Modeling and Analysis on Electric Vehicle Charging

by

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B. Eng., Northwestern Polytechnical University, 2009
M. Eng., Northwestern Polytechnical University, 2012

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Abstract

The development of electric vehicle (EV) greatly promotes building a green and sustainable society. The new technology also brings new challenges. With the penetration of electric vehicles, the charging demands are increasing, and how to efficiently coordinate EVs' charging activities is a major challenge and sparks numerous research efforts. In this dissertation, we investigate the EV charging scheduling problem under the public charging and home charging scenarios from different perspectives.

First, we investigate the EV charging scheduling problem under a charging station scenario by jointly considering the revenue of the charging station and the service requirements of charging customers. We first propose an admission control algorithm to guarantee the non-flexible charging requirements of all admitted EVs being satisfied before their departure time. Then, a utility based charging scheduling algorithm is proposed to maximize the profit for the charging station. With the proposed charging scheduling algorithm a win-win situation is achieved where the charging station enjoys a higher profit and the customer enjoys more cost savings.

Second, we investigate the EV charging scheduling problem under a parking garage scenario, aiming to promote the total utility of the charging operator subject to the time-of-use pricing. By applying the analyzed battery charging characteristic, an adaptive utility oriented scheduling algorithm is proposed to achieve a high profit and low task declining probability for the charging operator. We also discuss a reservation mechanism for the charging operator to mitigate the performance degradation caused by charging information mismatching.

Third, we investigate the EV charging scheduling problem of a park-and-charge system with the objective to minimize the EV battery degradation cost during the charging process while satisfying the battery charging characteristic. A vacant charging resource allocation algorithm and a dynamic power adjustment algorithm are proposed to achieve the least battery degradation cost and alleviate the peak power load, which is beneficial for both the customers and charging operator.

Fourth, we investigate the EV charging scheduling problem under a residential community scenario. By jointly considering the charging energy and battery performance degradation during the charging process, we propose a utility maximization problem to optimize the gain of the community charging network. A utility maximized charging scheme is correspondingly proposed to achieve the utility optimality for the charging network.

In summary, the research outcomes of the dissertation can contribute to the effective management of the EV charging activities to meet increasing charging demands.

Contents

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List of Abbreviation

AC .... Alternating Current

CC-CV .... Constant Current Constant Voltage

DC .... Direct Current

DOD .... Depth of Discharge

EMS .... Energy Management System

EV .... Electric Vehicle

EVCS .... Electric Vehicle Charging Station

PHEV .... Plug in Hybrid Electric Vehicle

PV .... Photovoltaic

QoS .... Quality of Service

RTP .... Real Time Pricing

SOC .... State of Charge

TOU .... Time of Use

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Zhe Wei, Victoria, BC, Canada

Dedication

To My Dear Family, Mentors, and Motherland.

Chapter 1

Introduction

1.1 Background

Environment pollution and climate change have become global concerned problems in recent decades. In order to reduce the dependence on traditional fossil fuels and the greenhouse gas emissions, governments worldwide actively find alternative energy resources and advocate to exploit clean energies to build a green and sustainable society. Electrification of the transportation system is a key to promote the sustainable energy development and addressing climate change issues. Despite various incentives are introduced by government to encourage people to purchase electric vehicles, the penetration rate of EV is still low. Limited cruising range and lack of convenient charging facilities are among the major obstacles for EV promotion. Moreover, without a good coordination, the aggregated charging demand of a large number of EVs may produce a large peak load which negatively affects the power grid. EV brings both challenges and opportunities to future smart grid. Consequently, to build a green, intelligent, and efficient transportation system, it is necessary and important for EVs, charging stations, and the smart grid to establish an effective charging scheduling mechanism.

