and optimized to facilitate practical implementations involving EVs and EV charging stations operating in SAE J1772 standard. User-level optimal strategies are also designed and proposed to help the system to achieve local optima, verified by numerical simulations.

4. Two experiments with workplace charging running Priority Round Robin for 15 months and 14 months are implemented to evaluate the effectiveness of the algorithm on the UCLA campus. The test site at PS2 has shown consistent local over-generation and demand-supply mismatch problems before the experiment. The experiment and data analysis using Welch’s t-test show that local solar consumption ratio has increased 37% with non-monetary incentives applied alone in PS2. The experiment with expanded scale in PS9 shows that a significant share of users in the system are willing to change their consumption behaviors and the system is effective in using the value of priority to promote the use of renewable energy.

5. A blockchain-based cryptocurrency trading framework is designed to provide monetary incentives to users to pass down the cost-savings of the aggregators. Unlike most cryptocurrencies that only work as an alternative currency, the proposed cryptocurrency has both the abilities to convert to fiat money and change the physical power flow, which is one of the first in the energy industry.

The rest of this chapter is organized as follows.

Section 2.2 explains the system design and its market mechanism. Section 2.3 and 2.4 show the fundamental prioritization algorithm and optimal strategies for incentivized drivers and aggregators. Section 2.5 shows the numerical simulation of the algorithm and Section 2.6 shows the experimental result of the algorithm, with discussion and conclusion in Section 2.7 and 2.8.
2.2 Incentive System Design

As commercial EV charging service providers do not have control over customer behaviors, such as when they arrive, leave or how much energy they request, it is essential to design an incentive system in which it is only reasonable for the user to follow the incentive guidance. Traditionally, this is achieved by posing different prices at different time. This section presents the system design to incentivize EV users to collectively adjust their charging time so that a better overall RES consumption could be achieved. As will be discussed in further details in Section 2.4 each incentivized user will find the best time with high RES generation to charge his/her EV considering the occupancy situation of other users.

Moreover, the incentive system design presented in this section can be generalized to incentivize any user behavior that will lead to cost savings for the aggregator.

2.2.1 System Overview

A microgrid is a group of local electricity load and sources that can operate together with external grid or independently [LP04]. A general EV aggregator equipped with RES generation can be considered as a microgrid. It is connected to the external power grid and serves to charge its users (EV). An overview of the hierarchy of the vertical system can be seen in Fig. 2.1.

An aggregator of EV chargers has a number of charging stations available to be used by EVs. To improve energy efficiency and reliability, many aggregators install distributed energy resources, such as RES and energy storage devices [MBZ16 ZCG16]. Local RES generation provides a source for clean and affordable energy. Energy storage systems can store local RES surplus, purchase cheap electricity and increase local peak output [FMM15].

Customers of aggregators are EVs. They can be personal vehicles, commercial fleet vehicles (including semi-trucks) or self-driving vehicles. This chapter focuses on personal EVs. Customers come to charging stations to receive certain amount of energy within a desired time frame. Their demand depends on their driving range, consumption pattern and
Figure 2.1: The system hierarchy for serving EVs in an electric grid.

Users usually look for fast, reliable and affordable services that can satisfy their energy needs [HJT18]. Environment conscious users may also prefer to receive their energy with clean and renewable sources.

Aggregators usually connect to the grid of their local utility and purchase electricity from it. Regional transmission organization (RTO) and independent system operator (ISO) in North America oversee the electric grid in larger geographic area than local utilities. To deliver electricity reliably and effectively, RTO/ISO and utilities provide pricing schemes, incentives and ancillary services, such as Demand Charge and Demand Response [SSSI6]. By coordinating energy usage, aggregators can save energy cost or earn incentives. For example, by reducing peak load with energy storage system, the Demand Charge cost can be decreased [McP14].

As will be discussed further in this section, a cryptocurrency system can be established between the grid, aggregators and users to provide another way to deliver incentives.

The rest of the chapter focuses on how an aggregator of a microgrid of EVs would incentivize EV drivers for desired consumption behaviors.

2.2.2 User Prioritization

The fundamental component of the system is user prioritization. The system should assign different “priority” to users to differentiate those who are more aligned with the system guidance than those not. The priority should be assigned to the elements that are critical to
users, such as charged energy, time or money. The detailed prioritization process is discussed in Section 2.3.

Generally, a system that requires prioritization has more demand than what it can provide. Examples are systems with an overflow of arriving EVs, and systems with larger maximum output power than its allowed input power. Such configurations can already be found in high EV demand areas where there is a large number of DCFCs but the input power is not enough to power all stations. ATC Power, a Chinese company, has also proposed a “Matrix Flexible Charging Stack” hardware design that can coordinate output power between different power outlets to address this issue.

Fig. 2.2 summarizes the mechanism of how prioritization incentives users and how cryptocurrency can extend the incentives. The incentive mechanism starts from prioritization.

(1) Non-monetary incentive: High priority will be given to users with encouraged behavior (“preferred users”) and low priority will be given to users without encouraged behaviors (“normal users”). By having extra priority for certain behavior, users will be incentivized to behave more in such way. (2) Monetary incentive: Having “preferred users” will lead to cost-saving for the aggregator. The aggregator can choose to convert the reduced cost to cryptocurrency to award to users. Naturally, “normal users” will have more cryptocurrency and “bad users” will have less cryptocurrency. With the cryptocurrency, users can choose to convert them to fiat money (dollar, euro, etc.) or more priority. Therefore cryptocurrency has value to users, and naturally users are incentivized to earn more cryptocurrency by behaving more in the encouraged way.

The following subsections discuss the details of the design.

2.2.3 Non-Monetary Incentive

With the implementation of user priority, it is straightforward to see the priority as a non-monetary incentive. In an ecosystem where some people are given higher priority than others, it is natural for others to explore ways to gain such priority. In this way, the priority itself is a non-monetary incentive. The effect of implementing prioritization on different users in
Figure 2.2: Incentive mechanism by prioritization. “Preferred user” refers to users with system’s desired consumption behavior and “normal user” refers to users without such behavior. The priority itself is a non-monetary incentive and cryptocurrency is a monetary incentive for encouraging user behavior. The incentives will encourage more users to be “preferred users”.

2.2.4 Monetary Incentives

For an aggregator or microgrid operator, the price to sell extra RES energy back to utilities is always lower than the price to buy electricity from utilities, so it is always cheaper to consume self-generated energy. Therefore, with increased RES usage, the aggregators can expect to see their energy cost decreased. However, non-monetary incentive does not pass down this cost saving to users like a tiered pricing system. The system can use a cryptocurrency called SMERCOIN to pass down the monetary savings from aggregators to users, further encouraging users to use more RES.

For each aggregator, there can be a certain conversion from how much RES is consumed to how much money is saved. SMERCOIN is distributed to each user with certain rate $\gamma$ set by each aggregator. Specifically, each user will obtain $\gamma$ SMERCOIN for every 1 kWh RES energy he/she consumes at the aggregator. At the same time, $\gamma$ SMERCOIN is deducted from the aggregator’s balance. Aggregator must buy back SMERCOIN with a fixed global
Table 2.2: Aggregator Buyback

<table>
<thead>
<tr>
<th>User</th>
<th>Aggregator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fiat Money</td>
<td>SMERCOIN</td>
</tr>
<tr>
<td>Consume 1kWh RES</td>
<td>$ +\gamma $</td>
</tr>
<tr>
<td>Sellback 1 SMERCOIN</td>
<td>$ +b $</td>
</tr>
</tbody>
</table>

rate $b$ per SMERCOIN set by the protocol if a user wishes to sell back. In this way, the $\gamma$ aggregators set up is how much “rebate” an aggregator wishes to compensate users for using RES energy, i.e. $\gamma b$ per kWh. The interaction between user and aggregator in the buyback is shown in Table 2.2 and illustrated in Fig 2.3.

The system can work with multiple aggregators with different rate $\gamma$ and users can sell their SMERCOIN earned at one place to elsewhere so fluidity is guaranteed. When one aggregator has positive SMERCOIN balance, it can sell its SMERCOIN to other aggregators so no aggregator is forced to pay out more than it has issued. However, when an aggregator has a negative balance, it cannot sell SMERCOIN to other aggregators to prevent “shorting”. Such rule can be enforced easily by using blockchain technology. In blockchain with public access of data as shown in Table 2.3, each transaction (issuing or buyback SMERCOIN) is open to public [Nak08], therefore the balance of each aggregator is known to all.

With enough competition, every aggregator will try to set the most optimal $\gamma$. If $\gamma$ is too high, aggregator may lose money by having to pay too much to buy back. If $\gamma$ is too low, users may prefer to charge at other competitors with higher $\gamma$, so that one may lose its customer base.

**Blockchain**

The emerging technology, blockchain [Nak08] is a decentralized, trustless and immutable ledger database for participants. Blockchain brings a new opportunity to provide incentives to users without going through the traditional pricing scheme posed by utility or aggregators. In a centralized database, any authorized administrator can perform any kind of operations
Figure 2.3: Interactions of aggregator buyback with EV users to guarantee base value of SMERCOIN.

he/she is authorized to perform, such as update, add or drop. A blockchain consists of a chain of blocks containing header and transaction information (thus the name “blockchain”). In a blockchain, all operations, such as transfer, add and reduce, are recorded in the transaction (tx) part of each block. The “miner” who gets to push the next block to the blockchain is selected through the consensus protocol of the specific blockchain. The new block will be inspected and verified by all the other participants before all participants and data hosts confirm the new operations and move on to produce the next block. Therefore, it is easy to understand the reason why most of current blockchain technologies have less speed and efficiency than centralized database. It is also no surprise that the most popular application of blockchain is cryptocurrency, given that they only involve easy operations (add/subtract) but they require high verifiability, reliability and security. More applications such as logistics management and social networks are also under development. An comparison between blockchain and centralized database in shown in Fig. 2.4.

Consensus algorithms, such as Proof of Work (PoW) and Proof of Stake (PoS), are used in blockchain to make sure data is verified and consistent. Different types of blockchains are designed in terms of who can participate in the consensus process. A summary of three
Figure 2.4: Comparison between blockchain and centralized database.

types of blockchains is shown in Table 2.3 [ZXD17]. For public blockchain, anyone can participate in the consensus process to verify the written transactions and all data is open to public. However, due to the large pool of consensus nodes, the efficiency of a public blockchain can be low. For consortium and private blockchains, only a set of nodes is selected to participate in the consensus process. Therefore, the efficiency of the network can be higher. The transaction data can also be restricted to participating nodes, making it suitable for enterprises wishing to keep their data private. However, due to the small number of consensus participants, there stands a chance for data on the blockchain to be tampered. So far, only a few efforts have been published on incorporating blockchain within the energy industry. Sikorski [SHK17] presented a market design to implement a blockchain-based electricity market in the chemical industry. Mengelkamp [MGR18] presented a case study of Brooklyn Microgrid implementing a local energy market with blockchain. While this blockchain market is active with trading activities, it is still “virtual” as it doesn’t change the actual power flow in the microgrid with the transaction. More practical use of blockchain with smart grid should be encouraged to reduce cost for users and aggregators and improve operation efficiency.
Table 2.3: Types of Blockchains

<table>
<thead>
<tr>
<th></th>
<th>Public blockchain</th>
<th>Consortium blockchain</th>
<th>Private blockchain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consensus participants</td>
<td>All miners</td>
<td>Selected set of nodes</td>
<td>One organization</td>
</tr>
<tr>
<td>(permissionless)</td>
<td></td>
<td>(permissioned)</td>
<td></td>
</tr>
<tr>
<td>Read Permission</td>
<td>Public</td>
<td>Public or restricted</td>
<td>Public or restricted</td>
</tr>
<tr>
<td>Efficiency</td>
<td>Low</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Data security</td>
<td>Very high</td>
<td>Could have data breach</td>
<td>Could have data breach</td>
</tr>
<tr>
<td>Example</td>
<td>Bitcoin, Ethereum, Litecoin</td>
<td>Corda, B3i</td>
<td>MultiChain</td>
</tr>
</tbody>
</table>

2.2.5 Incentives to Hold SMERCOIN

If SMERCOIN’s only use is for redemption to actual currency, all users will redeem it right away. However, the system design can introduce additional utility value to SMERCOIN when they are being held by users. The utility value will increase the SMERCOIN’s actual value from its base value $b$ defined in the aggregator buyback.

Let $v$ be the total fiat money value of one SMERCOIN,

$$v = b + e$$  \hspace{1cm} (2.1)

where $b$ is the base value of SMERCOIN and $e$ is the additional value (premium) of SMERCOIN from its utility value. When SMERCOIN has no utility value, $e$ is 0.

When users desire to use the utility power of SMERCOIN without enough balance, they may seek to trade with other users, leading to market demand and supply. The trading activity of SMERCOIN can be achieved by an user-level SMERCOIN exchange similar to general stock or cryptocurrency exchange and is illustrated in Fig. 2.5. Because aggregators are the underwriters/issuers of SMERCOIN, they are not allowed to participate in the user-level SMERCOIN exchange to prevent arbitrage.

The demand and supply of SMERCOIN among users can be formulated based on the demand-supply models \[Dou72, Sam41\],

$$D = D(e, y), \frac{\partial D}{\partial e} < 0, \frac{\partial D}{\partial y} > 0$$  \hspace{1cm} (2.2)
Figure 2.5: User can trade SMERCOIN using wallet.

\[ S = S(e, y), \quad \frac{\partial S}{\partial e} > 0, \quad \frac{\partial S}{\partial y} < 0 \]  

(2.3)

where \( D \) and \( S \) are the total demand and supply of SMERCOINs by users, and \( y \) is the utility value of one SMERCOIN within the system. \( y \) can be the value of time, convenience or prestige in the system, depending on the system design.

Equations (2.2) and (2.3) state that the more utility value \( y \) one SMERCOIN can provide with the same price, the more demand and less supply there will be. At the same utility value, the higher the market premium \( e \) a SMERCOIN has, the lower the demand and higher the supply there will be.

**Theorem 1.** In a demand and supply system defined by (2.2) and (2.3), at equilibrium with \( D = S \),

\[ \frac{de}{dy} > 0 \]  

(2.4)

Therefore, when the system design provides utility value \( y \), users can expect to see non-trivial \( e \), motivating them to keep the SMERCOIN among themselves instead of redeeming them with aggregators at base value \( b \). When users choose to hold on to their SMERCOIN, aggregators are able to stay in negative SMERCOIN balance. This leads to further cost reduction for aggregators, as they don’t have to buy back all the SMERCOIN they issue as illustrated in Fig. 2.6.
A bidding mechanism called “boosting” can be introduced to provide utility value to the system shown in Fig. 2.7. It allows a user with lower priority in queue to give up certain SMERCOIN to users with higher priority so that they will agree to let him/her to “cut in the line” or take over their share of power. By exchanging SMERCOIN with time, SMERCOIN provides utility value in the form of time value to users.

In the system design, only one boost is allowed for a group of users at one time and each boost can only be valid for one charging session. The algorithm for boost is shown in Algorithm 1 where \( B_i \) is the set of parameters set up by higher priority users how much SMERCOIN they wish to be compensated for delaying unit time. The delayed time \( g_i \) proposed by user \( i \) is based on his/her energy need and the station power capacity. After
looking at the total asking price $c_i$ from all users, user $i$ can decide whether to pay for the compensation.

**Algorithm 1 Boost For User $i$**

**Input:** $g_i, B_i$

**For Each** $m \in B_i$ **do**

$$c_i = c_i + mg_i$$

**end for**

**if** $c_i$ **is accepted** **then**

Give priority of users in $B_i$ to user $i$

user $i$ pays the respective amount of SMERCOIN to each users.

**end if**

In this case, setting the asking SMERCOIN $m$ for boosting is not a trivial task. While one may have a fiat money-to-time conversion in mind, the price of SMERCOIN is not fixed. Therefore, users may look at the user-level exchange to constantly update their asking SMERCOIN $m$. This process can also be automated by programs. With blockchain, such exchange can also be safely and effectively established.

A summary of user activities and their effect on the SMERCOIN market and all players in the market is shown in Table 2.4. Fig. 2.8 shows the flow of SMERCOIN and fiat money with each market activity.

It is worth noting that automatic programs, such as “wallet” in the context of blockchain, can help users to automate the process of purchasing and selling SMERCOIN. Wallets can implement transactions on behalf of users, with user’s authorization such as their private keys, and interface with the blockchain, so that users can avoid tedious manual operations. Additionally, there can be multiple programs developed by different parties for communication with a particular blockchain. Examples of wallet functions for SMERCOIN include (1) *limit order*: buy/sell certain number of SMERCOIN at a certain price or better. (2) *market order*: buy/sell immediately at the market price. (3) *boost order*: buy needed SMERCOIN using market order or limit order.
Table 2.4: Summary of User Activity

<table>
<thead>
<tr>
<th></th>
<th>Earn coin</th>
<th>Boost</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>User</strong></td>
<td>Increase coin balance; Temporary higher priority; Increase holding value</td>
<td>May buy coin from other</td>
</tr>
<tr>
<td><strong>Aggregator</strong></td>
<td>Save cost, issue coin</td>
<td>Adjust queue</td>
</tr>
<tr>
<td><strong>Total coin of all users</strong></td>
<td>Increase</td>
<td>Same</td>
</tr>
<tr>
<td><strong>Market price for coin</strong></td>
<td>May decrease</td>
<td>May update ask price</td>
</tr>
<tr>
<td></td>
<td>Sell to user</td>
<td>Sell to aggregator</td>
</tr>
<tr>
<td><strong>User</strong></td>
<td>Convert to fiat money (higher than fixed rate)</td>
<td>Convert to fiat money (fixed rate)</td>
</tr>
<tr>
<td><strong>Aggregator</strong></td>
<td>-</td>
<td>Pay out saved cost</td>
</tr>
<tr>
<td><strong>Total coin of all users</strong></td>
<td>Same</td>
<td>Decrease</td>
</tr>
<tr>
<td><strong>Market price for coin</strong></td>
<td>Update latest price</td>
<td>May increase</td>
</tr>
</tbody>
</table>

Figure 2.8: The flow of SMERCOIN and fiat money associated with each market activity.
2.3 Prioritization Algorithm

The operations of EV charging stations implementing user prioritization is discussed in this section.

2.3.1 RES Integration and User Behavior

In a microgrid setting with local RES generation and consumption, RES is considered to be consumed first locally and if there is redundant energy, it is exported to the outside grid, as shown in Fig. 2.9.

Therefore the overall local RES consumption rate by EV $u$ within a time period can be evaluated as

$$u = \frac{\sum_t \min(a_{p,t}, a_{s,t})}{\sum_t a_{s,t}}$$  \hspace{1cm} (2.5)

where $a_{p,t}$ is the power of RES generation at time $t$ and $a_{s,t}$ is the power of total EV consumption at time $t$. $a_{p,t}$ should be always equal to or larger than 0. However, in practice, the data reading from the meter of a PV panel could show small negative values, causing inaccuracy of the calculations. This can be solved by setting $a_{p,t} = \max(a_{p,t,\text{raw}}, 0)$ where $a_{p,t,\text{raw}}$ is the raw data output of the meter.

For ease of discussion, in the rest of the chapter, a “charging box” is referred as an aggregation of charging stations with fixed input and larger maximum output power so that prioritization of each sub-station is needed. The box power consumption is the sum of all sub-stations

$$a_{s,t} = \sum_v a_{v,t}$$  \hspace{1cm} (2.6)
where \( a_{v,t} \) is the power of sub-station with index \( v \). For a charging box with four charging stations, \( v \) is from 0 to 3.

### 2.3.2 Charging System with Prioritization

In a charging box defined in (2.6), users’ experience is different with prioritization compared to a fair sharing policy. In a fair sharing set-up, a set of users with starting time \( \bar{R}^f \) and stop time \( \bar{P}^f \) receives energy demand \( \bar{D}^f \). For each user \( i \) (\( i \) starts from 0 to \( |I_t| - 1 \), where \( I_t \) is the set of users requesting energy at time \( t \)), the energy \( D_i \) he/she receives is

\[
D_i^f = \sum_{t=R_i^f}^{P_i^f} \frac{a_{\text{max}}}{|I_t|} \tag{2.7}
\]

where \( a_{\text{max}} \) is the maximum charging rate a charging box can provide and \( I_t \) is the set of users requesting energy at time \( t \). For example, \( a_{\text{max}} \) is 6.6 kW for SAE J1772:2001 Level-2 AC stations [Std01].

In a priority charging system, there is a nonempty higher priority user subset \( I_{h,t} \) such that

\[
a_{i,t}^p > \frac{a_{\text{max}}}{|I_t|}, \quad \forall i \in I_{h,t}, \quad I_{h,t} \subset I_t, \quad |I_t| > 1 \tag{2.8}
\]

where \( a_{i,t}^p \) is the power user \( i \) receives at time \( t \) in a priority charging system. Because the total charging rate of the charging box is fixed, there is also a nonempty subset \( I_{l,t} \) such that

\[
a_{i,t}^p < \frac{a_{\text{max}}}{|I_t|}, \quad \forall i \in I_{l,t}, \quad I_{l,t} \subset I_t, \quad I_{l,t} \cap I_{h,t} = \emptyset, \quad |I_t| > 1 \tag{2.9}
\]

**Theorem 2.** In a priority charging system defined by (2.8) and (2.9) and \( \exists t \) such that \( |I_t| > 1 \), when compared to fair sharing defined in (2.7), the following is true:

(a) Given starting time \( \bar{R}^f \) and energy demand \( \bar{D}^f \), there will be a nonempty subset of higher priority users that finish their charging before their original stop time in \( \bar{P}^f \).

(b) Given stop time \( \bar{P}^f \) and energy demand \( \bar{D}^f \), there will be a nonempty subset of higher priority users that start their charging after their original start time in \( \bar{R}^f \).
(c) Given start time $R^f$ and stop time $P^f$, there will be two nonempty subsets of higher priority and lower priority users that receive more and less energy than their original energy demands in $D^f$ respectively.

Therefore, users with higher priority will have more flexibility on charging schedules. They may also receive more energy than they would in a fair sharing setup. On the contrary, users with less priority may receive less energy and have less charging flexibility. This will motivate users to seek “priority” in the system.

2.3.3 Ranking and Power Sharing Algorithms

In order to promote maximum usage of RES energy, the idea of giving higher charging priority to a user with higher RES usage is used. By looking at each user’s charging history and comparing against the RES usage, every user can be assigned a “solar score” based on how much their used energy comes from RES. While solar is only one form of RES, it is a more straightforward term for user understanding and most of the community microgrids are only equipped with solar panels. Therefore, RES and solar are interchangeable in the rest of the chapter.

The RES consumption rate $u_{i,n}$ for the $n$-th session of user $i$ occupying the $v$-th station of the box can be computed as

$$u_{i,n} = \frac{\sum_{t_{n,s}}^{t_{n,e}} \left( \min(a_{p,t}, a_{s,t}) a_{v,t} \right) a_{v,t}}{\sum_{t_{n,s}}^{t_{n,e}} a_{v,t}}$$ (2.10)

where $t_{n,s}$ and $t_{n,e}$ are the start and end time of user $i$’s $n$-th session.

Summing the RES consumption rate from all the sessions, users’ solar score can be evaluated as

$$s_i = \frac{\sum_{n=1}^{N} (u_{i,n} \sum_{t_{n,s}}^{t_{n,e}} a_{v,t})}{\sum_{n=1}^{N} \sum_{t_{n,s}}^{t_{n,e}} a_{v,t}}$$ (2.11)

Users’ priority is based on their solar score $s_i$, because $s_i$ reflects how much RES a user consumes in his/her lifetime usage. In principle, more priority should be given to the user with a higher solar score. Additionally, aggregators may wish to provide priority based on
other user features. For example, a system may assign higher priority to users with lower demand, so that more users can be served. This can be described with a priority weight function \( w(s_i, \bar{k}_i) \) that increases with \( s_i \). Therefore vector \( \bar{k}_i \) is used to contain other profile information of user \( i \) such as his/her demand.

Given users’ priority weights, two straightforward algorithms to implement the concept shown in Section 2.3.2 can be used (1) Priority Sharing (2) Priority Round Robin.

In Priority Sharing algorithm, power is distributed to every user proportionally to each user’s priority weight. The power \( a_{i,t} \) user \( i \) receives at time \( t \) is

\[
a_{i,t} = \frac{w(s_i, \bar{k}_i)}{\sum_i w(s_i, \bar{k}_i)} a_{\max}
\]

(2.12)

where \( a_{\max} \) is the maximum rate a charging box can provide. The algorithm of Priority Sharing is shown in Algorithm 2 where \( n \) is the number of users in the station, \( \bar{s} \) is the set of users’ solar score, \( \bar{K} \) is the set of user features and \( \bar{a} \) is the set of power provided to users.

It is worth noting, however, that \( a_{\max} \) is not necessarily equal to \( a_{s,t} \), the total station consumption in real practice. Based on the J1772 Level-2 AC standard, the charging station communicates the upper limit of power to the EV and EV determines the final \( a_{v,t} \) it draws (can be 0 when the available power is too low) [Std01]. So in practice \( a_{s,t} \) can be well below \( a_{\max} \). The maximum and minimum power for each type of EV is different and this makes Priority Sharing a difficult algorithm to implement in practice.

**Algorithm 2 Priority Sharing**

<table>
<thead>
<tr>
<th>Input:</th>
<th>( n, \bar{s}, \bar{K} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output:</td>
<td>( \bar{a} )</td>
</tr>
</tbody>
</table>

\[
i = 1
\]

\[
\text{while } i \leq n \text{ do implement (2.12) for } a_i; \ i = i + 1;
\]

<table>
<thead>
<tr>
<th>Algorithm 2 Priority Sharing</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_{i,t} = \frac{w(s_i, \bar{k}_i)}{\sum_i w(s_i, \bar{k}<em>i)} a</em>{\max} ) (2.12)</td>
</tr>
<tr>
<td>( a_{\max} ) is the maximum rate a charging box can provide.</td>
</tr>
</tbody>
</table>

In Priority Round Robin algorithm, maximum power is given to one user at a time and other active users are on hold. User with highest priority weight starts first. Each user session is provided with a fixed energy allowance \( \bar{E} \) in a single cycle, over which their
charging position will be given to other users. The order of the Priority Round Robin is determined by the order of each user’s priority weight $w(s_i, \bar{k}_i)$. The algorithm is shown in Algorithm 3 where $\bar{E}$ is the set of energy tracker for each cycle.

Algorithm 3 Priority Round Robin

Input: $n$, $\bar{s}$, $\bar{K}$, $\bar{E}$, $\tilde{E}$

Output: $\bar{a}$

while true do
  find $i$ with largest $w(s_i, \bar{k}_i)$
  if $E_i \geq \tilde{E}$ then
    adjust $K_i$ so that $w_i$ is the smallest among all users
    set $E_i = 0$
  else break
  end if
end while

set $a_{i,t} = a_{\text{max}}$

The implementations of fair sharing, Priority Sharing and Priority Round Robin are illustrated in Fig. 2.10. Algorithm 2 and Algorithm 3 are re-run every time a new user joins or leaves the station.

In the actual experimental phase, Priority Round Robin is chosen to be implemented.
The reason for the choice is (1) Priority Sharing is problematic to be implemented in practice. As discussed above, in current SAE J1772 standard, the feasible range of provided power can be very narrow, so it may not be possible to distribute very low power to low priority users. Moreover, the actual charging power taken by the EV may be lower than intended by the charging station, so high priority user may not get as much power as they deserve. (2) Actual implementation experience shows that users may not be aware of the change of the algorithm as much as they should. If Priority Sharing is implemented, users may still think they are being charged and wouldn’t notice the change of their situation. Subsequently the effectiveness of the incentive can be limited. (3) Round Robin is a simple and straightforward algorithm that is easy to implement and explain to users.

2.4 Optimal Strategies

In this section, the optimal strategies at the aggregator and incentivized drivers’ levels are discussed for charging boxes running Priority Round Robin algorithm. The algorithms are online as they are executed with new status updates. The input of the algorithms is real-time information and each user’s own estimation of RES.

2.4.1 Optimal Station Level Strategy

Given a set of users with starting time $\bar{R}$, stop time $\bar{P}$, energy demand $\bar{D}$ and solar generation $a_{p,t}$. The charging schedule is $\mathbf{a} = \{\mathbf{a}_i\}$ where individual charging schedule $\mathbf{a}_i$ is the set of $a_{i,t}$ at different time $t$. To make sure that the energy demand can be satisfied within the window of users’ presence by the charging schedule $\mathbf{a}$, the feasible set $\mathbf{F}$ is

$$\mathbf{F} = \{(\bar{R}, \bar{P}, \bar{D})|\exists \mathbf{a} (\forall t)(\forall i) [a_{s,t} \leq a_{\text{max}}$$

$$\text{and } \sum_{t=R_i}^{P_i} a_{i,t} = D_i] \}$$

(2.13)

If the user’s request is not feasible, one of more elements from $\bar{R}$, $\bar{P}$ and $\bar{D}$ can be adjusted in order to be feasible. The adjustment is up to each user and his/her respective ranking in
Figure 2.11: Optimal strategy for a charging box with four outlets with data collected on 04/04/2016. Top: original. Bottom: optimal.

the queue, which will be discussed in the next section.

The optimal charging strategy \( \mathbf{a} \) is

\[
\arg\max_{\mathbf{a}} \sum_{t} \min(a_{p,t}, a_{s,t})
\]

subject to \( (2.6), (\bar{R}, \bar{P}, \bar{D}) \in \mathbf{F}, \forall i, \sum_{t=R_i}^{P_i} a_{i,t} = D_i \) \( (2.14) \)

From inspecting (2.14), it is easy to see that the solution is not necessarily unique depending on the RES generation and user requests. An example of one strategy applied at one day of experiment (one box with four sub-stations) is shown in Fig. 2.11. As charging box does not have control over users’ behaviors, it needs users’ actions to achieve optimal RES usage.
2.4.2 Optimal Customer Level Strategy

If the incentives can indeed motivate users, for each rational customer, the objective is to consume as much RES as possible while reaching the desired energy demand. Additionally, users are assumed to be selfish and do not care about other users’ energy goal and schedule. If there are multiple maximum RES solutions, users would prefer to charge as soon as possible to counter the possibility that they might need to leave early or higher priority users arrive to interrupt their charging. In any case, it is also human nature to wish things to be done as soon as possible even though the results are the same in the end.

In order to achieve this, each user will need to identify (1) when RES will be generated; (2) when the charging box will be available to him/her without other higher priority users; (3) when user himself/herself is available to charge and how long time the user needs to charge. (1)(3) work to maximize the RES usage and (2) helps to optimize the interaction between users to avoid cases such as more demand than supply.

Each user searches for the optimal charging strategy/schedule $a_i$ which is the planned charging power at each time $t$. The schedule $a_i$ is a “plan of action” that user will do, including to charge ($a_{i,t} > 0$) or to stop ($a_{i,t} = 0$), at time $t$ according to the information given at current time and the user has no information on the future. When overall situation changes, user will get updates and find his/her new schedule.

The feasible set of user’s charging requests $F_i$ is

$$F_i = \{(R_i, P_i, D_i)|\exists a_{i,t} \leq a_{\max} \text{ and } \sum_{t \in T_i \cap [R_i, P_i]} a_{i,t} = D_i\}$$

where $R_i$, $P_i$ and $D_i$ are user’s start time, stop time and energy demand and $T_i$ is the open time slots available for user $i$ informed by the charging box server in Algorithm 4.

Let $T_i' = T_i \cap [R_i, P_i]$, then for each customer $i$, the optimal strategy $a_i$ is

$$\arg\max_{a_i} \sum_{t \in T_i'} \min(a_{p,t}, a_{i,t}) - \frac{1}{\rho} \sum_{t \in T_i'} a_{i,t}(t - R_i)$$

subject to $(R_i, P_i, D_i) \in F_i, \sum_{t \in T_i'} a_{i,t} = D_i$
where $a_{p,t}$ is user’s own estimation of RES generation and $\rho$ is the scaling factor that would limit the effect of the second term only to itself, so that the maximum utilization of RES will always prevail the importance of getting charged as soon as possible. User’s own estimation of RES generation is only used for user’s own planning, therefore this information can be private to each individual user. Such estimation can be achieved by an on-board estimation algorithm on each user’s device with parameters customized to user’s preference. However, a public RES generation feed may also be established if users do not wish to set up their own estimation. This optimization can be easily solved using backtracking and dynamic programming.

If user’s request $(S_i, P_i, D_i)$ is not feasible or the optimal strategy does not achieve a satisfactory RES consumption level, user can adjust his/her request as following

$$
\text{argmax}_{(R_i, P_i, D_i)} \frac{\sum_{t \in T'_i} \min(a_{p,t}, a_{i,t})}{D_i} \lambda_i
- l_i(|R_i - r_{io}|, |P_i - p_{io}|, |D_i - d_{io}|)
$$

subject to $(R_i, P_i, D_i) \in F_i$, $\sum_{t \in T'_i} a_{i,t} = D_i$

where $r_{io}, p_{io}$ and $d_{io}$ are user’s original request parameters, $l_i(|R_i - r_{io}|, |P_i - p_{io}|, |D_i - d_{io}|)$ is the loss function of user $i$ that increases with the deviation from the original parameters and $\lambda_i$ is the scale of user $i$ that balances the need to maximize RES usage and deviation from original plan. Change of $R_i$ and $P_i$ will change the available time slots $T'_i$. Users can leverage their own start/stop time to avoid highly popular time with high demand and find alternative high RES times with low peer competition. If user does not change any part of an infeasible request, the received energy $D_i$ will in effect decrease to the maximum of what can be achieved in the period. Each user has his/her own preference factor $l_i$ and $\lambda_i$.

The dominating first term of (2.16) makes sure that each user finds his/her own optimal strategy. As users are selfish, the choice of the higher priority users may not lead to global optima of (2.14). For practical consideration, it is assumed that only the user knows about his/her own charging request and system does not query such information. In practice for a Plug-And-Play system, the user may change his/her idea all the time but would not
necessarily bother to inform the system. It is, in fact, very difficult for a real system to accurately predict which user will come and each user’s demand. Selfish user may also lie to the system to gain more priority in scheduling. Therefore, for an online system, as shown in Section 2.6, local optima can provide good and realistic performance improvement.

The algorithm for the server to communicate the available time slot \( T_i \) is shown in Algorithm 4 where \( \tilde{D} \) is the estimated demand for each user by the system. This information can be obtained from statistics of previous user history [ZWC16]. The evaluation of \( T_i \) is only based on the current list of users, so this is an online algorithm with no need for advanced prediction. Algorithm 3 and 4 will be re-run every time a new user joins or an existing user quits the queue (when finished or wants to avoid low RES period).

**Algorithm 4** Available Time Slots For User \( i \)

**Input:** \( n, \bar{s}, \tilde{D}, i \)

**Output:** \( T_i \)

Let \( T_i \) be full time range

\( j = 1 \)

**while** \( j \leq n \) **do**

\[ \text{if} \ (w(s_j, k_j) > w(s_i, k_i)) \text{ then remove first } \left\lceil \frac{\tilde{D}_j}{a_{\text{max}}} \right\rceil \text{ elements from } T_i \]

**end if**

\( j = j + 1 \)

**end while**

For each user, his/her operation can be summarized as Algorithm 5. The structure and variables associated with each device are shown in Fig. 2.12. The user’s action is also online as he/she is given all the information in real-time in addition to his/her own estimation of RES generation for planning at (2.16).

### 2.4.3 Optimal Strategy With Multiple Charging Boxes

Previous sections discuss the situation with single charging box running Priority Round Robin algorithms. With multiple charging boxes, each box can run Priority Round Robin
Algorithm 5 User \( i \) Operation (Single Box)

Input: \( R_i, P_i, D_i, T_i \)

Output: \( a_i \)

\[
\text{if } (R_i, P_i, D_i) \in F_i \text{ then implement (2.16)} \\
\text{else implement (2.17) then (2.16)} \\
\text{end if}
\]

Figure 2.12: Structure of single-box operation

and finds its own local optima. However, for each user and the parking lot as a whole, it is always preferable to distribute cars evenly across different charging boxes to maximize resource usage. Therefore, Algorithm 6 shows user operation in a multi-box situation where \( \bar{T}_i \) is the set of available time slots for user \( i \) from all boxes and \( j \) is the index of chosen box.

Fig. 2.13 shows the general structure of how the multi-box infrastructure interacts with users. A summary flowchart of user’s optimal actions in the system is shown in Fig. 2.14.
Algorithm 6 User $i$ Operation (Multiple Boxes)

Input: $R_i, P_i, D_i, T_i, m$

Output: $a_i, j$

$j = 1$

while $j \leq m$ do

if for $T^j_i, (R_i, P_i, D_i) \in F_i$ then implement (2.16) and return

end if

end while

find $T^j_i$ to maximize the value in (2.17)

implement (2.16) and return

<table>
<thead>
<tr>
<th>Table 2.5: Simulated User Behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R(\pm \sigma_E)$</td>
</tr>
<tr>
<td>User 1 10:00($\pm$ 1h)</td>
</tr>
<tr>
<td>User 2 8:00($\pm$ 1h)</td>
</tr>
<tr>
<td>User 3 11:57($\pm$ 1h)</td>
</tr>
<tr>
<td>User 4 10:00($\pm$ 3h)</td>
</tr>
</tbody>
</table>

2.5 Numerical Simulation

In this section, a numerical Monte Carlo simulation is implemented to show how users’ decision would change the system’s RES usage and whether the Priority Round Robin algorithm would effectively respond to incentivized users’ behavior change.

User interactions are simulated and repeated for 30 times to eliminate the random effects. There are a total of 4 users simulated as customers of the charging box and they arrive to charge every day with a charging box with four sub-stations. On each day, users’ set of demand $\bar{R}$, $\bar{P}$ and $\bar{D}$ are randomly generated based on each user’s profile shown in Table 2.5 with Gaussian distribution. The parameters are based on the collected user behavior.

A single identical solar generation profile for all days is used to eliminate the effect of varying solar generation. The solar generation profile is the average generation from the on
campus 35kW solar panel and scaled down to 15kW to accommodate the relatively small consumption of a 6.6kW Level-2 box.

Fig. 2.15 shows the comparison of charged solar energy at the charging box level between uncontrolled charging (start charging when plugged in) and optimized charging as defined in (2.14) and (2.16). The optimized scenario runs an uncontrolled algorithm for the first 25 days and then switches to optimal control for the second 25 days. It can be seen that the average charged solar energy increases from 25.7 kWh to 29.1 kWh with optimized strategy.

Fig. 2.16(a) shows the simulation result of each user’s solar score and overall consumption
Figure 2.15: Total locally used solar energy for uncontrolled strategy vs optimized strategy. Blue shades indicate days when optimized strategy line switches from uncontrolled to optimal strategy.
for 300 days. It can be seen that User 1 and User 3 have higher solar scores (close to 1) and User 2 and User 4 have lower solar scores. The result is reasonable as User 1 arrives around the time when the solar generation is modest and has longer stay time in order to charge when solar generation is high. User 3 comes at later time when most of users have left. These are indeed the user behavior the aggregators would encourage. User 2, however, arrives at much earlier time and doesn’t have enough flexibility to wait until higher solar generation. User 4 has certain probability to arrive too early as well. These are indeed the user behavior that is causing general grid problems.

Fig. 2.16(b) shows the case when User 2 understands the incentive scheme and decides to change his/her start time $R_2$ and stop time $P_2$ to improve his/her own standing in the system according to Table 2.6. It is worth noting that the decision of behavior change depends on User 2’s perception of other users’ demand and RES supply. After realizing the high demand during morning, User 2 would switch to noon or afternoon for high RES supply with low demand. This is indeed the desired user coordination the incentive system wishes to achieve.

It can be seen that after User 2 decides to change consumption behavior, his/her solar score increases, surpassing that of User 4. The overall charging box level solar usage also increases from 29.6 kWh to 31.3 kWh, verifying that the algorithm indeed positively encourages overall use of solar energy. However, whether to change is still a decision of users themselves.

### 2.6 Experimental Results

If users are indeed incentivized by the priority system, they will optimize their action according to Algorithm 5 and Algorithm 6 and system consumption will improve similar to...
Figure 2.16: Comparison of (a) original behavior (b) changed user behavior of User 2 for improved solar utilization. Top: solar score of each user at different days. Bottom: locally consumed solar energy at charging box level. Blue shade: days when User 2 changes behavior.
Fig. 2.15 and Fig. 2.16. If the incentive system fails, they will remain “uncontrolled”. In order to verify actual users’ response to such design, an experiment was implemented with one charging box and 15 EV long-term employee (joining at a different time) for 15 months in a workplace parking lot (Parking Structure 2) of UCLA. The employees are charging with their own personal vehicles and getting charged for free on campus.

The experiment starts from 3/1/2016 with fair sharing algorithm to 5/18/2016. Subsequently, the Priority Round Robin algorithm is implemented from 5/18/2016 to 6/5/2017. The RES generation data is connected to the real-time generation of a 35 kW solar panel on campus and scaled down to 15 kW. The experiment implements the non-monetary component of the system and did not include the trading of SMERCOIN.

2.6.1 Experimental Setup

A multiplex J1772 Level 2 charging box [CCC14] is used to implement in the experiment. The charging box has a total of four plug outlets and a total max power of 6.6kW. The power of each outlet can be adjusted individually. A cloud-based software infrastructure is developed in order to control the charging boxes and interact with users effectively. Fig. 2.17 shows the structure of the components used in the experiment.

The charging box first ran on fair share algorithm as a reference use case. Fig. 2.18 shows the charging behavior statistics during the base test period from 3/1/2016 to 5/18/2016.

From Fig. 2.18(a)(c)(d), it can be observed that users often start before sunrise and stop around noon (time of peak generation). Fig. 2.18(b) and Table 2.7 show that, however, users generally have idle time after charging finishes. This verifies the general observation that EV users usually have the flexibility to adjust their schedule according to RES generation, at least to some degree. Therefore, it can be seen that proper motivation and incentives may guide users to maximize RES usage.

The solar consumption ratio $u_c$ is used to evaluate the difference before and after the change of algorithm. $u_c$ measures how much solar available to be consumed at the time is
Figure 2.17: Infrastructure scheme of the smart charging experiment.

Table 2.7: User behavior statistics before algorithm implementation

<table>
<thead>
<tr>
<th></th>
<th>Average (Time of the day)</th>
<th>Standard Deviation (time period)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plug-in time</td>
<td>10:04</td>
<td>3 Hour 34 Minutes</td>
</tr>
<tr>
<td>Plug-out time</td>
<td>14:50</td>
<td>2 Hour 56 Minutes</td>
</tr>
<tr>
<td>Session Stop Time</td>
<td>12:17</td>
<td>2 Hour 31 Minutes</td>
</tr>
</tbody>
</table>

actually consumed and can be calculated as follows

$$u_c = \frac{\sum_t \min(a_{p,t}, a_{s,t})}{\sum_t \min(a_{p,t}, a_{\max})}$$  \hspace{1cm} (2.18)

This parameter is needed to eliminate the effect of different solar generation rates at different days and seasons. During winter time, the solar generation power is less than that of summer, so the solar energy available to be consumed is less than that of summer, causing a decrease of solar score, reducing the effect of user’s behavior change.
Figure 2.18: Histograms of (a) plug-in time, (b) plug-out time (c) session stop time and (d) plot of average solar generation and power consumption.