Generally, EV charging activities involve three participants: power grid, charging aggregator, and customers. The EV charging problems thus mainly have been studied from three perspectives: smart grid oriented, charging aggregator oriented, and customer oriented. The first category addresses the issues related to the impact of EV charging activities on power grid, such as load flattening, frequency regulation, voltage regulation and so on. The charging aggregator bridges the power grid and EV customers. Specifically, a charging aggregator is responsible for maintaining a stable and reliable power system, while being responsible for satisfying EV customer's charging demand. For an aggregator the main motivation is still to make more profits, while for an EV charging customer the most concerned part is quality of service, for instance how fast is the charging completed, charging cost, battery health, etc.

Many existing works dealing with the EV charging scheduling problem often simply utilized the first-come-first-serve (FCFS) strategy without full consideration on other relevant factors, such as electricity price, battery SOC, etc. In some cases, so long as the charging can be finished before the deadline, it is preferable to schedule the charging flexibly not necessarily to follow the coming sequence. Some existing works scheduled the EV charging activities only considering the interest of either aggregator or customer, e.g., maximizing the profit for the charging aggregator or minimizing the charging cost for the customer. It is reasonable and important to have a comprehensive consideration to guarantee the interests of both parties while scheduling the charging requirements. The battery charging rate is also a varying parameter related to its state of charge (SOC). Overlooking this factor and assuming a constant charging rate during the whole process does not align with the real charging situation. Considering the battery intrinsic electrochemical characteristic is critical to reflect the real charging amount variation during the charging process. In addition, it also provides guide for effective charging scheduling design. As the heart of the EV energy supply, the battery performance plays a vital role in each EV's operation. Ensuring the battery health and efficient operation, extending the battery lifetime is an important issue during the charging process.

All those concerns mentioned above bring new challenges and opportunities to optimize the EV charging scheduling. Given the prospect of EV development and the needs to solve the above problems related to EV charging, this dissertation has shed some new lights on addressing the aforementioned challenges, which will be discussed progressively in the following sections.

1.2 Research Objectives and Contributions

1.2.1 Utility Maximization for Electric Vehicle Charging with Admission Control and Scheduling

Given the ever-increasing EV charging demands, more and more EV owners and users need to find a public charging station for charging.

Without a proper coordination of the charging activities, the charging operator may unnecessarily decline some charging requests resulting in revenue loss or the customers may lose the potential charging opportunities unwillingly. Most existing works mainly focus on the interest of one side, either minimize the cost for the customers or maximizing the profit for the charging station with no assurance for the interest of the other side. In addition, the EV mobility dynamics are also overlooked in some existing works. They require all the EVs' charging profiles being negotiated with the charging station one day ahead, which is not practical in real situation since for the randomly arrived customers all the charging information only can be revealed after the vehicle's arriving at the charging station. Thus, how to coordinate multiple EVs' charging demands to satisfy the requirements of the customers and also maximize the profit for the charging station is an important and challenging problem.

To tackle the above problem, we propose a utility based multi-charger framework for EV charging scheduling in a public charging station, which aims to maximize the profit of the charging station while satisfying the requirements of the customers. The QoS of the charging customers are guaranteed by the developed admission control mechanism and the profit for the charging station is maximized by utilizing the proposed scheduling algorithm. The performance of the proposed algorithm are evaluated with extensive simulations with the practical EV charging information consideration.

1.2.2 Intelligent Parking Garage EV Charging Scheduling Considering Battery Charging Characteristic

Different from the traditional cognition of a gas station styled charging station, it is anticipated that the future parking garages, such as the parking lots for office buildings, residential and business areas can provide charging services and function as charging stations. For the charging station operator, how to obtain the maximum profit under the premise of customer quality of service assurance is the most concerned topic.

The charging station operator not only provides charging service to the customers subject to a retail price, but also purchases electricity from the power grid under a wholesale price. Thus, the electricity pricing plays an important role on the profitable operation of the charging station, which needs to be well considered in the EV charging scheduling problem. Moreover, the battery charging rate is not constant during the whole charging process, which is neglected in many existing works. It is actually a varying parameter related to the battery SOC which significantly affects the charging efficiency. Thus, it is crucial for the charging operator to well schedule the different charging requirements taking into account the charging power variation and electricity price change.