2.6.2 Experiment Results

Fig. 2.19 shows overall solar score $u$ and $u_c$ over time. $u$ is defined as in (2.5). It can be seen that during winter time from 12/2016 to 03/2017, there is a significant decrease in the solar generation and solar score, verifying the impact from drop of solar generation.

The experiment is divided into three periods: uncontrolled, transition and implementation. It is observed during the experiment that even with extensive information communicated to users on the algorithm and rules, regular users do not understand the change of the system until much later. Therefore, the time from 5/18/2016 to 9/1/2016 is considered to be the transition period during which users learn how the algorithms work.

From Fig. 2.19 it can be seen that the consumption ratio is increased in the green region.
Figure 2.19: Top: total energy consumed and solar energy generation per day. Bottom: consumption ratio $u_c$ and overall solar score $u$ over time. Yellow shade: transition period for Priority Round Robin Algorithm. Green shade: Priority Round Robin implementation period.
than previous. Welch’s t-test is used to examine whether the increase of $u$ is statistically significant. The assumption to effectively use Welch’s t-test is the data before and after the algorithms are independent and the variance of the measurements are unknown. As reported in Chapter 5, user’s charging behavior is independent of the time and day of session, it is reasonable to assume that the users’ behavior before and after the algorithm are independent of each other. As their plug-in/out and session stop time variance is also unknown, it is assumed that these variables have different variances before and after the algorithm implementation. For the above reasons, it is suitable to use Welch’s t-test to examine the difference that the algorithm induces.

To compute the statistic t-value, we use

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}}$$

(2.19)

where $\bar{X}_1$ and $\bar{X}_2$ are the sample means, $s_1^2$ and $s_2^2$ are the sample variance and $N_1$ and $N_2$ are sample sizes.

The degrees of freedom of this variance estimate is approximated using the Welch-Satterthwaite equation as

$$\nu = \frac{(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2})^2}{\frac{s_1^4}{N_1^2\nu_1} + \frac{s_2^4}{N_2^2\nu_2}}$$

(2.20)

where $\nu_1 = N_1 - 1$ and $\nu_2 = N_2 - 1$ are the degrees of freedom of the two variance estimates.

The computed $t$ and $\nu$ can be fit in $t$-distribution to test the significance.

Table 2.8 shows the result of Welch’s t-test on $u_c$ and the daily total energy consumed $\sum D$. The mean of $u_c$ increased 37% and is statistically significant. Although the absolute energy consumption also increased statistically significantly (due to the increase of users and their demand), the mean only increased 14%, indicating the consumption ratio indeed increased on top of the rising trend of overall energy consumption.

The plug-in, plug-out and session stop time statistics after the prioritization algorithm is implemented is shown in Fig. 2.20. It can be observed that while users still charge during morning, there is a valley of consumption in the morning around sunrises. This can be caused by user behavior change. The statistics is shown in Table 2.9. T-test is used to verify
Table 2.8: Change Of Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean (± Std)</th>
<th>P-Value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_c$/Consump. Ratio (before)</td>
<td>0.37(±0.17)</td>
<td>$2.2 \times 10^{-9}$</td>
<td>Significant</td>
</tr>
<tr>
<td>$u_c$/Consump. Ratio (after)</td>
<td>0.51(±0.21)</td>
<td>0.006</td>
<td>Significant</td>
</tr>
<tr>
<td>Energy Consumed (before)</td>
<td>28(±15)kWh</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy Consumed (after)</td>
<td>32(±12)kWh</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2.9: User behavior statistics after algorithm implementation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Average (Time of the day)</th>
<th>Standard Deviation (time period)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plug-in time</td>
<td>9:56</td>
<td>3 Hour 03 Minutes</td>
</tr>
<tr>
<td>Plug-out time</td>
<td>15:09</td>
<td>2 Hour 59 Minutes</td>
</tr>
<tr>
<td>Session Stop Time</td>
<td>13:15</td>
<td>2 Hour 52 Minutes</td>
</tr>
</tbody>
</table>

the delay of session stop time. While the average stop time is delayed, it is not statistically significant ($p$-value is 0.13).

In order to further examine the effect of the seasonal change of solar generation on the result, Table 2.10 shows the correlation between $u$ and $u_c$ and the solar energy generation. It can be seen that the correlation between solar score and solar generation is high, again verifying the previous statement. The consumption ratio has a medium correlation with the solar generation. This is also reasonable as the consumption ratio considers available harvestable energy, countering the effect of the change of solar energy generation. However, the consumption ratio should still be related to solar generation to some degree, as it is still a solar-based parameter. Therefore, it can be concluded that the seasonal change of solar generation has only partial impact on the observed increase of solar consumption ratio and a major part of the increase is contributed by the incentivized user behavior change.

It is noticeable that in the experiment, there are relatively small number of users. With more users participating in the system, the competition will lead to more effectiveness of the system.
Figure 2.20: Plug-in, plug-out and session stop time after algorithm implementation statistics. Histograms of (a) plug-in time, (b) plug-out time, (c) session stop time. (d) average EV consumption and solar generation

2.6.3 Expansion to Parking Structure 9

After completing the experiment in Parking Structure 2, the algorithm is further expanded in Parking Structure 9 with 7 charging boxes (28 plugs). PS9 is also equipped with two PV panels (40 kW + 60 kW). Therefore, this setting provides a valuable setup to examine the effectiveness of the algorithm in a larger scale.

The prioritization algorithm is implemented from the first day of serving users on 2017/6/2, therefore it’s impossible to compare “before” and “after” of user behaviors in this case. The data is tested to understand the aggregated behaviors and whether there is an overall trend over time.
### Table 2.10: Correlation Of Parameters

<table>
<thead>
<tr>
<th>Correlation</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_c &amp; \text{Solar Energy}$</td>
<td>-0.31 $\times 10^{-8}$</td>
</tr>
<tr>
<td>$u &amp; \text{Solar Energy}$</td>
<td>0.62 $\times 10^{-35}$</td>
</tr>
</tbody>
</table>

### Table 2.11: User behavior statistics in Parking Structure 9

<table>
<thead>
<tr>
<th>Average (Time of the day)</th>
<th>Standard Deviation (time period)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plug-in time</td>
<td>10:34</td>
</tr>
<tr>
<td></td>
<td>3 Hour 35 Minutes</td>
</tr>
<tr>
<td>Plug-out time</td>
<td>14:36</td>
</tr>
<tr>
<td></td>
<td>4 Hour 03 Minutes</td>
</tr>
<tr>
<td>Session Stop Time</td>
<td>13:34</td>
</tr>
<tr>
<td></td>
<td>3 Hour 40 Minutes</td>
</tr>
</tbody>
</table>

The plug-in, plug-out and session stop time statistics of PS9 from 2017/6/2 to 2018/8/15 is shown in Fig. 2.21. It can be observed that while users charge during morning, a valley of consumption can be seen in the morning around sunrises. This can also be a signal for desired user behavior. The statistics is shown in Table 2.11.

It can be seen that the variances of all the data are larger than that of PS2, caused by larger number of users. The average plug-in time in PS9 is later than that in PS2 (after implementation) and the average plug-out time in PS9 is earlier than that in PS2 (after implementation). The average session stop time, however, is later than that of PS2 (after implementation). It can be observed that the aggregated user behavior is more homogeneous across the day, utilizing RES throughout the day.

The solar score, consumption ratio, energy consumed and solar energy used in PS9 experiments are shown in Fig. 2.22 and Table 2.12. The services were shut down in August 2017 and June 2018 due to infrastructure maintenance. It can be seen that the energy consumed in PS9 is stable over the year and is relatively low compared to the solar generation. The average energy consumed per box is 24.5 kWh, compared to that of 30 kWh in PS2. This partly causes the low consumption ratio in PS9. The consumption ratio of PS9 is 24% lower than PS2 (after implementation). Linear regression test shows that the consumption ratio
Figure 2.21: Plug-in, plug-out and session stop time of users in PS9. Histograms of (a) plug-in time, (b) plug-out time, (c) session stop time. (d) average EV consumption and solar generation does not have an overall trend over time (does not increase/decrease over time). However, the solar score of PS9 is similar to that of PS2. Given a wider spread of consumption behaviors and larger user base, the result can be seen as a favorable aggregated behavior for improved solar consumption.

To improve user convenience, a feature called automatic solar program is implemented for users in PS9. When users opt to enroll in this program, the system automatically pauses the charging of the user when solar generation is lower than a pre-defined threshold. This would prevent users from consuming low solar ratio energy and affecting their overall solar score. The program is equivalent to a very attentive user who monitors the solar generation all the time.
Figure 2.22: Top: total energy consumed and solar energy generation per day. Bottom: consumption ratio $u_c$ and overall solar score $u$ over time in PS9.
Table 2.12: Evaluation parameters in PS9

<table>
<thead>
<tr>
<th>Parameter</th>
<th>mean(±std)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_c$/Consump. Ratio</td>
<td>0.39(±0.25)</td>
</tr>
<tr>
<td>$u$/Solar Ratio</td>
<td>0.78(±0.18)</td>
</tr>
<tr>
<td>Energy Consumed (per box)</td>
<td>24.5(±14.8) kWh</td>
</tr>
</tbody>
</table>

Fig. 2.23 shows the top 20 users who have the longest time enrolled in the automatic program. Using linear regression between rank and length of enrollment for all 107 users in the system, it is found that approximately 3.22 days’ of enrollment can improve 1 rank with statistical significance. While the automatic solar program doesn’t necessarily make enrolled users prevail those who aren’t and users’ solar score is still largely dependent on their charging preference (time of charging and energy demand), enrollment in solar program shows that users are willing to change their behavior to improve their solar score.

As discussed in Appendix A.2 a centralized SMERCOIN system is implemented for users at PS9. Users are awarded 0.25 SMERCOIN per solar kWh. They can pay 25 SMERCOINs back to the system to “boost” to the top rank of the queue. Users can also trade between each other for their solar credit using SMERCOIN. Fig. 2.24 shows the summary of SMERCOIN activities across the year of experiment. It can be seen that “boost” becomes a popular feature after users understand the system mechanism.

There are 1040 SMERCOINs traded between user and system and 234 SMERCOINs between users for solar credit trading. This can be explained by the observation that most users try to buy solar credit using SMERCOIN but very few try to sell their solar credit – leading to many users trying to purchase solar credit from system. This shows that users think SMERCOIN is less valuable than their solar credit/rank. This, however, might change if base monetary value can be added to SMERCOIN.
Figure 2.23: Top 20 users’ enrollment time in the automatic solar program
Figure 2.24: SMERCOIN activities at different days: (a) net system issued SMERCOIN (b) SMERCOIN used to purchase solar credit from system (c) number of boost (d) SMERCOIN used to purchase solar credit from other users.
2.7 Discussion

Based on the results with the solar improvement programs, it can be seen that automatic programs can optimize grid efficiency and utilizations significantly if such program is enforced by default. However, the strong competition in the consumer market can hardly allow any serious commercial player to risk losing unconscious consumers’ satisfaction by restraining power flow on general public. Moreover, it is also found during prior experiments that enforcing large-scale scheduling may lead to customer dishonesty and exodus.

On the other hand, there will always be a portion of users who will not respond to the incentives as designed. Monetary incentives are intended to further attract unmotivated users to join the incentivized users. Further studies should be conducted to examine the effectiveness when monetary incentives are introduced.

It is also worth noting that incentivized users form a new set of user database that deserves separate and further investigations as discussed in Chapter 5.

2.8 Conclusion

In this chapter, a scalable renewable energy maximization system is presented, which incorporates electric vehicle charging dynamics, based on the concepts of user prioritization and blockchain cryptocurrency. The proposed system not only can reduce the transmission load of the distribution grids, which benefits the operators and customers, but also solve the over-generation problem of renewable energy, also known as the California duck curve. The proposed system and its novelties can be summarized as following:

1. The chapter proposed a hybrid incentive system and control algorithm for electric vehicle charging stations that incorporate non-monetary and monetary incentives to encourage electric vehicle users to achieve better overall renewable energy consumption collectively.

2. User priority, designed as a non-monetary incentive, can guide users to use more re-
newable energy. Users with high renewable energy consumption will save charging time and have more flexibility of choosing when to charge their vehicle over their peers.

3. Two experiments with workplace charging conducted on UCLA campus for 15 months and 14 months are used to verify the effectiveness of the non-monetary incentives. The test site showed problems with local over-generation and demand-supply mismatch before the experiment. After the incentive system was implemented, the local solar consumption rate is shown to increase 37% in Parking Structure 2, decreasing the energy cost of the aggregator. The follow-up experiment with larger scale in Parking Structure 9 shows that a large share of users are willing to change their consumption behaviors and the system provides effective incentives for users to use renewable energy.

4. The cryptocurrency mechanism provides monetary incentives to users without having to impose a dynamic/tiered pricing scheme and also further lowers aggregators’ operating cost. The cryptocurrency SMERCOIN has a base fiat money conversion value guaranteed by the issuing aggregator. Moreover, it also has value of temporarily adjusting a user’s priority and power assignment. Therefore, the ability of SMERCOIN to adjust physical layer further raises its intrinsic value beyond base value.

5. The system is designed to be flexible in terms of its incentive modules. It can work with non-monetary incentive alone and the optional cryptocurrency mechanism can be added to improve the effectiveness.

6. The operating algorithm for electric vehicle charging stations is also presented using Priority Sharing and Priority Round Robin. The algorithm is designed to be online and optimized to be practical and feasible with devices operating under the SAE J1772 standard. Optimal strategies for users are also developed to reach a Nash equilibrium local optima, followed by numerical simulation to show the effectiveness of the system.

7. While the system is designed based on a Photovoltaic generation system (which most new microgrids would be equipped with), it is also suitable to be used with other local intermittent renewable energy, such as wind power.
Finally, the work presented in this chapter can potentially be applied to commercial electric vehicle charging station aggregators looking to decrease their operating cost and increase the use of clean renewable energy.

2.9 Proofs of Theorems

Proof of Theorem 1

At equilibrium, the demand supply system is

\[
D = D(e, y) \tag{2.21}
\]

\[
S = S(e, y) \tag{2.22}
\]

\[
D = S \tag{2.23}
\]

Take the total differential of each equation,

\[
dD = \frac{\partial D(e, y)}{\partial e} de + \frac{\partial D(e, y)}{\partial y} dy \tag{2.24}
\]

\[
dS = \frac{\partial S(e, y)}{\partial e} de + \frac{\partial S(e, y)}{\partial y} dy \tag{2.25}
\]

\[
dD = dS \tag{2.26}
\]

Substituting (2.24) and (2.25) into (2.26),

\[
\frac{de}{dy} = \frac{\frac{\partial D(e, y)}{\partial y} - \frac{\partial S(e, y)}{\partial y}}{\frac{\partial S(e, y)}{\partial e} - \frac{\partial D(e, y)}{\partial e}} \tag{2.27}
\]

Given that \(\frac{\partial D(e, y)}{\partial e} < 0, \frac{\partial D(e, y)}{\partial y} > 0, \frac{\partial S(e, y)}{\partial e} > 0, \frac{\partial S(e, y)}{\partial y} < 0,\)

\[
\frac{de}{dy} > 0 \tag{2.28}
\]

This completes the proof.

Proof of Theorem 2

Each part of the theorem is proved as below

(a) In the fair share system, the superset of all sharing users is

\[
I_s = \cup I, I = \{I_t : |I_t| > 1\} \tag{2.29}
\]
For all the users within $I_s$, without loss of generality, user 1 can be assumed to have the highest priority. Let $P_1^p$ be the stop time of user 1 in the priority charging system, then

$$
\sum_{t=R_1^f}^{P_1^p} a_{1,t}^p = D_1^f
$$

(2.30)

Between $R_1^f$ and $P_1^p$, there must exist $t$ such that $|I_t| > 1$. (If this is not true, user 1 would charge alone with $a_{\text{max}}$ in both fair share and priority charging situations, which is contradictory to the problem setup.)

Because user 1 has the highest priority, according to (2.8), for all $t$ such that $|I_t| > 1$, user 1’s power consumption is always

$$
a_{1,t}^p > \frac{a_{\text{max}}}{|I_t|}
$$

(2.31)

Therefore, user 1 will receive higher power in priority system than fair share system and $P_1^p$ will be smaller than $P_1^f$.

In a system with more than two users, when user 1 is not present (has not arrived or already finished), the rest of the users may again have $t$ such that $|I_t| > 1$. Similarly in this case, there would be another user, user 2, that receives higher power and finishes earlier than in fair share situation.

Therefore, there is a nonempty subset containing these higher priority users who can finish charging earlier than in fair share situation.

(b) We prove this by contradiction. If all users start their charging as in $\bar{R}_1^f$, this would be the case in part (a). This means that there will be a nonempty set of users with stop time less than $R_1^f$. This is contradictory to the problem setup.

If some users start their charging earlier than original and the rest of users remain the same, the early starters would require less or equal energy at their original start time. This again means that there will be a nonempty set of users with stop time less than original.
Therefore there must be a nonempty set of users who start later than original. Based on (2.8) and (2.9), those users should be higher priority users.

(c) For users 1 and 2 in part (a), if their start and stop time remain the same, the total energy they receive would be larger than original,

\[
\sum_{t=R_{i}^{f}}^{P_{i}^{f}} a_{1,t}^{P} = D_{i}^{P} > D_{1}^{f}
\]  

(2.32)

For any time period occupied by one or more users, the total energy charged is constant,

\[
D_{\text{tot}} = \sum a_{\text{max}}
\]  

(2.33)

Therefore, if there is a nonempty set of higher priority users that receive more energy in such time period, there is another set of lower priority users that receive less. □

□
CHAPTER 3

Charging Process Automation

3.1 Introduction

While there are many existing charging stations and systems in the market today as discussed in Chapter 1, many of them are either a simple charger without any advanced control, or poorly designed for user experience. This hinders the further advancement and development of overall EVSE industry as well as innovative products within the ecosystem. UCLA Smart Grid Energy Research Center (SMERC) operates on-campus EV charging for EV drivers and campus fleet and develops advanced technology to improve data collection and user experience. The hardware and software optimization presented in this chapter are based on SMERC multiplex EV chargers.

The rest of the chapter is organized as follows. Section 3.2 introduces the US EV charging standard SAE J1772. Section 3.3 and 3.4 show the SMERC multiplex chargers and the mobile interfaces developed for the charging system. Section 3.5 presents the patent-pending automation designs on the SMERC charging systems. Section 3.6 concludes the chapter.

3.2 SAE J1772 Standard

SAE J1772 is the de-facto standard in the North America EV market for AC charging. Table 3.1 summarizes the main definition of different levels under SAE J1772.

The most rudimentary J1772 charger consists of the following components with layout shown in Fig. 3.1.

1. Controller
Table 3.1: SAE J1772 Configurations

<table>
<thead>
<tr>
<th>Terminology</th>
<th>Configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC Level 1</td>
<td>120V, 1.4 kW @ 12 amp</td>
</tr>
<tr>
<td></td>
<td>120V, 1.9 kW @ 16 amp</td>
</tr>
<tr>
<td>AC Level 2</td>
<td>240V, up to 19.2 kW (80A)</td>
</tr>
<tr>
<td>AC Level 3 (TBD)</td>
<td>&gt;20 kW, single phase and 3-phase</td>
</tr>
<tr>
<td>DC Level 1 (not finalized)</td>
<td>200-450V, up to 36 kW (80A)</td>
</tr>
<tr>
<td>DC Level 2 (not finalized)</td>
<td>200-450V, up to 90 kW (200A)</td>
</tr>
<tr>
<td>DC Level 3 (not finalized)</td>
<td>200-600V, up to 250 kW (400A)</td>
</tr>
</tbody>
</table>

Figure 3.1: Schematic of a basic J1772 charger.

2. (a) Pilot DC/DC Converter
   (b) Pilot Opamp
   (c) Pilot Voltage Measurement
   (d) Ground Fault Circuit Interpreter (GFCI)

3. Relay

4. Power Supply

SAE J1772 signals consist of 2 main types:

1. Proximity Detection: to prevent movement of the car while connected to the charger.
2. Control Pilot: EVSE generates a 1 kHz square wave at +/- 12 volts on the pilot pin to detect the presence of the vehicle, communicate the maximum allowable charging current, and control charging.

The total sequence of the signaling protocol can be summarized as

1. EVSE signals presence of AC input power
2. Vehicle detects plug via proximity circuit (thus the vehicle can prevent driving away while connected)
3. Control pilot functions begin
   (a) EVSE detects plug-in electric vehicle
   (b) EVSE indicates readiness to supply energy
   (c) PEV ventilation requirements are determined
   (d) EVSE current capacity provided to PEV
4. PEV commands energy flow
   (a) if a vehicle requires more current than the EVSE can supply, the vehicle can then choose not to charge. In general, this doesn’t happen, as EV manufacturers appear to have all chosen to be compatible with the lowest available (13A) charge current
5. PEV and EVSE continuously monitor continuity of safety ground
6. Charge continues as determined by PEV
7. Charge may be interrupted by disconnecting the plug from the vehicle

3.3 SMERC Charging Stations

SMERC multiplex charging stations follow the J1772 Level 2 standard. Each of the SMERC charging box has a total of four fully compliant Level-2 plug outlets (each of them is referred
as charging station in the future) and a total max power of 6.6kW. When multiple users
are plugged in and charging, the sum of their charging power cannot exceed 6.6kW. Fig. 3.2
shows a picture of the charging box installed on the UCLA campus. The details of the
charging box are reported in [CCC14].

3.3.1 System Infrastructure

The system infrastructure comprises front-end interface, charging infrastructure including
Level-1 and Level-2 EV charging stations, sensors and cloud-based servers called EV Control
Center (EVCC).

The EVCC is a central hub that collects power and status data from charging stations
and oversees all data storage. EVCC stores all critical user behavior data and provides
data services, such as status update and demand prediction, to users through front-end
interface and to upper level EMS. It also manages users’ charging requests and controls
the charging actions of charging stations. EVCC can also comply with external signals
from upper level EMS, including Demand Response (DR) and energy pricing from utility
and service providers, and execute by managing charging behaviors. The flowchart for the
system infrastructure is shown in Fig. 3.3

3.3.2 Data Collection and Remote Control

In order to understand user behavior and power consumption patterns, data of user oper-
ations and minute-by-minute power consumption is collected by EVCC. The main type of
data can be shown as following,

1. Power data: collected from Billion energy gateway; the following data is contained:
timestamp (s), entity id, active power (W), current (A), voltage (V), frequency, power
factor, apparent power (VA), main energy (kWh)

2. Relay data: collected from controller of the charging box; the following data is con-
tained: relay status (on/off), plug (plugged in/not plugged in), duty cycle (0%-50%)
Figure 3.2: SMERC level 2 charging box with 4 multiplexing charging outlets
3. User charging session: collected from mobile app and cloud server; the following data is contained: user id, entity id, status (submitted/charging/finished/error), request timestamp (s), start of charge timestamp (s), stop timestamp (s), start main energy (kWh), stop main energy (kWh), stopped due to being fully charged (true/false), stopped due to being unplugged (true/false).

In basic operations, the full cycle of communications between users, cloud server and the charging station during a charging session is as follows:

1. EV user submits his/her charging request to the smart charging server, including his/her desired charging station and his/her user id.

2. The system processes the requests to determine whether certain sessions are to be started or stopped.

3. The system sends out commands to charging stations.

4. When user is satisfied with their energy or needs to leave, he/she can request to stop
the charging session. In other cases such that system detects that no current is accepted by user’s EV (often caused by EV fully charged or connection not well established), the system automatically stops the charging session. This is followed by commands from the system to turn off the actual corresponding station.

Additionally, real-time power data of renewable energy collection is collected from a 35kW solar panel on the roof of Ackerman Union in UCLA.

### 3.3.3 Communication Methods

Data collection and remote control are the fundamental yet most deterministic elements for successful integration between the hardware and cloud servers. The goal of successful data collection and remote control can be defined as (1) maximal communication frequency, (2) minimal interruption and (3) effective transmission.

The general-purpose energy gateway by Billion Electric Co. is used inside the charging stations. The Billion gateways provide monitoring capability and generic API for communication.

There are three main communication methods between central server and local gateway: (1) Pull (2) Push (3) WebSocket. A summary of these methods for data collection is shown in Table 3.2.

Pull is a transmission method initiated by the server. Upon receiving the request, the local gateway returns the latest power data of the requested entity. This process is highly dependent on the internet communication stability. In 3G connectivity setup, occasional connection failure results in loss of data of the corresponding request. Pull requests require static IP for each Internet of Things (IoT) devices. Given limited supplies of IPv4 addresses and yet uncommon support of IPv6 addresses, assigning static IP for each IoT devices can be costly.

Push is another transmission method initiated by the client (gateway in this case). In this configuration, the gateway sends its data by pre-set time to the server. If connection fails, the local gateway keeps the failed data and retry in the next cycle with the new data.
Table 3.2: Pull vs. Push in terms of data transmission

<table>
<thead>
<tr>
<th></th>
<th>Data Density</th>
<th>Data Interruption</th>
<th>Network Transmission</th>
<th>Static IP on IoT device</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pull</td>
<td>1 per minute</td>
<td>Potential for data loss</td>
<td>2 per request</td>
<td>Yes</td>
</tr>
<tr>
<td>Push</td>
<td>1 per minute</td>
<td>Minimum</td>
<td>1 per request</td>
<td>No</td>
</tr>
<tr>
<td>WebSocket</td>
<td>1 per minute</td>
<td>Minimum</td>
<td>2 per request</td>
<td>No</td>
</tr>
</tbody>
</table>

In this case, because the connection is established by the gateway, only the cloud server needs a static IP. This setup doesn’t require IoT devices to have static IPs thus decreasing cost significantly.

WebSocket is a newly added communication method in the Billion gateway. In this case, WebSocket connection is first initiated by the gateway to the server. Subsequently, the server can send command/request to the gateway. In this way, WebSocket allows bi-directional communications between gateway and server without requirement for static IP on the gateway.

The summary of all methods are shown in Fig. 3.4.

For data collection, Push is the preferred method over Pull. As shown in Table 3.2, Push has higher reliability, better efficiency and lower cost in terms of network communications.

While data collections can be reliably done with push without static IP on the charging station, it is not possible to send command from the server to the charging station through Push initiated by charging stations. Therefore, in most of current implementations, control commands (turning on/off and current control) are sent through server-side Pull, requiring static IP on the charging stations. However, remote control with WebSocket has also been tested in a pilot project at UCLA Sunset Village serving fleet vehicles.

### 3.4 Mobile User Interface

An iOS and web based mobile interface, called EVSmartPlug™ is developed to facilitate the interactions between the user and the rest of the systems. It performs the following major
Figure 3.4: Communication methods supported by Billion gateways (a) Pull (b) Push (3) WebSocket.
functions

1. **Submit user charging request**: As the main function of the mobile application, the user interface facilitates the process for user to request charging service from the server. The request information includes user id, charger id, time of request, user’s estimate energy demand.

2. **Receive charging status updates**: The mobile interface also serves to update users with their charging status, including power, energy charged and additional information.

3. **Real-time solar energy indicator**: In the front tab of the app, the current level of solar generation is indicated (Fig. 3.7(a) bottom right corner).

4. **Ancillary services, information and configurations**: The application provides ancillary information related to the charging service including locations of the charging station, station occupancy status and personal consumption information (Fig. 3.7(b)(c)).

### 3.4.1 User Experience

“Zero touch” philosophy is applied on the iOS version of the EVSmartPlug to allow users to begin charging with minimal manual operations. This is initially achieved by assigning and attaching a “QR Code” on each charging station. Quick Response (QR) allows mobile devices with camera to quickly and accurately to translate an image to a string, thus allowing apps to identify designated station.

Each user starts using the app by creating a user profile with the EVCC. The profile will include history and detail of each of his charging sessions. Once the user is logged in, if the system finds no active charging session, it will prompt the QR Code scanner to scan the desired charging station. The user can otherwise choose to select charging stations through lists or his recently used stations. Once the station is chosen, the charging session starts instantaneously. The user can also manually start or stop the charging sessions by clicking the bottom button.

Fig. 3.5 shows the flowchart that describes the process. Within the flowchart, it shows
the physical appearance of the QR codes attached on the charging station (Subfig. 1) and the charging plug placed inside the EV (Subfig. 3). It also shows the interfaces of the mobile application from initiation (Subfig. 2), start of QR code scanner (Subfig. 4), scanning of QR code (Subfig. 5) to successfully recognition of code and starting charging (Subfig. 6).

Minimum user action to start charging is: 1, plug in EV; 2, start app; 3, move phone camera to shoot QR code. Additionally, the QR code can be replaced by a near-field RFID tap-on reader to perform equivalent functions, shown in Fig. 3.6. In this case, the RFID reader can be standby in the background and the user may not need to explicitly initiate camera.

Miscellaneous information regarding charging stations and user information is also shown in the application interface. As shown in Fig. 3.7, the main interface allows users to select designated charging station as well as their estimated energy demand from the three forecasts.
Figure 3.6: Flowchart of bluetooth tap-on station identification.
For the ease of user operation in the mobile devices, three values predicted by the system are presented to users for selection.

### 3.5 Processes Automation

In this section, designs and processes to further reduce user operation and improve automation beyond basic implementations are presented. Based on user experience and current hardware design, the process optimization design focuses on system automation on identifying the charging station.
3.5.1 Bluetooth Beacon with Plug-in Detection

The plug-in status data of all plugs combined with single Bluetooth beacon can be used to infer newly used plugs. User’s device looks for registered beacons in range and selects the closest box. The app subsequently sends welcome message to user and notifies user to plug in their car with their desired plug. If a new plug-in is detected from the charging box, the app will notify user and starts charging. This use case is illustrated in Fig. 3.8.

The workflow of the above processes is shown in Fig. 3.9. Subfig. 1 shows the Bluetooth beacon placed in the gateway within the charging station. Subfig. 2 shows the charging box. Subfig. 3 shows a plugged-in plug. Subfig. 4 shows the mobile phone’s notification interface when user enters the beacon region. Subfig. 5 shows the main interface. Subfig. 6 shows the detected plug and confirmation. Subfig. 7 shows the interface of sending command. Subfig. 8 shows the interface when command is successfully sent.

Potential error may arise when two or more users plug into the same charging box during the same period that the server checks for plug-in status update. Though this can be rather unlikely to happen, the following approaches can be used to solve/alleviate the problem:

1. Confirm charging station with user.

2. Using statistics, machine learning or other observation to see the preferred plug to be used. Due to physical location and other factors, there may be some spots that are more likely to be occupied by users thus the plug corresponding to it. The server can
Figure 3.9: Flowchart of Bluetooth beacon plug-in detection.
use this order to assign the more preferred plug to the user who enters the beacon range earlier. The following user is assigned to the next preferred plug.

3. As different plugs are located at different distances from the box, the box can make use of the signal strength of the user to infer the distance between the user and the box. According to the distance, the box will infer the plug closest matched to the distance estimate. In this case, the beacon should be placed on one side of the box so that every plug’s distance to the beacon is different.

4. The charging box hardware will record the plug in time/order. The server can assign the first used plug to the user who enters the region first and similarly with the following users/plugs.

This process can be further developed to substitute the role of user’s phone app with EV’s on-board RFID module. By detecting proximity between EV and charging box, the EV module or the charging box can send or process charging request automatically. This solution can be particularly important for driverless autonomous vehicles. The flowchart for the case with requests sent by charging box serving EV equipped with passive tags is shown in Fig. 3.10.

3.5.2 Automatic Trip Logging

Given the proprietary nature of EV CAN bus information and lack of communication standards, today it is challenging to obtain critical vehicle on-board information, such as State of Charge (SOC) and geographical location. These data, however, are important input for service providers for effective demand and service scheduling. In order to obtain such information, geographical tracking can be used to calculate user’s movement with the vehicle and estimate their energy consumption and subsequently their SOC. Every time user is fully charged, the system uses the event as a calibration and reset scenario.

RFID modules such as Bluetooth can be used to establish connections with user’s phone. When user approaches the vehicle and connect their phone to the the RFID module of
Figure 3.10: Flowchart for automatic charging request.
the EV, the app either reconnects to previously stored EV or creates new EV information. Subsequently, the app will record location and speed and store in its local database. The flowchart of this process is shown in Fig. 3.11.

3.5.3 Validation on Server

Following the “send charging command” section in the previous flows, the process for the central server to process the charging request is shown in this section. The verification process is run through a back-end program and requires frequent access to the database of charging events.

The process starts with a request to charge with user id, user class and location id of the requested charging station. The algorithm first evaluates if the user has another active charging request. In the case where each user is only associated with one vehicle, only one active charging request is allowed at one time. This is also to prevent multiple unintended submissions due to network and other errors. If the user has another charging request, the server will report error to the user and close the charging request. The server subsequently checks for the availability of the charging station. If there is another active charging request on the station, an error will be reported to user. The process is also intended to prevent cases such as multiple charging requests due to network and operational errors. The server then checks for whether the user class is allowed to use such charging box. This is used to control multiple user group privileges from the server side. Lastly the server checks if the charging station is open for use.

After the above verification, the request submission proceeds. The system checks for whether there is Demand Response signals in action at the moment. If so, the charging request will be hold off until the Demand Response signal is cleared. The system then proceeds to see whether the system has any specific individual management plan for the user in action. In reality, this could include multiple kinds of user consumption plans in order to, for example, limit user’s energy consumption mix (renewable energy, off-peak electricity, etc) and other personal preference. If all above is cleared, the system proceeds to send charging
Figure 3.11: Flowchart of automatic trip logging.
command to the charging box. Fig. 3.12 shows the flowchart of the above processes.

The event monitor interface is shown in Fig. 3.13. The system operator can see the charging activities for all of his managed charging stations. The operator is able to monitor the current user, charging status, active power, current, relay status, plug status and duty cycle. The monitor can also show the time it receives the latest data.

3.6 Conclusion

In this chapter, hardware and software design optimization based on SMERC mutiplex charging stations is proposed and presented. While a simple charging station can most likely satisfy a EV driver’s basic need (get his/her vehicle charged), onerous steps may be required for users. Also, many important and valuable data can be missed.

The presented cloud infrastructure facilitates data collection on user behavior and power usage. The advanced connectivity incorporated in the charging stations improves the user interactive experience with the charging system in light of large infrastructure expansion. Using the presented system design, users can start charging with a maximum of 1 click and monitor station occupancy, power generation and consumption data as well as their private charging status.
Figure 3.12: Flowchart for starting charging request.
Figure 3.13: Event monitor interface.
CHAPTER 4

Two-Tier Energy Management System

4.1 Introduction

In this chapter, the architectures, functions and implementations of the Energy Management System (EMS) called Super Control Center (SCC) are introduced and discussed. The system setup and control algorithms are presented, followed by the data collection and analysis on power consumption and energy management throughout the project procurement over years in different geographic locations.

The purpose of this chapter is focused on exhibiting local power grid management with monitoring and controlling the load from EV charging stations. Load control helps maintaining the stability of the local grid by delaying or re-scheduling the EV charging sessions until the overall load decreases or a demand response event is completed. Shedding non-critical load during peak consumption hours can increase power grid stability and avoid demand charge. It can also reduce fuel consumed by peaking generators, as well as delay generation and transmission system upgrades. Additionally, by transferring loads to off-peak periods, it creates a more evenly distributed daily demand curve.

The rest of the chapter is organized as follows. Section 4.2 and 4.3 introduce the two-level EMS and its upper-level controller SCC. Section 4.4 and 4.5 show the implementation on data collection and load management in SCC. Section 4.6 and 4.7 present SCC’s signal delivery mechanism and experimental results. Section 4.8 discusses the security of SCC and Section 4.9 concludes the chapter.
4.2 System Structure

A two-tier management system is set up to facilitate the control of different EV charging boxes and other devices with different interfaces. It also provides a versatile platform for EMS algorithms to implement and test with.

The upper level system, Super Control Center (SCC), serves the purpose of an operator in the regional aggregator or microgrid manager level who oversees the energy consumption and generation of each entity under its management. SCC does not control the specific activities of those entities, but monitors and manages the overall health and efficiency of the microgrid. SCC issues Demand Response (DR) signals based on system management algorithms.

The lower level management system, Electric Vehicle Control Center (EVCC), manages specific equipment and services (e.g. EV charging stations and related distributed energy resources) at local level. EVCC runs local algorithms that incorporate different supply and demand data and determine operational activities subsequently. While SCC issues less frequent DR signals, EVCC algorithms work in a quasi-real-time fashion and manage user’s activities from minute to minute.

SCC does not take direct control over specific EV charging nor receives power data from individual charging stations. Simulating the role of electric utility, SCC issues macro-scale DR signals to EVCC. Subsequently EVCC make decisions regarding specific operations. SCC observes aggregated power data rather than monitoring individual station status or their management. This infrastructure facilitates future expansion of enrolled entities and reduces complexity for macroscopic control algorithms. For a larger network with multiple EVCC, each EVCC can own its individual management algorithm in microscopic scale, so to satisfy the signal from the SCC.

In summary, benefit of the SCC design includes:

1. High level control of EV charging load for managing aggregated power control

2. Reduce complexity of scheduling algorithm programming
3. Scalable to a large size of EV charging network.

4. Easy integration with renewable energy source, additional loads from different devices (such as LED, appliances, etc), Power Quality Analyzer (PQA), Battery Energy Storage System (BESS), etc.

### 4.3 Super Control Center

The Smart Grid Energy Research Center (SMERC) manages over 100 EV Charging Stations located at different Parking Structures on the campus microgrid of UCLA. The SCC serves as a centralized portal for all entities within the UCLA SMERC microgrid, including Battery Energy Storage System (BESS), solar panel, Level-3 DC charging stations and EV charging stations managed by EVCC.

Fig. 4.1 shows the basic operating structure of SCC. The SCC can be divided into three major functional components:

1. Data collection and storage;
2. Load management algorithms;
3. DR signal delivery;

### 4.4 Data Collection

The communication methods (discussed in Chapter 3) supported by entities managed by SCC are listed in Table 4.1. Whenever Push is available on the local IoT device, it is chosen as the preferred communication method. In BESS, two monitoring devices have been installed to monitor the incoming/outgoing circuit (Billion) and internal battery condition (Siemens controller).

The collected power data statistics is shown in Table 4.2.
Figure 4.1: Super Control Center infrastructure.

Table 4.1: Communication methods available

<table>
<thead>
<tr>
<th>Device</th>
<th>Monitoring Device</th>
<th>Supported Communication</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar panel</td>
<td>Billion gateway</td>
<td>Push, Pull, WebSocket</td>
</tr>
<tr>
<td>BESS</td>
<td>Billion Gateway</td>
<td>Push, Pull, WebSocket</td>
</tr>
<tr>
<td>Siemen Controller</td>
<td></td>
<td>Pull</td>
</tr>
<tr>
<td>EVCC</td>
<td>Microsoft .NET Server</td>
<td>Pull</td>
</tr>
<tr>
<td>V2G station</td>
<td>Billion Gateway</td>
<td>Push, Pull, WebSocket</td>
</tr>
</tbody>
</table>
Table 4.2: Charging sessions and total energy by month

<table>
<thead>
<tr>
<th>Month</th>
<th>Sessions</th>
<th>Total Energy (kWh)</th>
<th>Average kWh per session</th>
</tr>
</thead>
<tbody>
<tr>
<td>Santa Monica Civic Center 7 level 2 smart chargers (14 plugs)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>January</td>
<td>643</td>
<td>4876</td>
<td>7.58</td>
</tr>
<tr>
<td>February</td>
<td>649</td>
<td>5341</td>
<td>8.23</td>
</tr>
<tr>
<td>March</td>
<td>707</td>
<td>5197</td>
<td>7.35</td>
</tr>
<tr>
<td>April</td>
<td>362</td>
<td>2736</td>
<td>7.56</td>
</tr>
<tr>
<td>May</td>
<td>500</td>
<td>3998</td>
<td>8</td>
</tr>
<tr>
<td>June</td>
<td>532</td>
<td>4634</td>
<td>8.71</td>
</tr>
<tr>
<td>July</td>
<td>563</td>
<td>4679</td>
<td>8.31</td>
</tr>
<tr>
<td>August</td>
<td>575</td>
<td>5022</td>
<td>8.73</td>
</tr>
<tr>
<td>Colorado fleet yard 16 dedicated level 1 chargers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>January</td>
<td>82</td>
<td>222.971</td>
<td>2.72</td>
</tr>
<tr>
<td>February</td>
<td>142</td>
<td>236.8851</td>
<td>1.67</td>
</tr>
<tr>
<td>March</td>
<td>134</td>
<td>280.4667</td>
<td>2.09</td>
</tr>
<tr>
<td>April</td>
<td>98</td>
<td>312.1009</td>
<td>3.18</td>
</tr>
<tr>
<td>May</td>
<td>93</td>
<td>297.8318</td>
<td>3.2</td>
</tr>
<tr>
<td>June</td>
<td>118</td>
<td>347.2627</td>
<td>2.94</td>
</tr>
<tr>
<td>July</td>
<td>83</td>
<td>271.9637</td>
<td>3.28</td>
</tr>
<tr>
<td>August</td>
<td>98</td>
<td>272.3768</td>
<td>2.78</td>
</tr>
<tr>
<td>SM Hospital 1 level 2 smart charger with 2 dedicated 40 Amp Circuits (4 plugs)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>January</td>
<td>200</td>
<td>1493.025</td>
<td>7.47</td>
</tr>
<tr>
<td>February</td>
<td>179</td>
<td>1458.278</td>
<td>8.15</td>
</tr>
<tr>
<td>March</td>
<td>187</td>
<td>1388.603</td>
<td>7.43</td>
</tr>
<tr>
<td>April</td>
<td>212</td>
<td>1945.325</td>
<td>9.18</td>
</tr>
<tr>
<td>May</td>
<td>250</td>
<td>2279.737</td>
<td>9.12</td>
</tr>
<tr>
<td>June</td>
<td>219</td>
<td>2036.493</td>
<td>9.3</td>
</tr>
<tr>
<td>July</td>
<td>215</td>
<td>2033.376</td>
<td>9.46</td>
</tr>
<tr>
<td>August</td>
<td>263</td>
<td>2164.368</td>
<td>8.23</td>
</tr>
</tbody>
</table>
4.5 Load Management

The main mission of SCC is to implement algorithms with an overall consideration of demand and support. To this end, SCC has two main operating modes: manual and automatic.

Manual operations are usually issued by an EMS operator or utility operator. Therefore, they are designed to have higher priority than automatic operation. SCC has two interfaces to issue manual operations: Graphic User Interface (GUI) and OpenADR 2.0a Protocol.