To address the above issues, we are motivated to devise an intelligent adaptive utility oriented scheduling algorithm to optimize the total utility for the charging operator under the widely adopted time-of-use (TOU) pricing, which can robustly achieve low task declining probability and high profit. We also consider the charging information mismatching situation with vehicle stochastic arrivals and propose a reservation mechanism for the charging operator to mitigate the performance degradation caused by the information mismatching. Extensive simulations based on realistic EV charging parameters are conducted to evaluate the superior performance of the proposed charging scheduling scheme.

1.2.3 Electric Vehicle Charging Scheme for a Park-and-Charge System Considering Battery Degradation Costs

A major factor preventing the proliferation of electric vehicle in the current auto market is the high cost of EV batteries. EV battery replacement cost is still high nowadays, which makes a lot of people hesitated to choose this new transportation technology. For each existing EV owner ensuring the healthy and efficient operation of the battery and extending the battery lifetime is one of the most concerned issues. It is also a very important issue from the charging service provider's perspective when they provide charging service to the customers.

Many internal and external factors affect the battery performance and lifetime. The natural aging of battery itself is inevitable, but reducing the inappropriate operation during the charging process could effectively slow down the battery degradation. It has been found that a higher large charging power, which makes the battery temperature rise rapidly, leads to faster battery degradation. Thus, how to minimize the EV battery charging degradation cost while satisfying the battery charging requirement is an important and challenging task.

To resolve the above mentioned issues, we explore the features of the battery degradation cost minimization problem and find that it can be decomposed into two sub-problems. A vacant charging resource allocation algorithm and a dynamic power adjustment algorithm are proposed to minimize the battery degradation cost.

Several simulations based on realistic EV charging settings are conducted to evaluate the effectiveness and applicability of the proposed algorithms in achieving the most degradation cost reduction and peak load relieving.

1.2.4 Maximum Utility Scheduling for Residential Community Electric Vehicle Charging

The previous chapters mainly discussed the EV charging problem under the public charging scenario. As another important and common scenario for EV charging, home charging is pervasive and convenient for those EV owners who have their own parking garages. They can plug in their EVs for charging during the night time and unplug the charged EV the next morning.

However, unlike the public charging stations that are deliberately designed for EV charging, a large number of EVs charging at home simultaneously can cause a new peak load and pose great stress to residential community transformers which are designed without considering the high-demanding load from EVs. Therefore, it is necessary to have a charging aggregator within the residential community to control EVs' charging activities. Meanwhile, as we introduced in last subsection, the charging process itself has some impacts on the battery performance. With the increase of battery SOC the charging efficiency is substantially decreased. The gained energy from accumulated charging may be less than the cost of battery degradation. Thus, how to effectively maximize the total gain of the charging community under the premise of ensuring the expected charging energy of the charging request customers is an important and challenging topic, which attracts us to study.

To achieve the goal, we propose a utility maximization problem to comprehensively evaluate the gain of the charging activity by jointly considering the charging energy and battery performance degradation during the charging process. After proving that the proposed problem is a concave optimization problem, we devise a utility maximized charging scheme to achieve the maximum gain for the whole community charging network. Simulation results verify the effectiveness and practicability of the proposed scheme.

1.3 Dissertation Organization

This work focuses on the modeling and analysis on electric vehicle charging scheduling. The remainder of the dissertation is organized as follows.

In Chapter 2, we discuss the utility maximized EV charging scheduling problem under a charging station scenario. A win-win situation is achieved for both the charging station and charging customers, where the charging station can enjoy a higher profit and the customers can enjoy more cost savings.

In Chapter 3, we integrate the electricity pricing and battery charging characteristic on EV charging scheduling problem under the workplace parking garage scenario. By applying the designed scheduling algorithm and reservation mechanism the charging operator can achieve a low task declining probability and a high profit.