The GUI serves as the general monitor for everything in action in the microgrid, including current power condition and any Demand Response (DR) event. It allows to fine-tune the system and choose automatic algorithms. A snapshot of the SCC GUI is shown in Fig 4.2. Latest one hour of different load are shown at the top. Authorized operator can specify load shedding commands on any PS level load.

The flowchart for executing manual operation and OpenADR commands is shown in Fig 4.3. This API can be used for real-time/emergency DR signals or to schedule any event in advance. Manual operations have higher priority than automatic DR algorithms, so any manual action will override the current decision made by the automatic algorithm. In GUI, user can directly select any entity to perform DR, define start and stop time and send DR signals directly to the controller through browser.

4.5.1 OpenADR

OpenADR 2.0a is a standard for EMS to receive external control signals and is supported by SCC. OpenADR instructions are parsed and regarded as manual operations. SCC provides a designated API for OpenADR requests. The API decodes XML requests in OpenADR 2.0b standard and executes commands supported in OpenADR 2.0a standard. The OpenADR functionality is tested with VTN softwares developed by EPRI shown in Fig. 4.4.
Figure 4.2: SCC graphic user interface.
Figure 4.3: Manual control flow.
Figure 4.4: VEN Management Interface (image captured while running OpenADR test through Quality Logics’ website).
4.5.2 Automatic Control Algorithms

The automatic algorithms operate based on current grid conditions. The flowchart for implementing real-time automatic program is shown in Fig. 4.5. The algorithm considers previously scheduled DRs but has the capability to change them based on real-time situations, excluding manual operations.

The SCC can implement multiple algorithms designed by the grid manager. Therefore, it can serve as a real-life testbed for various control algorithms. System operators select desired algorithm in the SCC interface, as shown in Fig 4.6.

Algorithm 7 shows a solar curtailment algorithm that uses a 35kW solar panel generation as an input indicator for decisions. The algorithm takes 15kW as a solar power generation threshold. Under this value, all charging station will be commanded to work under minimum output and the batteries are directed to backfeed to the grid with a current of 50A.

Battery protection is also considered in the algorithm. The battery implements “emergency charging” when its State of Charge (SOC) is under 10%. It charges with a current of 20A overriding all previous operations. In between 10% and 40% of SOC, the battery implements back-up charging where it charges with a current of 20A if no manual operation is enforced. Over 40% of SOC, the battery is available to participate in automatic algorithms by discharging current to support local grid.

In Algorithm 7, $P_{\text{solar}}$ is the power generated by solar panel, $\vec{S}_{\text{battery}}$ is the vector of SOC of all batteries and $S_{\text{battery},i}$ is the $i$-th battery’s SOC.

4.5.3 Load Curtailment on Local Generation

A demonstration experiment using the solar curtailment algorithm discussed above is presented here. In the experiment, when PV generation is lower than 15 kW, the EV charging will be set to minimum power.

Fig. 4.7 (a) shows that between 06/05/2015 12:22 PM and 12:47 PM, there was a sudden decrease of solar panel generation. At 12:25 PM, the PV generation dropped to less than 10
Figure 4.5: Automatic control flow.
Algorithm 7 Solar curtailment and battery protection algorithm

**Input:** $P_{solar}, S_{battery}$

if $P < 15$ then

Minimum load output

**For Each** Battery $i$ do

if $S_{battery_i} \geq 40$ **then** Backfeed at 50A

end if

end for

else

Regular load output

**For Each** Battery $i$ do

if $S_{battery_i} \geq 40$ **then** Idle

end if

end for

end if

**For Each** Battery $i$ do

if $S_{battery_i} < 10$ **then** Emergency Charge (Override All) at 20A

else if $S_{battery_i} < 40$ **then** Backup Charge (Low Priority) at 10A

end if

end for
kW. SCC detected the drop of generation in the next minute and issued DR signals to the EVCC for minimum power output at PS4 and PS8 at 12:26 PM. EVCC reported the reduced power consumption in the next minute at 12:28 PM. When solar generation resumed past 15 kW at 12:36 PM, SCC issued a new DR signal to resume normal power consumption to EVCC at 12:37 PM. Subsequently, the reported EV charging power consumption ramped up from 12:38 PM.

The ratio of solar usage for EV charging during this process is shown in Fig. 4.7 (b), defined as

\[
\text{solar usage} = \frac{\text{solar power}}{\text{total consumed power}} \quad (4.1)
\]

Assuming local generated solar energy is first consumed locally, the solar usage ratio is an indicator of how much the load is supported by local renewable energy. It can be seen that for most of the time, the solar usage ratio is well above 1. Between 12:25 PM to 12:27 PM, the ratio is lower than 1 due to sudden drop of solar generation. The ratio increased significantly at 12:37 PM with the return of solar power. However, for most of the time, the ratio is kept between 1 and 3 controlled by the algorithm.

4.6 Signal Execution and Delivery

DR database stores all manual operation and automatic DR generated by algorithms. SCC execute or generate DR operations from reading the DR database, as shown in Fig 4.8.

To deliver a DR signal from SCC to EVCC, the following procedure is implemented,

1. SCC requests authorization from EVCC with its username/password;

2. EVCC returns authorization token to SCC;

3. SCC sends control signal to EVCC with authorization token;

   (a) For min output command, the start time, stop time, PSID for operation are specified;
Figure 4.7: SCC response to a drop of solar power generation (a) power generation and consumption (b) solar usage ratio

Figure 4.8: Flowchart for executing DR events and prompting new automatic decisions.
Table 4.3: Participating Charging Stations

<table>
<thead>
<tr>
<th>Location</th>
<th>Voltage</th>
<th>Connector Type ($)</th>
<th>Plug Points</th>
<th>Max Power (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PS 9 Level 4</td>
<td>120 V</td>
<td>NEMA 5-15</td>
<td>4</td>
<td>1.8</td>
</tr>
<tr>
<td>PS 9 Level 6</td>
<td>120 V</td>
<td>NEMA 5-15</td>
<td>4</td>
<td>1.8</td>
</tr>
<tr>
<td>PS 8 Level 2 South</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
</tr>
<tr>
<td>PS 8 Level 2 North</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
</tr>
<tr>
<td>PS 2 Level 2</td>
<td>120 V</td>
<td>NEMA 5-15</td>
<td>4</td>
<td>1.8</td>
</tr>
<tr>
<td>PS 3 Level 4</td>
<td>120 V</td>
<td>NEMA 5-15</td>
<td>4</td>
<td>1.8</td>
</tr>
<tr>
<td>PS 3 Level 2</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
</tr>
<tr>
<td>PS 4 Box 1</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
</tr>
<tr>
<td>PS 4 Box 2</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>4.2</td>
</tr>
<tr>
<td>PS 2</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
</tr>
<tr>
<td>DCFC PS4</td>
<td>480 V</td>
<td>CHAdeMO</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td><strong>41</strong></td>
<td><strong>94.4</strong></td>
</tr>
</tbody>
</table>

(b) For resume command, SCC inquiries the current event ID in action and requests to resume the event with the returned ID.

4. EVCC subsequently returns success/failure status message.

4.7 Experiment Results

In this section, experiments implemented by SCC for demonstration and research projects of SMERC over the years is summarized.

4.7.1 Participating Charging Network

Table 4.3 shows a list of participating smart charging station from UCLA EV charging network – total of 40 plug points and 44.4 kW max power for management.

Additionally, a charging station with Vehicle-to-Grid (V2G) capability is also managed.
by SCC. The Princeton Power V2G system is integrated into the SMERC smart charging infrastructure to share data and receive aggregated control signals.

The Princeton Power V2G charging station has one CHAdeMO charging port. This charging port can perform regular DC fast charging to any vehicle using CHAdeMO EVPS-002 V1.0 standard. V2G can also be performed by the same charging port but currently only limited to Nissan Leaf with V2G technology enabled (model year 2013 and later). There are communication devices built within the charging station so that it can be reached via the Internet.

The Princeton Power V2G charger utilizes a Modbus TCP protocol. To realize remote control and data collection, a router is installed as a gateway for the network communication and a smart meter to measure power consumption data. The router equipment is installed in the SMERC labeled box next to the charger as shown in Fig. 4.9.

4.7.2 DR Configurations of Charging Stations

In practice, based on the type of EV chargers in EVCC, different load reductions are performed during a load shedding event as shown in Table 4.4.

During a DR event, all Level 1 chargers will be turned off and all new charging session will not be accepted. For Level 2 charger, depending on the number of connected vehicles in a box, the minimum power will be different as shown in Table 4.5.

The total output of a level 2 SMERC EV charger is 30A. The 12% duty cycle is the lowest duty cycle recommended for reliable charging based on current EV models.

4.7.3 Summary of Completed Operations

Table 4.6 lists the load shedding operations between 2015-10 to 2015-02.

Additional DR experiments are conducted in Santa Monica testbed. There are two types of DR conducted: (1) Pure DR – the power from the charger is reduced to minimum, and (2) DR with V2G – the vehicle discharges power to perform reverse power flow and therefore
Figure 4.9: Network communication equipment box with Princeton Power V2G charger.
Table 4.4: EV Charger Load Reduction during a load shedding event.

<table>
<thead>
<tr>
<th>Location</th>
<th>Voltage</th>
<th>Connector</th>
<th>Plugs</th>
<th>Max Power</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>PS 9 Level 4</td>
<td>120 V</td>
<td>NEMA 5-15</td>
<td>4</td>
<td>1.8</td>
<td>turn off</td>
</tr>
<tr>
<td>PS 9 Level 6</td>
<td>120 V</td>
<td>NEMA 5-15</td>
<td>4</td>
<td>1.8</td>
<td>turn off</td>
</tr>
<tr>
<td>PS 8 Level 2 South</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
<td>minimum power</td>
</tr>
<tr>
<td>PS 8 Level 2 North</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
<td>minimum power</td>
</tr>
<tr>
<td>PS 2 Level 2</td>
<td>120 V</td>
<td>NEMA 5-15</td>
<td>4</td>
<td>1.8</td>
<td>turn off</td>
</tr>
<tr>
<td>PS 3 Level 4</td>
<td>120 V</td>
<td>NEMA 5-15</td>
<td>4</td>
<td>1.8</td>
<td>turn off</td>
</tr>
<tr>
<td>PS 3 Level 2</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
<td>minimum power</td>
</tr>
<tr>
<td>PS 4 Box 1</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
<td>minimum power</td>
</tr>
<tr>
<td>PS 4 Box 2</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>4.2</td>
<td>turn off</td>
</tr>
<tr>
<td>PS 2</td>
<td>208 V</td>
<td>J1772</td>
<td>4</td>
<td>6.6</td>
<td>minimum power</td>
</tr>
<tr>
<td>DCFC PS4</td>
<td>480 V</td>
<td>CHAdeMO</td>
<td>1</td>
<td>50</td>
<td>cannot control</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td>41</td>
<td>94.4</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.5: Level 2 Smart charger behavior during a DR event.

<table>
<thead>
<tr>
<th>Connected vehicles</th>
<th>Before a DR event</th>
<th>During a DR event</th>
<th>After a DR event</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>30A × 1 = 30A</td>
<td>up to 7.2A × 1 = 7.2A</td>
<td>30A × 1 = 30A</td>
</tr>
<tr>
<td>2</td>
<td>15A × 2 = 30A</td>
<td>up to 7.2A × 1 = 14.4A</td>
<td>15A × 2 = 30A</td>
</tr>
<tr>
<td>3</td>
<td>9.6A × 3 = 28.8A</td>
<td>up to 7.2A × 3 = 21.6A</td>
<td>9.6A × 3 = 28.8A</td>
</tr>
<tr>
<td>4</td>
<td>7.2A × 4 = 28.8A</td>
<td>up to 7.2A × 4 = 28.8A</td>
<td>7.2A × 4 = 28.8A</td>
</tr>
</tbody>
</table>
Table 4.6: Level 2 Smart charger behavior during a DR event.

<table>
<thead>
<tr>
<th>Start Time</th>
<th>Stop Time</th>
<th>Operation</th>
<th>Approximate Load Reduction (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10/11/15 15:55</td>
<td>10/11/15 16:00</td>
<td>Manual</td>
<td>10019</td>
</tr>
<tr>
<td>10/12/15 10:14</td>
<td>10/12/15 10:27</td>
<td>Manual</td>
<td>5769</td>
</tr>
<tr>
<td>10/12/15 11:26</td>
<td>10/12/15 11:54</td>
<td>Manual</td>
<td>6368</td>
</tr>
<tr>
<td>10/12/15 15:05</td>
<td>10/12/15 15:15</td>
<td>Manual</td>
<td>6843</td>
</tr>
<tr>
<td>12/1/15 9:49</td>
<td>12/1/15 10:10</td>
<td>Manual</td>
<td>6314</td>
</tr>
<tr>
<td>12/7/15 13:44</td>
<td>12/7/15 13:51</td>
<td>Manual</td>
<td>6039</td>
</tr>
<tr>
<td>1/13/16 10:26</td>
<td>1/13/16 10:36</td>
<td>Manual</td>
<td>10124</td>
</tr>
<tr>
<td>2/19/16 15:20</td>
<td>2/19/16 15:25</td>
<td>Automatic</td>
<td>18351</td>
</tr>
</tbody>
</table>
Table 4.7: Pure Demand Response Power Reduction in Santa Monica.

<table>
<thead>
<tr>
<th>Begin Power (w)</th>
<th>Min Power (w)</th>
<th>Ave Power (w)</th>
<th>Start Time</th>
<th>Stop Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>14031</td>
<td>3629.63</td>
<td>3303.37087</td>
<td>6/3/17 14:12</td>
<td>6/3/17 14:21</td>
</tr>
<tr>
<td>11805.04</td>
<td>2052.17</td>
<td>1636.363636</td>
<td>6/2/17 18:50</td>
<td>6/2/17 18:57</td>
</tr>
<tr>
<td>17278.4</td>
<td>4195.05</td>
<td>3854.389722</td>
<td>6/2/17 15:15</td>
<td>6/2/17 15:30</td>
</tr>
<tr>
<td>6565.74</td>
<td>3425.46</td>
<td>7092.537313</td>
<td>6/2/17 13:58</td>
<td>6/2/17 14:03</td>
</tr>
<tr>
<td>5557.98</td>
<td>2602.64</td>
<td>3904.411765</td>
<td>6/2/17 13:38</td>
<td>6/2/17 13:48</td>
</tr>
</tbody>
</table>

provides effective V2G capability that is beyond (i).

The result for pure DR is shown in Table 4.7 and Table 4.8.

4.8 Security

The security practice of SCC is implemented in three levels: IP specific access, user authorization and database management.

Access to charging stations is limited to specific IP range to prevent unauthorized operations. As IoT devices have rising influence in the physical world, this can be an efficient way to protect IoT devices. SCC access requires verified user credential and HTTPS, as shown in Fig. 4.10(a). The password is stored as salted-hash form, to protect the original password. Different groups of user are given different levels of privileges. MySQL database is used to manage data, supported by Linux/cPanel user management system and accessed by PhPMyAdmin, shown in Fig. 4.10(b).

4.9 Conclusion

In this chapter, a two-level EMS system is proposed to manage the demand and supply in a microgrid. The upper level EMS, Super Control Center, is proposed to control lower-level controllers, such as local Electric Vehicle Control Center. The system is designed to be
Table 4.8: DR with V2G support in Santa Monica.

<table>
<thead>
<tr>
<th>Consumed Energy (kWh)</th>
<th>Backfeed Energy (kWh)</th>
<th>Start Time</th>
<th>Stop Time</th>
<th>Pure (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.76</td>
<td>-2.13</td>
<td>2/25/17 12:10</td>
<td>2/25/17 12:18</td>
<td>-1.37</td>
</tr>
<tr>
<td>0</td>
<td>-0.944</td>
<td>2/25/17 12:22</td>
<td>2/25/17 12:24</td>
<td>-0.944</td>
</tr>
<tr>
<td>0.6</td>
<td>-4.239</td>
<td>2/25/17 12:40</td>
<td>2/25/17 12:49</td>
<td>-3.639</td>
</tr>
<tr>
<td>0.81</td>
<td>-4.49</td>
<td>3/20/17 11:00</td>
<td>3/20/17 11:09</td>
<td>-3.68</td>
</tr>
<tr>
<td>2.46</td>
<td>-4.815</td>
<td>4/28/17 10:00</td>
<td>4/28/17 10:09</td>
<td>-2.355</td>
</tr>
<tr>
<td>0.72</td>
<td>-2.581</td>
<td>5/31/17 11:10</td>
<td>5/31/17 11:16</td>
<td>-1.861</td>
</tr>
<tr>
<td>0.56</td>
<td>-1.498</td>
<td>5/31/17 11:22</td>
<td>5/31/17 11:25</td>
<td>-0.938</td>
</tr>
<tr>
<td>1.64</td>
<td>-4.65</td>
<td>7/26/17 18:21</td>
<td>7/26/17 18:30</td>
<td>-3.01</td>
</tr>
<tr>
<td>0.69</td>
<td>-1.979</td>
<td>7/26/17 18:35</td>
<td>7/26/17 18:39</td>
<td>-1.289</td>
</tr>
<tr>
<td>0.5</td>
<td>-1.583</td>
<td>7/26/17 18:46</td>
<td>7/26/17 18:49</td>
<td>-1.083</td>
</tr>
<tr>
<td>0.09</td>
<td>-0.515</td>
<td>8/24/17 14:01</td>
<td>8/24/17 14:03</td>
<td>-0.425</td>
</tr>
</tbody>
</table>

Figure 4.10: Security implementation for SCC (a) Super Control Center login interface (b) PhPMyAdmin Database Manager.
compliant with OpenADR standard and receives OpenADR requests with highest priority. SCC can implement multiple pre-programmed scheduling algorithms that manage the overall demand and supply in the microgrid while leaving the microscopic management role to local controllers. This configuration can allow a flexible structure for further scaling up.

In addition, the following lessons are learned from the implementation experience:

1. An intermediate agent (middleware) is needed to aggregate and control a group of devices so that the upper-level EMS system such as SCC can successfully implement the commanding role in overall energy management.

2. The smart EV charging stations may be able to respond to a turn off command in less than a minute (depending on the network connection). It may take about 3 min for the load shedding result initiated from SCC to reach each individual EV charger.

3. A frequent change of charging current on an EV charging station may result in malfunction on the EV charger and a manual re-start of the EV charger will be needed.

It is learned that for a complicated and distributed system, the best practice for an EMS is to only manage a macroscopic view at the PS level while giving local distributed operator its own operation ability for microscopic adjustment over each charging station.
CHAPTER 5

User Demand and Consumption Pattern

5.1 Introduction

On the UCLA campus, most of the data on EV charging behavior and power consumption is collected and managed by SMERC. Users registered with SMERC are long-term employees of UCLA, therefore the data represents the campus workplace charging scenario.

The charging records are stored in the WINSmartEV™ EV Control Center (EVCC), discussed in Chapter 4. The data includes start time, stop time, location of the charging, user index, and energy consumed for each charging session. With a large dataset, the charging record allows a data-based study and to find appropriate methods to understand user behaviors and consumption patterns. For service providers and EMS, it is fundamental and critical to understand and predict users’ energy demand. In this chapter, campus EV user data is studied to find the best approach to characterize any user’s energy demand based on his/her past charging history.

The rest of the chapter is organized as follows. Section 5.2 examines potential probability distributions to fit user behavior data. Section 5.3 tests the correlations between different parameters and energy demand. Section 5.4 finds the best method to predict user’s energy demand based on the past history. The discussion and conclusion on the presented work are shown in Section 5.5 and 5.6.
5.2 Fit of Probability Distributions

As discussed in previous chapters, user’s behavior is not fixed or deterministic. There will always be certain random deviation in terms of time of arrival and departure and energy consumption over time. Therefore, users’ behavior should be regarded as a random process. If their behaviors share the same distribution over time, based on Law of Large Numbers, the consumption profiles would follow normal distributions for large users regardless what the original distribution is.

Therefore, in this section, charging data for frequent users are fit with two distributions: normal and logistic. As each user has different EV model, daily travel routine and access to EVSE, their energy demand and consumption profiles should be considered separately. As an initial step, data can be filtered by users and four frequent users with large sample sizes are picked to visually examine their distributions.

Chi-square goodness-of-fit is used to see whether user consumption fits any specific distributions. In statistics, chi-square goodness-of-fit tests are used to determine whether sample data are consistent with a hypothesized distribution [Wik18a]. In the chi-square goodness-of-fit test, $\chi$ can be compared with a chi-square distribution with $(k - c)$ degree of freedom to determine whether the fit is good or not. $k$ is the number of non-empty cells and $c$ is the number of estimated parameters of the distribution plus one. $\chi$ is calculated as

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$  \hspace{1cm} (5.1)

where $O_i$ is the observed frequency for bin $i$ and $E_i$ is an expected frequency for bin $i$.

The expected frequency is

$$E_i = (F(Y_u) - F(Y_l))N$$  \hspace{1cm} (5.2)

where $F$ is the cumulative distribution function for the distribution being tested, $Y_u$ is the upper limit for bin $i$, $Y_l$ is the lower limit for bin $i$ and $N$ is the sample size.

As the results shown in Table 5.1, the tested user profiles do not fit to normal distribution nor logistic distribution. The discrepancy can also be easily observed visually in Fig. 5.1 and
Table 5.1: Chi-Square Goodness-of-Fit Test

<table>
<thead>
<tr>
<th>Index of User</th>
<th>Sample Size</th>
<th>Normal Distribution Test Result</th>
<th>Logistic Distribution Test Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>153</td>
<td>224</td>
<td>Not good</td>
<td>Not good</td>
</tr>
<tr>
<td>130</td>
<td>212</td>
<td>Not good</td>
<td>Not good</td>
</tr>
<tr>
<td>238</td>
<td>168</td>
<td>Not good</td>
<td>Not good</td>
</tr>
<tr>
<td>286</td>
<td>148</td>
<td>Not good</td>
<td>Not good</td>
</tr>
</tbody>
</table>

Fig. 5.2 shows the histograms of energy consumption per session. For each user, there can be multiple charging sessions per day, caused by session interruption, change of stations or multiple accesses at different time. Fig. 5.2 shows the energy consumed by users in each day he/she is present, merging energy demand from multiple sessions in one day.