In Chapter 4, we investigate the EV charging problem of a park-and-charge system with the objective to minimize the battery degradation cost while satisfying the battery charging characteristic. The proposed charging scheme could achieve the least degradation cost and effectively alleviate the peak power load.

In Chapter 5, we study another commonly experienced residential community charging scenario. By comprehensively evaluating the gain of the whole charging network, we propose a utility model incorporating the total charging energy and corresponding battery degradation. Optimal utility of the whole charging network is achieved with the proposed utility maximized charging scheme.

Chapter 6 concludes the dissertation and suggests the future research directions.

1.4 Bibliographic Notes

Most of the works reported in this dissertation have appeared or been submitted as research papers. The work in Chapter 2 has been published in [1]. The work in Chapter 3 was published in [2] and will be published in [3].

Chapter 2

Utility Maximization for Electric Vehicle Charging with Admission Control and Scheduling

2.1 Introduction

The emergence of electric vehicle promoted the development of green transportation, but also brought a greater challenge to meet the large amount of charging demands [4]. There is a great demand for building charging stations in densely populated areas, such as the airports, shopping centers, office buildings, and other business and residential places. However, for the operator of a charging station how to coordinate multiple EVs' charging activities to satisfy their requirements and also maximize the operational profit is an important and challenging problem.

In this chapter, to facilitate a win-win situation, a utility-based multi-charger charging framework is developed, aiming to maximize the charging station's profit while satisfying the non-flexible charging requirements of all admitted EVs. First, from the customer's perspective, we classify the charging requirements of an EV into a non-flexible charging requirement for its necessary daily usage, and a flexible charging requirement that is associated with a lower price but without charging service guarantee. In other words, the flexible charging requirement may or may not be served depending on the availability of idle chargers. Second, we formulate a utility optimization problem to maximize the profit of the charging station. Then, we develop the admission control and scheduling algorithms to solve the problem.

Furthermore, we conduct extensive simulations to evaluate the performance of the proposed algorithms. The results demonstrate that the proposed algorithms can outperform the state-of-the-art solution in terms of total utility, so that the charging station can enjoy a higher profit and the customers can enjoy more cost savings.

2.2 Related Work

Recently, a lot of researches have been conducted on the EV charging scheduling problem [5–21]. For instance, [7] applied Nash equilibrium to develop a decentralized charging control algorithm for large populations of EVs and achieved social optimality. It requires all EVs to negotiate with the charging station about their charging profiles one day ahead. This assumption does not hold with the practical case that most randomly arrived EVs' charging profiles can only be revealed after its arrival at the charging station. In [9–13], the scheduling algorithms can efficiently coordinate the EVs' charging requirements and achieved revenue gains. For example, [12] designed an online speeding optimal scheduling algorithm and achieved a known competitive ratio. The charging station's service capacity is not taken into consideration for the aforementioned works.

The authors in [16, 17] made efficient use of the distributed power of EVs and maximized the revenue of the aggregator. But these methods mainly considered the aggregator's interest, which may not necessarily lead to the maximum benefit for customers. Chen et al. utilized the Least Laxity First (LLF) algorithm of CPU scheduling in EV charging scheduling [9] and showed that it was optimal for single charger. However, it cannot be guaranteed optimal for multi-charger scenarios. [18] proposed an effective Receding Horizon Control (RHC) algorithm for scheduling the deferrable electric loads, and the usage of instant grid generation was effectively decreased, while the computation complexity was too high to be implemented. [19, 20] well controlled and coordinated multiple EVs' charging to minimize the peak loads and load profile variability, but the fairness for each customer was not well concerned.

For multi-charger charging, how to ensure the service requirements of the customers while maximizing the charging station profit and the cost savings for customers is an open, challenging issue, which motivates us to study on this problem.

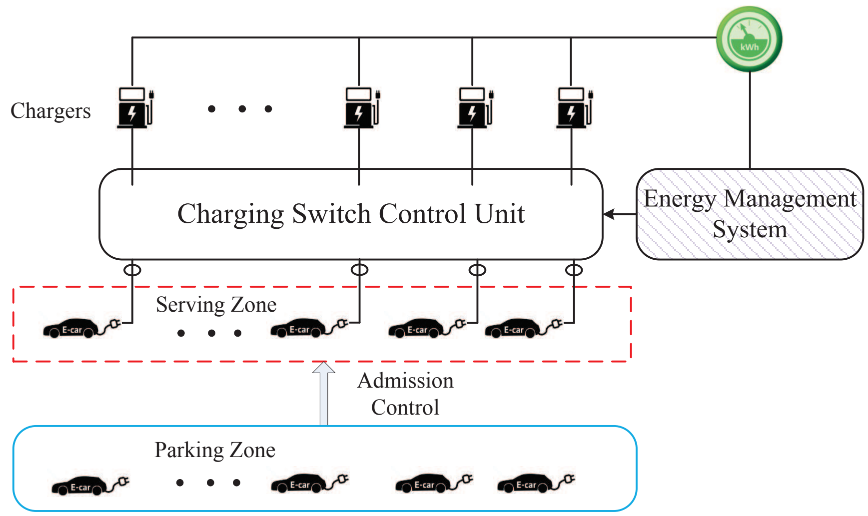


Figure 2.1: System model.

2.3 System Model and Problem Formulation

We consider the problem of how to maximize the profit of a charging station by scheduling the charging of multiple EVs to satisfy their inflexible requirements without missing their specified deadlines. As illustrated in Fig. 2.1, when an EV arrives at the charging station, it reports its charging requirement and departure time to the charging station control center. The control center then makes a decision on admitting or declining the customer's requirement based on its admission control mechanism. Once an EV is admitted, it enters the serving zone and is connected to the charger. Then, the Energy Management System (EMS) controls a Charging Switch Control Unit (CSCU) to switch the power supply to activate or de-active the charging of in-facility EVs to maximize the profit of its operation.

2.3.1 EV Charging Model

Consider an EV charging station comprising of M chargers. The total business hours for the charging station is divided into time slots with the slot duration of Δt, and the total number of time slots available for charging per day is T. Assuming that the arrivals of EVs follow the Poisson distribution with an average arrival rate λ (number of vehicles per slot). During service, each EV draws a constant charging rate to fill up its battery. The charging requirement of an EV can be regarded as a *Task*, which is defined as follows.

*Definition 1 (**Task**)*:The ith EV arrives at the charging station at time t_i^a with the inflexible minimum charging requirement r_i^{min}, the desired maximum charging requirement $r_i^{desired}$, and expected departure time t_i^d, the charging requirement is parameterized by a vector $T_i = (i, t_i^a, t_i^d, r_i^{min}, r_i^{desired})$, which is defined as *Task i*.

Given the constant charging rate, each EV's charging requirement can be converted into an integer number of charging slots. This rounding procedure simplifies the analysis and enables the development of efficient scheduling algorithms. We also allow tasks to be preemptive, i.e., there can be interruptions during their service time, so an EV may be charged in non-consecutive slots.

2.3.2 Utility Model

Different from previous works, we consider a utility function mapping the charging amount to the profit. For each EV, it has a minimum charging requirement to guarantee its daily usage and a desired charging requirement to reach certain level of the battery capacity. Hence, we consider a piecewise utility function for the two charging phases. Before each EV's inflexible, minimum requirement being satisfied, the utility function keeps flat; after that, the utility function gradually decreases. This is reasonable because the customers prefer spending less money on the non-essential extra charging once their necessary minimum requirements are satisfied. On the other hand, this will give more opportunities for the newly arrived EVs which would like to pay more money to be served to satisfy their inflexible requirements. When the served charging capacity exceeds the total inflexible requirements, the charging station begins serving the tasks' flexible requirements so that the charger utilization can be increased and a higher profit can be achieved. The per-slot profit (price paid by the customer minus a fixed cost) is used as the per-slot utility, which is represented as follows:

$$U = F_U(R, r_{min}, r_{desired}), \tag{2.1}$$

where R is the accumulated charging amount of an EV.