5.3 Correlation of Time, Weekday and Duration

As frequent user’s behavior is shown to not follow normal or logistics distribution, some may argue that users’ behavior may be different on different days under separate scenarios. Therefore, this section investigates if there exist factors that could influence energy demand of any specific session. Popular industry factors, such as start time of the charging event (ranging from 0:00 to 23:59 of each day), the weekday of the session and duration of the charging, are studied in this section.

Given that different users could have different consumption preferences, the impact of each parameters on the results should be considered separately and independently (grouped by each user) as well. It is important to separate the effect of each user from another, while taking the overall look across all users.

Therefore, linear mixed effects model [LLS13] is used to investigate the relationships and see whether energy demand is statistically related the above mentioned parameters in the data. Linear mixed-effects models are based on linear regression models and are extended...
Figure 5.1: Distribution of consumption per session (fitted with logistic regression) of four users in different colors (from top left to bottom right: (a) user 44 (b) user 130 (c) user 238 (d) user 41.
Figure 5.2: Distribution of consumption per day the user is present (fitted with logistic regression) of four users in different colors (from top left to bottom right: (a) user 44 (b) user 130 (c) user 238 (d) user 41.
for data associated with groups as

\[ Y_{ij} = x_{ij}\beta + u_{ij}\gamma_i + \epsilon_{ij} \]  \hspace{1cm} (5.3)

where \( Y_{ij} \) is the response of subject \( i \) at \( j \)-th measurement, \( n_i \) is the number of measurements for subject \( i \), \( m \) is the number of objects, \( x_{ij} \) is covariate vector of \( i \)-th subject at \( j \)-th measurement for fixed effects \( \beta \in \mathbb{R}^p \), \( u_{ij} \) is covariate vector of \( i \)-th subject at \( j \)-th measurement for random effects \( \gamma_i \in \mathbb{R}^q \), \( \beta \) is the fixed effects parameter, \( \gamma_i \) is the random effect parameter and \( \epsilon_{ij} \) is the random error.

Assume the following

\[ \gamma_i \sim N_q(0, D), \ D \in \mathbb{R}^{q \times q} \]  \hspace{1cm} (5.4)

\[ \epsilon_i = \begin{bmatrix} \epsilon_{i1} \\ \vdots \\ \epsilon_{im} \end{bmatrix} \sim N_{n_i}(0, \Sigma_i), \ \Sigma_i \in \mathbb{R}^{n_i \times n_i} \]  \hspace{1cm} (5.5)

\( \gamma_1, \ldots, \gamma_m, \epsilon_1, \ldots, \epsilon_m \) independent \hspace{1cm} (5.6)

\( D = \) covariance matrix of random effects \( \gamma_i \) \hspace{1cm} (5.7)

\( \Sigma_i = \) covariance matrix of error vector \( \epsilon_i \) \hspace{1cm} (5.8)

With known covariances, by joint maximization of log likelihood of \((Y, \gamma)\) with respect to \((\beta, \gamma)\), the Mixed Model Estimation equation is given by \[ \text{[WWG14, FKL07]} \]

\[
\begin{bmatrix}
X^TR^{-1}X & X^TR^{-1}U \\
U^TR^{-1}U & U^TR^{-1}R + G^{-1}
\end{bmatrix}
\begin{bmatrix}
\tilde{\beta} \\
\tilde{\gamma}
\end{bmatrix}
=
\begin{bmatrix}
X^TR^{-1}y \\
U^TR^{-1}y
\end{bmatrix}
\]  \hspace{1cm} (5.10)
where

\[
G = \begin{bmatrix}
D \\
\vdots \\
D
\end{bmatrix} \in \mathbb{R}^{mq \times mq} \tag{5.11}
\]

\[
U = \begin{bmatrix}
U_1 \\
U_2 \\
\vdots \\
U_m
\end{bmatrix} \in \mathbb{R}^{n \times (mq)} \tag{5.12}
\]

\[
R = \begin{bmatrix}
\Sigma \\
\vdots \\
\Sigma
\end{bmatrix} \in \mathbb{R}^{n \times n} \tag{5.13}
\]

In our case, the covariance is unknown. Let

\[
V = UGUT + R \tag{5.15}
\]

where \(G\) and \(R\) are only known depending on the variance parameter \(\theta\)

\[
V(\theta) = UG(\theta)U^T + R(\theta) \tag{5.16}
\]

\(\theta\) can be estimated by maximum likelihood (ML) estimation or restricted maximum likelihood (REML) estimation. The fixed effects \(\beta\) and random effects \(\gamma\) are estimated by

\[
\hat{\beta} = (X^T\hat{V}^{-1}X)^{-1}X^T\hat{V}^{-1}Y \tag{5.17}
\]

\[
\hat{\gamma} = \hat{G}U^T\hat{V}^{-1}(Y - X\hat{\beta}) \tag{5.18}
\]

where \(\hat{V}\) is estimated by \(\hat{V} = V(\hat{\theta}_{\text{ML}})\) or \(\hat{V} = V(\hat{\theta}_{\text{REML}})\).

Under the assumption that \(\hat{\beta}\) is asymptotically normal with mean \(\beta\), the common statistical hypothesis tests can be used:

\(H_0 : \beta_j = 0\) versus \(H_1 : \beta_j \neq 0\)

Reject \(H_0 \iff |t_j| = \left|\frac{\hat{\beta}_j}{\hat{\sigma}_j}\right| > z_{1-\alpha/2} \tag{5.19}\)
Table 5.2: Mixed Effect Linear Model Test of Various Factors on User Energy Demand

<table>
<thead>
<tr>
<th>Factor</th>
<th>Significance</th>
<th>p value</th>
<th>Estimated effect (standard error)</th>
<th>Intercept(standard error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Start Time</td>
<td>Significant</td>
<td>$4.4 \times 10^{-79}$</td>
<td>-0.1386(±0.0073) kW</td>
<td>6.308(±0.2028) kW</td>
</tr>
<tr>
<td>Weekday</td>
<td>Not significant</td>
<td>0.44</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Duration</td>
<td>Significant</td>
<td>0</td>
<td>0.21(±0.0046) kW</td>
<td>3.8034(±0.1867) kWh</td>
</tr>
</tbody>
</table>

Therefore, linear mixed effects model suits the need to study the data generated by different users. In this case, different users serve as the random grouping variable that effects the regression results due to different user condition and preference. Factors under investigation, i.e. start time, weekday or duration, are the fixed effects in the model. The response of the model is energy demand. The result of the linear mixed effect model tests with 18,599 samples and 340 users is shown in Table 5.2.

From Table 5.2, it can be seen that the effect of start time and duration of an event is statistically significant to the energy demand. However, as the large sample size may lead to low p-value, it is necessary to investigate the magnitude of the impact factors with statistically significance. While the effects of the start time and duration are small, they are not negligible. Therefore, these effects are examined by testing their effectiveness in the prediction algorithms in Section 5.4. An interesting fact to note is that the effect of duration is smaller than standard Level-1 and Level-2 charging rate (2kW and 6.6kW). This can be due to charging delays from scheduling, current sharing algorithms and lower current commanded by EVs using J1772 standard as discussed in Chapter 3.

5.4 Prediction Algorithm

In this section, methods for user-specific prediction algorithms are investigated. While prediction algorithm is critical for system effectiveness and planning, it can also serve as a test to see any of the previously discussed parameters are indeed meaningful factors. While statistically significant, the parameters might still be minor impact factors rising from
imperfect data collection. From the analysis in the previous section, a universal demand approach, three basic prediction approaches, and their adjustments are proposed.

1. Universal demand (linear): As shown in Table 5.2, the linear model finds an intercept value as energy estimation for midnight (00:00) each day. The intercept value is used as an universal consumption across all users. The demand is adjusted with time of day based on (5.20). This naive method can be regarded as a baseline for error benchmark.

2. Mode of the histogram (mode): As shown in Fig. 5.1 and Fig. 5.2, most users have a preferred segment of energy use range that has occurred much more often than the other segments in the histogram. This has suggested users have a certain travel mode that they choose to stay in and seldom deviate from. The travel consumption amount is rather stable and is not evenly distributed. This special feature of user consumption can be addressed by taking the mode of the consumption histogram as input.

3. Average of user consumption (mean): The mean value of every user’s consumption from each session is used as the basic consumption need input.

4. Median of user consumption (median): The median value from each user’s consumption is used as the basic consumption need input.

5. Adjustment term: An adjustment term can be used to address the correlation between time and energy consumption as obtained from Section 5.3, as following

\[ E_{adj} = \beta(t - t_{max}) \]  \hspace{1cm} (5.20)

where \( E_{adj} \) is the adjustment energy term, \( \beta \) is the effect of time on the consumption, \( t \) is the starting time of the charging session and \( t_{max} \) is the latest time that the user ever begins his charging. The adjustment term is added to the previous three basic consumption terms.
5.4.1 Training and Performance Analysis

User data is used to evaluate the accuracy and performance of the above proposed prediction algorithms. There are seven algorithms under investigation, as described in [5.4]: (1) mean (2) median (3) mode (4) mean with adjustment (5) median with adjustment (6) mean with adjustment (7) universal. Each user’s profile is used independently to predict the particular user and error is subsequently computed. Within each user data set, the first 90% of the data is training set and the rest of 10% is testing set. Symmetric mean absolute percentage error (SMAPE) is used as a measure of accuracy, as following

\[
\text{SMAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|F_i - A_i|}{(|A_i| + |F_i|)/2} \tag{5.21}
\]

where \(F_i\) is the forecast value and \(A_i\) is the actual value of the user demand of that session.

As different users use the system with different frequency, the sample size of each user varies from only one charging record to 413 records. Therefore, users are grouped differently based on their sample size. In this way, the performance of the algorithms on different sizes of samples can be evaluated.

The result of the SMAPE evaluation with the seven algorithms is shown in Fig. 5.3. It can be seen that the “median” algorithm outperforms all the rest of the algorithms in all minimum sample sizes. Moreover, by increasing the minimum sample size, the SMAPE decreases for all algorithms. This is partly due to the reason that users with more charging sessions use the charging stations more regularly and their charging behavior is more homogeneous. Lastly, by adding the adjustment term of time effect, the accuracy does not uniformly increase on all algorithms. The adjustment helps with the “mode” algorithm, which performs the worst, while decreases the accuracy of “average” and “median” algorithms. This indicates that starting time may not play an actual effective role in the energy consumption prediction.

The “median” algorithm has the least error, but the absolute SMAPE value is still high, indicating a non-ideal prediction accuracy. This may be due to the complexity of the charging scenarios and many invalid charging sessions that the data is unable to specify.
Figure 5.3: Analysis of prediction algorithms (a) minimum sample size versus SMAPE for six algorithms (b) number of users corresponding to the minimum sample size.
(such as the charging station plug disconnects during charging, charging box goes offline or user unintentionally stops charging). Indeed, the discrete and random nature of human energy demand is difficult to predict compared to a conventional and well-developed time series machine-learning problem seen in [MQC15]. This study provides a preliminary and practical guidance for an easy and quick implementation in real-life prediction deployments. Such deployment may need to deal with heavy traffic and intensive access to database and an easy prediction algorithm will help to guarantee a reliable service.

5.5 Discussion

While user behaviors studied in this chapter are focused on workplace charging, same analysis methodology can be applied on different scenarios such as household charging or highway charging. The results may not be the same with what is reported in this chapter (median), but the methodology can be followed to find a best way to characterize user demands based on different dataset.

Additionally, after user behavior is changed through incentivization in Chapter 2, it is essential to reiterate and analyze how users’ behaviors are expected to change and which method is the best to characterize an incentivized user.

5.6 Conclusion

In this chapter, EV user consumption data collected through the public usage of on-campus EV charging stations at UCLA is investigated. The relationship between users’ energy need and their charging starting time, weekday and duration of the charging sessions is analyzed. By using mixed effect linear model to analyze the correlation, it is found that:

1. The starting time has statistically significant effect, though small in magnitude, on the energy effect. However, this effect is not helpful in the adjustment for energy demand prediction. This may mean that the starting time does not play an actual role in determining the energy demand.
2. The duration of charging sessions is also statistically significant on the charging energy consumption, but the estimated effect does not directly reflect the charging capacity of the charging stations. This is partly due to different scheduling algorithms and hardware settings at different charging stations.

3. The weekday of the charging session, however, does not have any statistically significant effects on the charging session energy consumption.

By analyzing each user’s charging profile and history, median of a user’s demand history is found to be the most efficient and consistent approach to estimate his/her demand. This also shed light on user’s preference to skew toward a particular energy demand range in the long term.
CHAPTER 6

Aggregated Charging Behavior Modeling

6.1 Introduction

In this chapter, a stochastic model is proposed and studied to estimate the aggregated stochastic behavior of EVs and the service provider. Stochastic operations of each vehicle (taxi and bus) is first established. Then, the service provider receives business and generates revenue. Based on this interaction, the capacity of service providers and their profitability are studied. Lastly, an analytic solution is proposed to estimate the result of the Monte-Carlo simulation.

The rest of this chapter is organized as follows. Section 6.2 defines the stochastic models. The evaluation results for served vehicles and the service providers are presented in Section 6.3 and 6.4 respectively. The analytic solutions are presented in Section 6.5. The potential use case of the presented model is discussed in Section 6.6. The difference between the results and intuition is discussed in Section 6.7 followed by conclusion in Section 6.8.

6.2 Stochastic Model

The Monte-Carlo simulation is implemented from bottom-up. That is, the stochastic behavior of the elements in the system, i.e. Taxis, Buses, Charging Stations (CS), and the interaction between them are defined. After simulation, their aggregated behaviors are measured. In the following sections, the set up of these elements is described.
6.2.1 Players in Model

The players and their roles in the stochastic model simulation are shown in Fig. 6.1. The model of the entire society consists of two main classes of participants, one is vehicle operators and the other is service providers.

Vehicle operators are companies that operate service vehicles such as buses and taxis. Their income is the service fee paid by passengers while their cost is the electricity fee paid to the service providers. Service providers are companies that operate charging services for EVs using CSs. The net income for service providers is the fee paid by their EV customers minus the electricity cost.

Figure 6.1: Roles in the Monte-Carlo simulation and their capital flow.

6.2.2 Taxi Fleet

Behavior of taxi drivers is modeled as a Markov process consisting of: (a) operation mode (whether they are charging/swapping or running on the road), (b) battery State of Charge (SOC) $B$, and (c) total income for each taxi.

The change of driver’s operation mode is modeled as a Bernoulli process. Parameters $p_l$ and $p_c$ are the probabilities to change from charging to running and from running to charging, restrictively. They depend on the SOC $B$ and the time $t$. 
The battery capacity $B_{x,t}$ at time $t$ can be calculated as:

$$B_{x,t} = B_{x,t-1} + \mathbb{1}_{\text{running}} \eta_x V_{x,t} + \mathbb{1}_{\text{charging}} e_t,$$

(6.1)

where $\eta_x$ is the battery energy consumption rate (kWh/mile) for taxis, $V_{x,t}$ is the taxi speed at time $t$, and $e_t$ is the energy (kWh) injected into the vehicle at time $t$ (equal to 0 during waiting).

The total income of the taxi $U_{x,t}$ at time $t$ considering earning and cost for energy is:

$$U_{x,t} = U_{x,t-1} + \mathbb{1}_{\text{hired}} u_t V_{x,t} - \mathbb{1}_{\text{charging}} e_t r,$$

(6.2)

where $u_t$ is the taxi’s income rate when hired ($$/mile) and $r$ is the unit energy cost per kWh.

### 6.2.2.1 Time segmentation

The model for taxis with a 24-hour shift consists of \[RZX15\]: (a) peak time: between 6 p.m. to 9 p.m. when taxis are motivated to drive more, (b) rest time: from 2 a.m. to 5 a.m. when drivers prefer to charge their vehicles, (c) normal: the remaining time when taxi drivers drive normally.

### 6.2.2.2 Operation mode

During normal hours, $p_c$ and $p_l$ depend on the amount of battery capacity left and charged:

$$p_c = e^{-B},$$

(6.3)

$$p_l = e^{B-c_x},$$

(6.4)

where $c_x$ is the battery capacity of a taxi. $B = c_x$ when fully charged.

During break time, drivers charge if possible:

$$p_c = \begin{cases} 
1, & \text{if } t_{r, st} < t < t_{r, end} \text{ and } B < 0.9c_x, \\
0 & \text{else},
\end{cases}$$

(6.5)

where $t_{r, st}$ and $t_{r, end}$ are the start and end time of the break time, respectively.
Around the start of the peak time, there is higher probability that drivers will leave CSs:

\[ p_t = e^{t_{b, st} - t}, \text{ if } t > t_{b, st}. \]  

(6.6)

6.2.2.3 Travel Speed

The taxi speed \( V_{x,t} \) is a random variable generated at each discrete time \( t \) as:

\[
V_{x,t} = \begin{cases} 
\max(\mathcal{N}(v_h + v_{tr}, \sigma_v), 0), & \text{hired} \\
\max(\mathcal{N}(v_a, \sigma_v), 0), & \text{not hired, } t < t_{r, st}, t > t_{r, end} \\
\max(\mathcal{N}(v_m, \sigma_v), 0), & \text{else}
\end{cases}
\]  

(6.7)

where \( v_a \) is the average traveling speed when taxi is available for hire, \( v_h \) is the average speed when taxi is hired, \( v_m \) is the average speed when taxi is not hired during the remaining period, \( v_{tr} \) is the average traffic adjustment, and \( \sigma_v \) is the speed standard deviation.

Taxis are assumed to travel at different speeds when hired and not hired. The probability for getting hired is the highest during peak hours, lower during normal hours, and the lowest during the rest hours.

6.2.2.4 Summary

The operation of taxis is summarized in Algorithm 8, where \( W_{\text{charging}} \) is the power of CS/time period.

**Algorithm 8** Taxi Operation

**Input:** \( B_{x,t}, U_{x,t} \)

**Output:** \( B_{x,t+1}, U_{x,t+1} \)

if charging then decide whether to charge

else decide whether to leave CS

end if

Implement (6.1), (6.2)
6.2.3 Bus Fleet

In general, buses have the following differences from taxis:

1. The battery in buses has larger capacity.

2. Buses follow a fixed route with a predetermined distance. They charge their battery with fixed schedule at a bus park.

3. The income of bus/mile depends on the random number of passengers at the time.

4. Only a fraction of buses will run during night shifts.

The battery capacity of buses $B_{b,t}$ is calculated as:

$$B_{b,t} = B_{b,t-1} - \mathbb{1}_{\text{running}} \eta_b V_{b,t} + \mathbb{1}_{\text{charging}} e_{t^r},$$ \hspace{1cm} (6.8)

where $\eta_b$ is the battery energy consumption in terms of kWh/mile for buses and $V_{b,t}$ is the bus speed at time $t$.

The income of the bus $U_{b,t}$ at time $t$ is:

$$U_{b,t} = U_{b,t-1} + \mathbb{1}_{\text{running}} \max(\mathcal{N}(u_b, \sigma_b), 0) V_{b,t} - \mathbb{1}_{\text{charging}} e_{t^r},$$ \hspace{1cm} (6.9)

where $u_b$ is the average bus income rate per mile and $\sigma_b$ is the standard deviation. Similar to taxis, buses have the highest $u_b$ during peak hours, lower $u_b$ during normal hours, and the lowest $u_b$ during night shift.

The speed for bus is:

$$V_{b,t} = \max(\mathcal{N}(v_b + v_{tr}, \sigma_v), 0).$$ \hspace{1cm} (6.10)

The bus operation is described in Algorithm 9.

6.2.4 Charging Station

A service provider has a certain number of CSs that provide charging services.
Algorithm 9 Bus operation

Input: \( B_{b,t}, U_{b,t} \)

Output: \( B_{b,t+1}, U_{b,t+1} \)

if charging then charge until fully charged
else run until predetermined distance is reached
end if

Implement (6.8), (6.9), and (6.10)

The operations of the CS is described in Algorithm 10, where \( N_t \) is the number of vehicles in charging/swapping at time \( t \), \( e \) is the energy injected to all vehicles, and \( r_{\text{net}} \) is the net electricity income (\$/kWh) considering the cost of purchasing electricity from utility.

Algorithm 10 CS operation

if new vehicle to charge then
    add vehicle to queue
end if

while there is open slot for pending vehicles do
    move vehicle to charge
end while

\( U_{t+1} = U_{t+1} + N_{t+1} r_{\text{net}} \)

6.3 Performance Evaluation of Served Vehicles

In order to evaluate the performance of the served vehicles, the vehicles’ earning with CSs is used for comparison. Simulations of daily operations are used to find out the aggregated income of all vehicles. The values of parameters for the daily simulations is shown in Table 6.1. The values are based on statistics of common services vehicles and rates in real life [Tax14, Bei16].