One example of the per-slot utility function is shown in Fig. 2.2. At each time slot, the task being served will obtain a certain utility. Corresponding to Fig. 2.2, the per-slot utility function can be mathematically expressed as a discrete piecewise function, which is defined as

$$U_i(t) = \begin{cases} U_1, & R_i(t) \le r_i^{min} \text{ and } t < t_i^d, \\ aR_i(t)^b + c, & R_i(t) \ge r_i^{min} \text{ and } t < t_i^d, \\ 0, & \text{otherwise.} \end{cases} \tag{2.2}$$

where a, b and c are the parameters determined to ensure the win-win situation of the charging station and customers. For instance, in the simplest linear case ($b = 1$), a represents the slope and c is a constant related to U_1 and r_{min}. U_1 is determined by the charging station and r_{min} is determined by each customer.

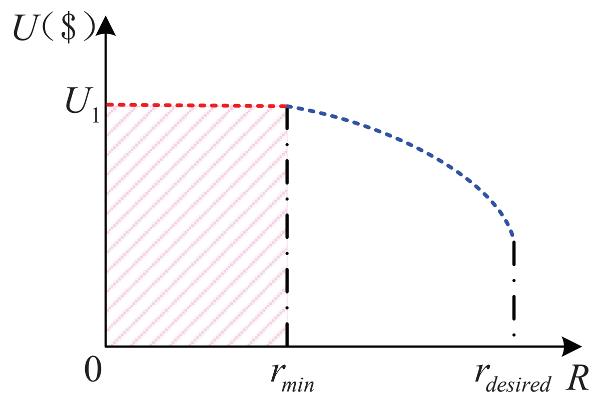


Figure 2.2: An example of per-slot utility function.

2.3.3 Problem Formulation

Let N_t be the total number of EVs arriving at the charging station during t time slots.

As the overall number of chargers is limited, each time slot there will be at most M (the number of chargers) EVs being served in the charging station. For the tth time slot, the decision for all incoming EVs can be represented by a vector:

$$\mathbf{A}(t) = \{a_1(t), a_2(t), \cdots, a_{N_t}(t)\}, \tag{2.3}$$

where

$$a_i(t) = \begin{cases} 1, & \text{the } i\text{th EV is charged,} \\ 0, & \text{the } i\text{th EV is NOT charged.} \end{cases} \tag{2.4}$$

Due to the limited service capability of the charging station, there is a constraint

$$\sum_{i=1}^{N_t} a_i(t) \leq M \tag{2.5}$$

for $\mathbf{A}(t)$, which means that at most M EVs can be charged simultaneously at each time slot.

It is important to guarantee the service quality for customers, e.g., the inflexible requirement must be ensured before the customer's departure time, while minimizing the number of customers being declined for the service. In this chapter, an admission control mechanism is utilized to solve this problem: Once a task is admitted, both the inflexible minimum requirement and deadline constraint are guaranteed; otherwise, the task will be declined. Consequently, the problem turned to be a deadline restricted utility maximization problem (UMP) as follows.

For the ith EV, once it is admitted, it will be allocated several time slots to be charged before its deadline. During its whole stay in the charging station, the decision vector with it can be represented as follows:

$$\mathbf{A}_i(t) = \{a_i(t_i^a), \cdots, a_i(t)\},\ t_i^a \leq t \leq t_i^d. \tag{2.6}$$

Then the accumulated served requirement for the ith EV at time t can be expressed as

$$R_i(t) = \sum_{k=t_i^a}^{t} a_i(k). \tag{2.7}$$

The goal of this chapter is to find a best charging scheduling such that the total utility is maximized in T time slots (one business day). We thus formulate the utility maximization problem (UMP) as follows.