The daily operations of 100 taxis and 20 buses are simulated. The simulation shows the operation of 5 CSs. The result is shown in Fig. 6.2.
### Table 6.1: System Parameters

<table>
<thead>
<tr>
<th>$t_{b, st}$</th>
<th>$t_{b, end}$</th>
<th>$t_{r, st}$</th>
<th>$t_{r, end}$</th>
<th>$P_{h, b}$</th>
<th>$P_{h, r}$</th>
<th>$P_{h, n}$</th>
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<th>$v_m$</th>
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<td>18</td>
<td>21</td>
<td>2</td>
<td>5</td>
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<td>0.1</td>
<td>0.6</td>
<td>30</td>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>h</td>
<td>h</td>
<td>h</td>
<td>h</td>
<td>mph</td>
<td>mph</td>
<td>mph</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$\eta_t$</th>
<th>$u_t$</th>
<th>$\eta_b$</th>
<th>$u_{b, n}$</th>
<th>$u_{b, b}$</th>
<th>$u_{b, e}$</th>
<th>$\sigma_{u, b}$</th>
<th>$v_b$</th>
<th>$\bar{O}$</th>
<th>$\epsilon_{charge}$</th>
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</thead>
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<td>2</td>
<td>2</td>
<td>5.5</td>
<td>9</td>
<td>2</td>
<td>1.5</td>
<td>25</td>
<td>145</td>
<td>0.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
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<th>$C_b$</th>
<th>$\sigma_v$</th>
<th>$v_{tr}$</th>
<th>$v_{tr}$</th>
<th>$W_{\text{charging}}$</th>
<th>$v_{tr}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>324</td>
<td>10</td>
<td>-3</td>
<td>3</td>
<td>(busy)</td>
<td>3 (rest)</td>
</tr>
<tr>
<td>kWh</td>
<td>kWh</td>
<td>mph</td>
<td>mph</td>
<td>mph</td>
<td>kW</td>
<td>mph</td>
</tr>
</tbody>
</table>

Figure 6.2: Simulation results of daily operation 5 CSs for (a) Buses (b) Taxis. Top: the aggregated income; Bottom: the number of vehicles in charging, running and waiting. The green shade and the red shade indicate the rest and busy period, respectively.
6.4 Performance Evaluation of Service Provider

In this section, the cost of building a CS is considered to compare the saturated cost benefits and the service capacity of the two kinds of infrastructures.

6.4.1 Service Capacity and Saturated Cost Benefits

The service capacity is defined as the number of vehicles served by CSs, over which the income of the aggregated served vehicle and CSs does not increase when adding more vehicles in the model. In other words, the service capacity is the number of customers (running and charging) one facility can take with all the time being fully occupied. Saturated profit is defined as the converged profit generated by the aggregated served vehicle and the charging stations at their service capacity.

6.4.1.1 Service Capacity

In the simulation shown in Fig. 6.3 (a), it is found that for taxis, 74 CSs saturate at 1,050 taxis (service capacity) and 210 CSs saturate at 420 buses.

6.4.1.2 Cost Estimation and Return On Investment

In the calculation, the cost of building a CS $C_{\text{init,c}}$ is considered to be around $15,000, including the typical cost of a DC fast charger and installation.

The cost of purchasing a battery $H_{\text{battery}}$ is set to be $227C$, where current battery cost of around $227$ per kWh is assumed. It is well known that the lifetime of a battery depends on the number of cycles, depth of discharge and the speed of charging [PAW10, VNW05]. DC fast CSs generally have high charging speed. Vehicle batteries using a DC CS will, therefore, have less lifetime. In the study, it is assumed that the cycle life of batteries is the time from new to 80% of the maximum capacity as most battery companies provide battery life information based on 80% of capacity and professional services vehicles require a good health of batteries. It is assumed that the battery life using DC charging to be 250 based
Figure 6.3: Income for served vehicle and service provider with respect to the number of vehicles for (a) taxi, and (b) buses. Top: Income of served vehicle. Bottom: Income of service provider.

The cost of each charging session in terms of battery degradation is

$$H_c = \frac{C}{250}, \quad (6.11)$$

Taking into account the above considerations, the cost benefit of CS for bus and taxis is studied. The subject of study is the owner of the charging service provider and the entire society (charging service providers + vehicle operators). For charging service providers, the income is the charging fee paid by the customer and the cost is the construction, electricity and battery cost. For the entire community, the income is the fee paid by customers, and the cost is the purchase price of EVs, construction, electricity and battery cost. Because DC charging services does not purchase batteries, the cost of batteries is afforded by vehicle operators.

The cost benefit analysis result is shown in Fig. 6.4.
6.4.2 Service Capacity with Different Parameters

As certain parameters set previously in the simulation may not reflect the current and future scenarios, it is of interest to see the effect of different parameters. The change of saturated service capacity is studied subject to the change of following three parameters: (a) battery capacity $C_x, C_b$, (b) charging power $W_{\text{charging}}$, and (c) moving speed $v_b, v_h$. Each plot is the average of 30 independent simulations. Note that the absolute saturation numbers here are less meaningful as they depend on the number of CSs. Instead, their trend with the change of parameter is important. For buses, $N_{\text{CS}} = 23$. For taxis, $N_{\text{CS}} = 5$. If different numbers are chosen, only the absolute saturation number will change and the relative trend will remain the same.

6.4.2.1 Battery Capacity

$C_x$ is varied from 15 kWh to 50 kWh and $C_b$ from 250 kWh to 600 kWh. The trend is shown in Fig. 6.5. For larger $C_b$, the fixed route length $\bar{O}$ is increased proportionally. The increased $C$ extends vehicles’ running time between charges. In this case, vehicles may need to stay longer to finish charging. So, the benefit of larger battery is reduced for taxis. For buses, with larger battery capacity, the service capacity is slightly decreased.
Figure 6.5: The number of saturation vs. battery capacity for (a) taxi, and (b) bus.

Figure 6.6: The number of saturation vs. charging power for (a) taxi, and (b) bus.

6.4.2.2 Charging Power

$W_{\text{charging}}$ is changed from 7 kW to 120 kW, covering range of charging speed from popular Level-2 AC CS to fastest available DC CS. The trend with different $W_{\text{charging}}$ is shown in Fig. 6.6. It can be seen that with larger $W_{\text{charging}}$, the saturation number increases linearly. This is intuitively reasonable as larger charging power shortens the time of charge thus providing more temporal space for new vehicles to charge.
6.4.2.3 Vehicle Moving Speed

$v_b$ is changed from 10 mph to 45 mph and $v_h$ from 15 mph to 50 mph. The change in saturation numbers is plotted in Fig. 6.7. It can be seen that with larger moving speed, the saturation number is decreased as energy demand is higher within the same amount of time.

6.5 Boundary Analysis

Given a number of participants, the income of taxis $U_{x,t}$ and buses $U_{b,t}$ at any time $t$ in the stochastic system can be evaluated by numerical or analytical approaches. This section presents the analytical approach for both types of vehicles in the system.

6.5.1 Taxis

**Theorem 1.** The expected income $U_x$ is

$$\mathbb{E}(U_x) = \mathbb{E}(M_{\text{hired}})u_t - \eta_x\mathbb{E}(M)r$$

(6.12)

where $M$ is the taxi’s total mileage and $M_{\text{hired}}$ is the total hired mileage.

The total mileage $M$ is the sum of hired mileage $M_{\text{hired}}$ and non-hired mileage $M_{\text{avail}}$.

$$M = M_{\text{hired}} + M_{\text{avail}}$$

(6.13)
Lemma 1. The expected mileage for taxi when hired and available can be calculated as,

\[
\mathbb{E}(M_{\text{hired}}) = \mathbb{E}(V_{x,t}|\text{hired})P_h\mathbb{E}(T_r) \tag{6.14}
\]
\[
\mathbb{E}(M_{\text{avail}}) = \mathbb{E}(V_{x,t}|\text{avail})(1 - P_h)\mathbb{E}(T_r) \tag{6.15}
\]

where \(T_r\) is the total length of taxi’s running time.

Remark 1. For a given total time period \(p\),

\[p = T_r + T_c \tag{6.16}\]

where \(T_c\) is the total time at CS.

All variables except \(\mathbb{E}(T_r)\) from Theorem 1 and Lemma 1 are easy to find. Therefore, the main goal for the rest of the section is to find \(\mathbb{E}(T_r)\) in order to calculate \(\mathbb{E}(U_x)\).

6.5.1.1 Taxis

Because taxi drivers have distinctive behaviors at different time, in order to analyze each period separately, four periods are denoted \(l_1\) (normal hours 9 PM-2 AM), \(l_2\) (rest hours 2 AM-5 AM), \(l_3\) (normal hours 5 AM-6 PM), \(l_4\) (peak hours 6 PM-9 PM).

The number of charges \(n_c\) each taxi requests and the amount of energy in each charging session determine the pure charging time at the CS excluding waiting time.

The stochastic model sets the chance of getting hired in busy hour to be the highest and taxi drivers are given higher probability to drive more in this period. However, as taxis still have their battery limit and they may not have the capacity to fully run during peak time, how each independent taxi operates exactly is unknown.

Therefore, two extreme situations are considered in terms of expected number of charges \(\mathbb{E}(N_c)\) during peak: best and worst. In best scenarios, taxis are assumed to not charge in busy hours. Their consumption during that period is carried over to the rest period when earning is lowest. In worst scenario, it is regarded that taxis do not leave early for busy hour and operate normally.
**Theorem 2.** In best scenario, $\mathbb{E}(N_c)$ can be computed as

$$
\mathbb{E}(N_c) = \begin{cases} 
\eta_x \mathbb{E}(M_1) / \tilde{B}_x & \text{for } l_1 \\
\max(\eta_x \mathbb{E}(M_4) / \tilde{B}_x, 1) & \text{for } l_2 \\
\eta_x \mathbb{E}(M_2 + M_3) / \tilde{B}_x & \text{for } l_3 \\
0 & \text{for } l_4
\end{cases}
$$

(6.17)

where $M_1$, $M_2$, $M_3$, $M_4$ are the total mileage in each respective period and $\tilde{B}_x$ is the expected kWh per CS session.

$\tilde{B}_x$ can be computed as

$$
\tilde{B}_x = \mathbb{E}(B_{x,\text{out}}) - \mathbb{E}(B_{x,\text{in}})
$$

(6.18)

The expected remaining battery when charging in this case is

$$
\mathbb{E}(B_{x,\text{in}}) = \begin{cases} 
\mathbb{E}(B_{x,\text{in,normal}}) & \text{for } l_1, l_3, l_4 \\
C - \mathbb{E}(R_4) & \text{for } l_2
\end{cases}
$$

(6.19)

where $B_{x,\text{in,normal}}$ is the battery capacity when taxi decides to go into CS in normal hour.

**Lemma 2.** $\mathbb{E}(B_{x,\text{in,normal}})$ can be calculated by,

$$
\mathbb{E}(B_{x,\text{in,normal}}) = \sum_{B=0}^{c_x} Be^{-B} \frac{P(B|\text{running})}{P(\text{decide to leave CS})}
$$

(6.20)

**Lemma 3.** The fraction $\frac{P(B|\text{running})}{P(\text{decide to charge})}$ can be evaluated by

$$
\sum_{B=0}^{c_x} e^{-B} \frac{P(B|\text{running})}{P(\text{decide to charge})} = 1
$$

(6.21)

**Theorem 3.** In worst scenario, $\mathbb{E}(N_c)$ can be computed as

$$
\mathbb{E}(N_c) = \begin{cases} 
\eta_x \mathbb{E}(M_1) / \tilde{B}_x & \text{for } l_1 \\
1 & \text{for } l_2 \\
\eta_x \mathbb{E}(M_2 + M_3) / \tilde{B}_x & \text{for } l_3 \\
\eta_x \mathbb{E}(M_4) / \tilde{B}_x & \text{for } l_4
\end{cases}
$$

(6.22)
The expected remaining battery $\mathbb{E}(B_{x,in})$ when charging in this case is

$$
\mathbb{E}(B_{x,in}) = \begin{cases} 
\mathbb{E}(B_{x,in,normal}) & \text{for } l_1, l_3, l_4 \\
0.9c_x & \text{for } l_2 
\end{cases}
$$  \hspace{1cm} (6.23)

In both cases, the expected leaving battery capacity $B_{x,out}$ is set as

$$
\mathbb{E}(B_{x,out}) = \mathbb{E}(B_{x,out,normal})
$$  \hspace{1cm} (6.24)

**Lemma 4.** $\mathbb{E}(B_{x,out,normal})$ can be calculated by

$$
\mathbb{E}(B_{x,out,normal}) = \sum_{B=0}^{c_x} Be^{B-c_x} \frac{P(B|\text{charging})}{P(\text{decide to charge})}
$$  \hspace{1cm} (6.25)

$$
\sum_{0}^{c_x} e^{B-c_x} \frac{P(B|\text{charging})}{P(\text{decide to charge})} = 1
$$  \hspace{1cm} (6.26)

The expected time spent on charging with CS (excluding waiting time) $T_g$ can be computed as

$$
\mathbb{E}(T_g) = \frac{\mathbb{E}(B_{x,out}) - \mathbb{E}(B_{x,in})\mathbb{E}(N_c)}{w_{\text{charging}}}
$$  \hspace{1cm} (6.27)

where $w_{\text{charging}}$ is the fixed charging speed of the CS.

When the number of total CS is smaller than that of vehicles, queuing should be considered. Two extreme scenarios are again considered: worst and best. In the worst scenario, all vehicles come at the same time with their energy demand, thus all vehicles are in queue. In the best scenario, all vehicles arrive uniformly across the time frame. Neither scenario is likely to happen in real or simulated cases, but these two settings give us a lower and upper bounds for the vehicles’ income.

The duration of each taxi when not running is

$$
\mathbb{E}(T_c) = d\mathbb{E}(T_g)
$$  \hspace{1cm} (6.28)

where $d$ is the extension factor for the total time of waiting and charging from actual charging time.
Figure 6.8: Two extremal EV arrival scenarios at a CS: (a) no overlap, and (b) simultaneous.

**Theorem 4.** In worst scenario, the extension factor \( d \) is

\[
d = \begin{cases} 
\frac{1}{2}(1 + \frac{n_{\text{taxi}}}{n_{\text{charger}}}), & \text{if } N_c \leq 1 \\
\frac{1}{2E(N_c)}[(1 + \frac{n_{\text{taxi}}}{n_{\text{charger}}}) + (1 + q)(E(N_c) - 1)], & \text{if } N_c > 1 
\end{cases} \quad (6.29)
\]

\[
q = \max\left(\frac{n_{\text{taxi}}}{n_{\text{charger}}}, 2 \frac{n_{\text{taxi}}}{n_{\text{charger}}} - \frac{w_{\text{charging}}}{\eta x E(V_x)}\right) \quad (6.30)
\]

**Theorem 5.** In best scenario, the extension factor \( d \) is 1.

**Theorem 6.** \( E(T_r) \) in each segment of \( l_1, l_2, l_3 \) and \( l_4 \) can be solved using equation system \( (6.13), (6.16), (6.17)/(6.22), (6.27) \) and \( (6.28) \).

Substituting \( E(T_r) \) in Lemma 1, \( E(U_x) \) can be calculated with Theorem 1.

### 6.5.2 Buses

The general approach to analyze buses is similar to taxis, but simpler.

**Theorem 7.** The expected income \( U_b \) is

\[
E(U_b) = E(M_b)E(U_b) - \eta_bE(M_b)r \quad (6.31)
\]

where \( M_b \) is the mileage of bus, \( U_b \) is the rate of income/mile for buses (a random variable with different distribution at \( l_1, l_2, l_3, l_4 \)).

**Lemma 5.** The expectation of \( M_b \) is

\[
E(M_b) = E(V_{b,t})E(T_{r,b}) \quad (6.32)
\]
As buses follow a fixed schedule, it is straightforward to see that the expected number of charges in each time period $\mathbb{E}(N_{c,b})$ is

$$\mathbb{E}(N_{c,b}) = \frac{\mathbb{E}(M)}{\bar{o}}$$  \hspace{1cm} (6.33)

where $\bar{o}$ is the fixed trip between charges. $B_{out}$ is always equal to the bus battery capacity $c_b$, so the time each bus spends on charging with CS is

$$\mathbb{E}(T_{g,b}) = \eta_b \frac{\mathbb{E}(N_{c,b})}{w_{charging}}$$  \hspace{1cm} (6.34)

The worst and best queuing scenarios for taxis can be applied to buses as well,

$$\mathbb{E}(T_{c,b}) = d_b \mathbb{E}(T_{g,b})$$  \hspace{1cm} (6.35)

**Theorem 8.** For worst case, $d_b$ can be calculated as

$$d_b = \begin{cases} \frac{1}{2}(1 + \frac{n_{bus}}{n_{charger}}) & \text{if } \mathbb{E}(N_{c,b}) \leq 1 \\ \frac{1}{28(N_{c,b})}[(1 + \frac{n_{bus}}{n_{charger}}) + (1 + q_b)(\mathbb{E}(N_{c,b}) - 1)] & \text{else} \end{cases}$$  \hspace{1cm} (6.36)

$$q_b = \max\left(\frac{n_{bus}}{n_{charger}}, 2 \frac{n_{bus}}{n_{charger}} - \frac{w_{charging}}{\eta_b \mathbb{E}(v_b)}\right)$$  \hspace{1cm} (6.37)

In best scenarios, $d_b$ is 1.

**Theorem 9.** $\mathbb{E}(U_b)$ can be solved in each respective time period by using the equation system (6.16), (6.31), (6.32), (6.33), (6.34) and (6.35).

### 6.5.3 Saturation Analysis

Due to the random nature of vehicle routing, it is necessary to consider the limit of the service capacity of the service provider. That is, within the certain period, the service provider cannot provide charging service longer than the length of that time period. In other word, for taxis and buses in each period $i$,

$$\sum_{cars/EVSE} \tau_{g,i} = \tau_{g,i} \frac{n_{car}}{N} \leq |l_i|$$  \hspace{1cm} (6.38)
Once the sum of $\tau_{g,i}$ is over the length of each period, the service capacity is considered to be reached.

Note that in previous analysis, time is divided into four separate periods and the saturation is bounded within each period. However, in reality/simulation, these four periods are not cut off from each other – the charging time of one period can be “compensated” by another neighboring period less saturated.

6.5.4 Numerical Comparison of Analytical Boundary and Simulation

In order to evaluate the accuracy of the analytical solution, the incomes for different number of vehicles in six months are computed and compared to the results of the Monte-Carlo simulation.

The result of the simulation and theoretical boundaries are shown in Fig. 6.9. It can be seen that the simulation result is narrowly located between the lower and upper boundaries. When approaching saturation, the simulation result gets closer to the lower boundary, which is reasonable as the charging queue gets more congested.

6.6 Use Case

The presented analytical solution can serve as an evaluation function for CS service operations without the need to run expensive numerical simulations. It can also assist in evaluations of larger system with CS as one of its component.

Examples of use cases of this model can be:

1. Prediction of income: By putting the estimated number of customers within a time period and their behavior in the model, CS service operators can easily evaluate their expected income over the period. This can be valuable for income report and corporate decisions.

2. Infrastructure planning: When a service provider plans to construct EVSE in certain
Figure 6.9: Comparison of theoretical boundaries and simulations in terms of income of aggregated vehicles and number of vehicles for (a) taxis, and (b) buses
market, the model can quickly evaluate service capacities of different options of EVSE infrastructure for specific customers, so that investors or planners can decide on the optimal infrastructure specifications to satisfy customer without overcapacity.

3. Optimal operation and bidding: Large scale CS operators may be able to bid in the grid ancillary service market. These services may require load cut, which will result in the decrease of service revenue and capacity. This model can help the service providers to quantify such decrease, and provide reference for making bids and finding optimal approach to operate under load cut.

6.7 Discussion

While the stochastic models try to emulate the random behaviors of each user as close to reality as possible, there are several assumptions in the numerical evaluations that need further improvement and studies:

1. The traveling to the CS service provider is neglected.

2. All vehicles are assumed to follow a diligent working pattern (work every day) and come to the designated CS without considering competition from other service providers.

3. The study also neglected the degradation of battery life over usage, and the State of Health (SOH) of serviced vehicles is considered to remain the same while being relatively healthy (> 80% maximum capacity).

4. The electricity pricing scheme used in the simulation is from Southern California Edison. Given different electricity prices at different locations in the world, the base cost for operation may also be different.
6.8 Conclusion

In this chapter, a Monte-Carlo model is developed to study the service capability and profitability of EV drivers and service providers. The stochastic interaction between EV drivers and service providers is simulated. Impact of key parameters, including battery capacity, vehicle speed and charging power, on the system profitability is evaluated. The model can be valuable to policymakers and EVSE service providers by providing evaluations of expected profitability with given customer estimates and infrastructure.

An analytic approach to evaluate the boundary conditions of the stochastic interactions is also proposed. Upper and lower boundaries of operating revenues are found by adding boundary users behaviors and arrival orders. The analytic approach provides additional insight into the complex stochastic model and facilitates future evaluations when system parameters are changed without computational expensive simulations.

6.9 Proofs of Theorems and Lemmas

Proof of Theorem 1. Based on (6.2),

\[ U_x = \sum_{t \in T} U_{x,t} = \sum_{t \in T_h} u_t V_{x,t} - \sum_{t \in T_c} e_t r \]  

(6.39)

where \( T \) is the set of all time slots, \( T_h \) is the set of time slots where taxi is hired and \( T_c \) is the set of time slots where taxi is charging. \( T_h \cap T_c = \emptyset \) and \( T_h \cup T_c \in T \).

Therefore \( \sum_{t \in T_h} V_{x,t} \) is the total mileage the taxi has traveled when hired and \( \sum_{t \in T_c} e_t \) is the total consumed energy.

The energy consumed by taxi is linearly dependent on the total traveled mileage, as shown in (6.1), so

\[ \sum_{t \in T_c} e_t = \eta_x M \]  

(6.40)

Substituting back in (6.39), (6.12) is proved.

Proof of Lemma 1. The relationship can be proved using Wald’s equation, considering each
time slot to be either hired or available,

$$E(M_{\text{hired}}) = E(V_{x,t}|\text{hired})E\left(\sum_{t=0}^{T_r} \mathbb{1}_{\text{hired}}\right)$$

$$= E(V_{x,t}|\text{hired})E(T_r)P_h$$

$$E(M_{\text{avail}}) = E(V_{x,t}|\text{avail})E\left(\sum_{t=0}^{T_r} \mathbb{1}_{\text{avail}}dt\right)$$

$$= E(V_{x,t}|\text{avail})E(T_r)(1 - P_h)$$

(6.41)

Proof of Theorem 2. With a large enough vehicle fleet, using law of large numbers, it can be assumed that on average the aggregated energy consumption within each time period gets filled within the same time period. So for $l_1$, $E(N_c) = \eta_xE(M_1)/\tilde{B}_x$.

As set up in (6.3) and (6.5), all taxis will charge during rest period almost surely at the beginning of $l_2$, so taxis will charge at least once and the mileage taxis traveled during $l_2$ will be carried over to $l_3$. So for $l_3$, $E(N_c) = \eta_xE(M_2 + M_3)/\tilde{B}_x$ for $l_3$. As assumed in the best scenario, taxis do not charge during $l_4$ and the energy used in $l_4$ is charged during $l_2$. Therefore for $l_2$, $E(N_c) = \max(\eta_xE(M_4)/\tilde{B}_x, 1)$.

Proof of Lemma 2. This can be seen by using the definition of expectation and Bayes’ Theorem. Let the driver’s state $s_t$ be a Markov process. $s_t$ can be $r$ (running) or $c$ (charging or swapping). When a driver decides to charge at time $t$, $s_t = c$ and $s_{t-1} = r$.

$$E(B_{x,\text{in,normal}}) = E(B|\text{decide to charge})$$

$$= \sum_{B=0}^{C_s} B \cdot P(B|s_t = c, s_{t-1} = r)$$

$$= \sum_{B=0}^{C_s} B \frac{P(s_t = c|B, s_{t-1} = r)P(B|s_{t-1} = r)}{P(s_t = c|s_{t-1} = r)}$$

(6.42)

$$= \sum_{B=0}^{C_s} B e^{-B} \frac{P(B|s_{t-1} = r)}{P(s_t = c|s_{t-1} = r)}$$

$$= \sum_{B=0}^{C_s} B e^{-B} \frac{P(B|\text{running})}{P(\text{decide to leave CS})}$$

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\( P(s_t = c | s_{t-1} = r) \) is a constant and \( P(B | s_{t-1} = r) \) is approximated to be constant for all \( B \) for simplicity.

\[ \text{Proof of Lemma 3} \] From the proof of Theorem 2,

\[
P(B | s_t = c, s_{t-1} = r) = e^{-B} \frac{P(B | s_{t-1} = r)}{P(s_t = c | s_{t-1} = r)}
\]

(6.43)

Since \( B \) can only be from 0 to \( c_x \),

\[
\sum_{B=0}^{c_x} P(B | s_t = c, s_{t-1} = r) = 1
\]

(6.44)

\[ \text{Proof of Theorem 3} \] For \( l_1 \) and \( l_3 \), the reasoning is the same with Theorem 2. Since the assumption that drivers behave normally in busy hours, for \( l_4 \), \( \mathbb{E}(N_c) = \eta_x \mathbb{E}(M_4) / \tilde{B}_x \) for \( l_4 \).

During rest period, drivers are still expected to charge exactly once.

\[ \text{Proof of Lemma 4} \] The proof of this lemma is identical to Lemma 2 and Lemma 3.

\[ \text{Proof of Theorem 4} \] If \( N_c \) is smaller than 1, no taxi will make recurring trip to the CS. The first taxi in line will have no waiting time, the second taxi will have the waiting time of the first taxi and the last taxi will need to wait for the rest of the taxis to finish. So the average \( d \) is the total charging and waiting time of all vehicles per CS divided by the number of taxis per CS.

\[
d = \left( \sum_{i=1}^{n_{\text{taxi}}/n_{\text{charger}}} i \right) / \left( n_{\text{taxi}} / n_{\text{charger}} \right)
\]

(6.45)

\[
d = \frac{1}{2} \left( 1 + \frac{n_{\text{taxi}}}{n_{\text{charger}}} \right)
\]

If \( N_c \) is larger than 1, a line extension should be considered for the case that when the next round of vehicles arrive, vehicles from previous round has not yet finished. The number of vehicles in this situation is \( \frac{\tilde{B}_x}{\eta_x \mathbb{E}(V_x)} / \frac{\tilde{B}_x}{w_{\text{charging}}} \). In this case, the length of the line is

\[
q = \frac{n_{\text{taxi}}}{n_{\text{charger}}} + \max(0, \frac{n_{\text{taxi}}}{n_{\text{charger}}} - \frac{\tilde{B}_x}{\eta_x \mathbb{E}(V_x)} / \frac{\tilde{B}_x}{w_{\text{charging}}})
\]

(6.46)

\[
= \max(\frac{n_{\text{taxi}}}{n_{\text{charger}}}, 2 \frac{n_{\text{taxi}}}{n_{\text{charger}}} - \frac{w_{\text{charging}}}{\eta_x \mathbb{E}(V_x)})
\]

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So for $N_c > 1$, $d$ is

$$d = \frac{1}{2 \mathbb{E}(N_c)} \left[ \left( 1 + \frac{n_{\text{taxi}}}{n_{\text{charger}}} \right) + (1 + q)(\mathbb{E}(N_c) - 1) \right] \quad (6.47)$$

Proof of Theorem 5. In best scenario, taxis arrive uniformly across the time frame. Therefore, if the total charging time is less than the length of the period, there should be no waiting time for any vehicle (each taxi arrives at a time with idle CS).

Proof of Theorem 6. In this system, the unknowns are $T_c$, $T_r$, $T_g$, $M$, $N_c$. There are five equations (6.13), (6.16), (6.17)/(6.22), (6.27) and (6.28). Therefore, the system is solvable.

Proof of Theorem 7. The proof of this theorem is identical to Theorem 1.

Proof of Lemma 5. The proof of this theorem is identical to Lemma 1. Specifically, as set up in the stochastic model, the speed of running bus (average speed) is independent of the total running time.

Proof of Theorem 8. The proof is identical to Theorem 4 and Theorem 5.

Proof of Theorem 9. There are six unknowns, $U_b$, $M_b$, $T_{g,b}$, $T_{r,b}$, $T_{c,b}$, $N_{c,b}$ and six equations. Therefore, the system is solvable.
CHAPTER 7

Discussion

Today, the trends for large battery EVs (including semi-trucks) and high power charging stations are clear. The electric grid will face larger challenges to balance and manage the load from EVs. The incentive mechanism presented in this dissertation can be adopted in such scenarios. However, in order to have a truly effective incentive and load management system, special attention of research and technology development should be paid in the following areas:

1. **Interoperability between devices:** Currently the data available from EVs to aggregators or utilities is limited over concerns of proprietary data and security. However, in order to effectively manage load and provide incentives, more data should be accessible for upstream entities. For example, charging stations should be able to understand and anticipate how EVs’ Battery Management System (BMS) will decrease its asking charging rate over time in a charging session (BMS’ strategy to protect battery health). EVs and charging stations should also be able to operate collectively and process a wide range of control signals from aggregators and utilities.

2. **Understanding of user behaviors:** All technologies are designed to serve the users eventually and it’s important to understand user behaviors, needs and responses to different scenarios. More varieties of experiments, surveys and big data analyses should be conducted to better understand user behavior.

3. **Protection of user privacy:** User’s daily pattern and energy demand can be sensitive private matters. While more data is better for effective system control, it is important to develop technology to protect the anonymity, security and privacy of user’s data.
4. *Popularization of V2G technology:* While V2G is widely discussed in academia and industry today, it has not seen commercial success yet. In addition to problems on hardware standardization and infrastructure support, there still lacks an effective commercialization strategy. Users worry more about V2G’s damage to their battery life than the small compensation provided in return. Therefore, it is important to enable users to make well-informed decisions and provide compensations they deserve. Innovative incentives, integrated energy management system and disruptive technologies (such as self-driving) can be keys to a feasible commercialization solution for V2G in the future.
CHAPTER 8

Conclusion

The fast growing number of electric vehicles is adding more energy demand onto the electric grid. However, electric vehicles usually use high power to charge their batteries, amplifying the demand-supply discrepancy in today’s grid, most famously described by the “California Duck Curve”. Therefore, it is critical to manage this new wave of energy demand effectively. This dissertation presents comprehensive efforts to improve the current state-of-art on using electric vehicles to mitigate the supply-demand disparity through incentive designs, infrastructure optimization and user behavior analysis. The presented system provides unique insights and experience on designing and deploying the next-generation electric vehicle charging systems.

The contribution of the dissertation can be summarized as following:

1. An incentive system integrated with priority-based ranking system is proposed, studied and verified to mitigate the supply and demand discrepancy in the electric grid. The system is designed considering realistic concerns and limitations.

2. The prioritization framework is the first in the existing electric vehicle charging systems to provide incentives without the need for dynamic pricing and forced control on users. This makes the system suitable and flexible for commercial deployments.

3. The consumption ratio is defined to counter the impact of seasonal variations of solar generation to measure user behaviors.

4. Experiments are designed to verify the system effectiveness. Solar consumption ratio has increased by 37% in the 15 months experiments in Parking Structure 2. More than...
23% of the participants in the 14 month experiments in Parking Structure 9 use the automatic system algorithms regularly to improve their consumption behaviors.

5. Experiments in Parking Structure 9 show that the system is effective in promoting the value of solar credit and priority.

6. In-system virtual currency incorporated with blockchain technology is designed to provide monetary incentives to users.

7. Extensive design improvements and algorithm optimization have been implemented on the hardware and software of the charging equipment and system.

8. Electric Vehicle Supply Equipment components are modernized to incorporate smart mobile applications and advanced connectivity.

9. A two-level Energy Management System has been proposed, designed and implemented to conduct energy coordination for projects over 3 years in different geographic locations.

10. Data for 18,599 charging session with 340 users is analyzed to find the best way to characterize user consumption patterns.

11. A comprehensive stochastic model is proposed to model the income of electric vehicle drivers and charging service providers based on their stochastic interactions.
APPENDIX A

Implementation of Smart Charging Algorithms

The detailed implementation of smart charging algorithm is discussed in the appendix. The presented algorithm is deployed in UCLA PS2, PS9 and Santa Monica Civic Center.

A.1 Incentive (Priority Round Robin vs Priority Current Sharing)

A.1.1 Priority Round Robin

The detailed algorithms to implement Priority Robin is shown in this section.

A.1.1.1 Recurrent Checker

\[
\begin{align*}
\text{box.station} & \leftarrow \text{all station associated with box} \\
\text{allBox} & \leftarrow \text{all boxes} \\
\text{ongoingSession} & \leftarrow \text{all ongoing sessions} \\
\text{pausedSession} & \leftarrow \text{all paused sessions} \\
\text{cycleThreshold} & \leftarrow \text{energy threshold for large charging sessions} \\
\text{solarThreshold} & \leftarrow \text{critical threshold for solar generation} \\
\text{solarEnrolledUsers} & \leftarrow \text{list of users who enrolled in the automatic solar program} \\
& \text{check for charging without session}
\end{align*}
\]

For Each box in allBox do

For Each station in box.station do

if station is charging in the last 5 min then
if station is not in ongoingSession.station then
turnOff(station)
end if
end if
end for
end for

For Each session in ongoingSessions do
  ▷ check for finished charging sessions
  if session.station is not charging within last 10 minutes and started for more than 15 minutes then
    requestStop(session)
  else
    ▷ check for user with very large demand
    if session.chargedPower > cycleThreshold(session.round + 1) then ▷ the initial value for session.round is always 0
      session.round session.round + 1
      evaluateChargingQueue(session.box)
    end if
    if session.station is unplugged then requestStop(session)
  end if
end if
end for

▷ check for solar generation and if any change exists for solar program enrolled users
if solarGeneration > solarThreshold then
  if any pausedSession.pausedDueToSolar == True then
    evaluateChargingQueue(solarPausedSession.box)
  end if
else
  if ongoingSession.user in solarEnrolledUsers then

evaluateChargingQueue(sessionWithEnrolledUser.box)

end if
end if

A.1.1.2 evaluateChargingQueue(box)

Input: the box to evaluate the charging ranking

activeSession ← all active sessions (including ongoing and paused) within the box, sorted
first by session.boost from high to low, session.round from low to high and by session.user.solarScore
from high to low

solarThreshold ← critical threshold for solar generation

allowedStation ← 1

index ← 0

For Each session in activeSession do
    if index < allowedStation then
        ▶ high ranked user to start charging
        if session.user is not enrolled in solar program then
            charge← 1
        else
            if solarGeneration > solarThreshold then State charge ← 1
                else charge← 0
            end if
        end if
    end if
    if charge == 1 then
        if session.station is charging then
            status ← True
        else
            status turnOn(session.station)
        end if
    end if
    if status == True then

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if session.startTime is null then
    \[\text{first time the session is being started}\]
    session.onGoing $\leftarrow$ True
    session.startEnergy $\leftarrow$ session.station.getEnergy()
    session.startTime $\leftarrow$ currentTime
else
    session.onGoing $\leftarrow$ True
end if
else if
    \[\text{the user is being paused due to low solar generation, move on to next user}\]
    if session.station is not charging then
        status $\leftarrow$ True
    else
        status $\leftarrow$ turnOff(session.station)
    end if
if status == True then
    session.paused $\leftarrow$ True
    session.pausedDueToSolar $\leftarrow$ True
    allowedStation $\leftarrow$ allowedStation + 1
end if
else
    \[\text{pause lower ranked users}\]
    if session.station is not charging then
        status $\leftarrow$ True
    else
        status $\leftarrow$ turnOff(session.station)
    end if
if status == True then
    session.paused ← True
    session.pausedDueToSolar ← False
end if

end if

index ← index + 1
end for

A.1.1.3 requestStop and requestStart

In addition to being called in other algorithms, requestStart() and requestStop() are also called when users manually request to start and stop their charging sessions respectively. Functions turnOn() and turnOff() are direct commands to turn on and off the charging stations through HTTP commands, and return True if the commands succeed. The method within the station class getEnergy() is to get the reading of the accumulative energy counter of the station so that we can calculate the consumed energy during each charging session. A detailed user interface on the different scenario in the algorithm is shown in Fig A.1.

A.1.2 Priority Current Sharing

A special smart charging scheme is implemented in Santa Monica Civic Center for public use. In order to encourage smart charging of users by observing real-time solar energy generation and other Demand Response signals, the following incentive scheme is published and implemented to users.

In general, users will share the 30 A circuit when they are plugged in on the same charger. Users do not need registration to activate the charger. However, registered users can associate their account with a smart plug to accumulate Solar Score (see below) and build up their solar usage profile. A registered user with higher solar score will receive higher charging power.

The Amperage distribution is shown in Table A.1.
Algorithm 11 requestStop(session)

Input: the session to stop

if session.startEnergy is null then
    session.onGoing ← false
else
    if session.station is not charging then
        status ← True
    else
        status ← turnOff(session.station)
    end if
    if status == True then
        session.onGoing ← false
        session.finishEnergy ← session.station.getEnergy()
    end if
end if

Algorithm 12 requestStart(station, user)

Input: the station to start, the user who requests the session

Create activeSession with the requested station and user

evaluateChargingQueue(session.box)
Figure A.1: Mobile iOS interface with ranking algorithm (a) paused scenario with second rank (b) system explanation to the user on the algorithm (c) boost confirmation interface (d) result of a boost session / first ranked non-paused scenario.

Table A.1: Amperage distribution for current sharing scenario

<table>
<thead>
<tr>
<th>Plug 2</th>
<th>Not used</th>
<th>Higher Score</th>
<th>Lower Score</th>
<th>Unregistered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plug 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not Used</td>
<td>N/A</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Higher Score</td>
<td>0</td>
<td>15</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>Lower Score</td>
<td>30</td>
<td>18</td>
<td>15</td>
<td>18</td>
</tr>
<tr>
<td>Unregistered</td>
<td>30</td>
<td>12</td>
<td>12</td>
<td>12</td>
</tr>
</tbody>
</table>

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Table A.2: Amperage in boost session

<table>
<thead>
<tr>
<th>Number of Vehicles plugged in</th>
<th>Vehicle 1 (Boosting Mode)</th>
<th>Vehicle 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>24 A</td>
<td>6 A</td>
</tr>
</tbody>
</table>

Table A.3: Reward rate for user participation in DR

<table>
<thead>
<tr>
<th>SMERCOIN Rewards</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 2 EV Chargers</td>
<td>20 SMERCOINS™ Turned off for 10 minutes at 30 min DR event</td>
</tr>
<tr>
<td>DCFC (Charging)</td>
<td>40 SMERCOINS™ Turned off for 10 minutes at 30 min DR event</td>
</tr>
<tr>
<td>DCFC (Discharging)</td>
<td>10 SMERCOINS™ /kWh Discharged at 30 minute DR event.</td>
</tr>
</tbody>
</table>

In this case, algorithm `evaluateChargingQueue` is changed into Algorithm A.1.2.

Additionally, `getTheOtherStation(station)` returns the station that belongs to the the same box but different than the input station. `changeDutyCycle(dutyCycle)` changes the station duty cycle into the input value. If the duty cycle is 0, it is equivalent to turning off. If initially the station is turned off, the function also turns on the station before changing into the designated duty cycle. The function has no effect for station with no car plugged in or car is fully charged.

Users will receive 0.25 SMERCOINS per kWh when the vehicle is charged with solar energy.

User can use their SMERCOINS to boost their charging power to 24 A on a Level 2 EV charger when both plugs are used. A fixed amount of 25 SMERCOINS will be deducted during a boost session as shown in Table A.2.

A registered user can choose to manually and completely turn off their charging session from the mobile app during that 30 min and receive SMERCOINS Reward during a DR event. A registered DCFC user can also choose to discharge their battery to help the power grid and receive SMERCOINS rewards. The reward rate is shown in Table A.3.
Algorithm 13 evaluateChargingQueue (box)

Input: the box to evaluate the charging ranking

activeSession ← all active sessions (including ongoing and paused) within the box, sorted first by session.boost from high to low, session.round from low to high and by session.user.solarScore from high to low

onStation ← all stations that are charging

if activesession == 1 then
    onDuty = onStation.number == 1? 50:30
    offDuty = onStation.number == 1? 0:20
else
    onDuty = 30
    offDuty = 20
end if

index ← 0

For Each session in activeSession do

    if index < allowedStation then

        if session.boost == 1 then

            onDuty = 40
            offDuty = 10

        end if

        theOtherStation = getTheOtherStation(session.station)
        theOtherStation.changeDutyCycle(offDuty)
        session.station. changeDutyCycle(onDuty)

    end if

    index ← index + 1

end for
A.2 SMERCOIN Trading System

Users can trade their solar credit with other users or the system with SMERCOINS. Their new Solar Score will be increased (if they buy higher solar usage profile from others) or decreased (if they sell solar usage profile to others). The user score after trading for buyer and seller can be computed as the following

\[ u_{\text{buyer}} = \frac{E_{\text{solar, buyer}} + E_{\text{trade}}}{E_{\text{total, buyer}} + E_{\text{trade}}} \]  \hspace{1cm} (A.1)

\[ u_{\text{seller}} = \frac{E_{\text{solar, seller}} - E_{\text{trade}}}{E_{\text{total, seller}} - E_{\text{trade}}} \]  \hspace{1cm} (A.2)

When selling their solar credit, user can either sell it directly to system, which is instantaneous, or put it on the market to wait for other users to buy. The system purchase price is fixed but user can define their own price if they decide to put it on the market for others to buy.

When purchasing solar credit, the system first looks for user listing and sort them from low to high and automatically provides the cheapest purchasing price for the amount of solar credit user wants to buy. If no user listing, user can purchase solar credit directly from system. The interface associated is shown in Fig. A.2.

The trading is anonymous. The purchasing algorithm is shown as below.

**Input:** user, amount of solar credit to purchase, price to pay, if purchase from system

systemPrice ← Price of buying solar from system

allListing ← All solar credit offerings from all users, sorted from low price to high price

if system == 1 then

  if solar·systemPrice == price then
    user.solarCredit += solar
    user.coin -= solar·systemPrice
  else
    return Error

  \[ \triangleright \text{purchase from system} \]
Figure A.2: Mobile iOS interface with trading (a) sell solar page (b) purchase page (d) trading history
end if
else
    pricePrime = 0
    energyPrime = solar
    Index = 0
    For Each listing in allListing do
        if energyPrime > listing.energy then

            energyPrime -= listing.energy
            pricePrime += listing.price * listing.energy
            transaction[index].listing = listing
            transaction[index].energy = listing.energy
        else

            pricePrime += listing.price * energyPrime
            transaction[index].listing = listing
            transaction[index].energy = energyPrime
        end if
    index++
end for
if pricePrime == price then
    for buyIndex = 0:index-1 do
        user.coin -= transaction[buyIndex].listing.price * transaction[buyIndex].energy
        user.solar += transaction[buyIndex].energy
        transaction[buyIndex].listing.user.coin += transaction[buyIndex].listing.price * transaction[buyIndex].energy
        transaction[buyIndex].listing.user.solar -= transaction[buyIndex].energy
    end for
else
    return Error
end if
end if

end if

end if
REFERENCES


Mostafa Rezaei Mozafar, M Hadi Amini, and M Hasan Moradi. “Innovative appraisement of smart grid operation considering large-scale integration of electric