$$\mathbf{max}\ \sum_{t=1}^{T} \sum_{i=1}^{N_t} U_i(t) \cdot a_i(t) \tag{2.8}$$

$$\mathbf{s.t.}\ \ a_i(t) \in \{0, 1\}, \tag{2.9}$$

$$\sum_{i=1}^{N_t} a_i(t) \leq M, \tag{2.10}$$

$$r_i^{min} \leq R_i(t_i^d) \leq r_i^{desired}. \tag{2.11}$$

Unfortunately, it is difficult to solve the above UMP due to the following challenges. First, since the objective function is not differentiable, the classical Lagrange or Dual decomposition method cannot be used to solve the optimization problem. Second, the utility function depends on two random variables $R_i(t)$ and N_t, and the decision $a_i(t)$ is related to these two random variables and the historical scheduling of EVs, and thus it is a coupled unseparated random optimization problem. Furthermore, given the deadline constraints, the optimal scheduling decision at certain time instant requires the full knowledge of future arrivals till the Tth time slot, which is impossible to know in practice. Nevertheless, the UMP problem can be used as a benchmark since it achieves the highest utility in each time slot, and in the following section a heuristic greedy algorithm based on current known information is designed correspondingly.

2.4 Admission Control and Scheduling Algorithms

In this section, an admission control algorithm MLLF and a scheduling algorithm UMP are designed.

2.4.1 Admission Control Algorithm

Note that the traditional LLF scheduling algorithm considered the effect of time urgency and unsatisfied requirement comprehensively, and can ensure the most urgent tasks be served first. Hence, we design a modified LLF algorithm (MLLF) as the admission control mechanism for the newly arrived EVs.

*Definition 2 (**Task Energy State**)*: Let t be the current time slot index and $R_i(t)$ be the accumulated served requirement in (2.7). Then, $E_i(t)$ is defined as the energy state of task T_i at time slot t, which is given by

$$E_i(t) = r_i^{\min} - R_i(t). \tag{2.12}$$

*Definition 3 (**Flexibility**)*: The difference between the amount of remaining time to complete a task and the energy state of the task is defined as flexibility of a task, denoted by $\phi_i(t)$, satisfying

$$\phi_i(t) = t_i^d - t - E_i(t). \tag{2.13}$$

The flexibility factor considers both the effect of time urgency and unsatisfied requirement comprehensively. The LLF algorithm only considers the flexibility when scheduling tasks, and the task with less flexibility will be given a higher priority. When two EVs have the same flexibility value but different per-slot utility, LLF method cannot make a good decision to obtain more profits. Considering that serving a larger requirement will bring a higher profit, with the same flexibility, the EV with a higher energy state should be given a higher priority. Therefore, we modify the flexibility factor as follows:

$$\Phi_i(t) = \frac{\phi_i(t)}{E_i(t)} = \frac{(t_i^d - t)}{E_i(t)} - 1. \tag{2.14}$$

In the modified flexibility, both the flexibility and energy state are considered. The admission control procedure of the MLLF algorithm can be treated as a virtual scheduling mechanism which can be illustrated as follows. All the admitted tasks whose inflexible requirements haven't been finished are stored in an urgent set S_u. When each new task arrives, it is put into a set S_a together with all the tasks in S_u. Then all tasks in S_a can be scheduled by the MLLF algorithm, and each task's estimated finishing time can be obtained. If any task's finishing time is larger than its deadline, the new arrival will be declined. The virtual scheduling decision of each time slot is made by

$$I^a(t) = \arg \min_{i \in 1, \cdots, N_t} \Phi_i(t), \tag{2.15}$$

where $I^a(t)$ denotes the task index which is chosen to be virtually served at slot t.

The admission control algorithm is shown in Algorithm 1. Lines 6 to 20 depict the procedure of virtually assigning EVs to the M chargers based on their flexibility. Lines 21 to 25 describe the admission decision making procedure. In the MLLF admission control algorithm, the minimum requirement of each admitted task can be satisfied before its deadline. All the admitted tasks will be put into an urgent set S_u to be scheduled for charging. The charging scheduling algorithm will be introduced in the next subsection.

2.4.2 Scheduling Algorithm

As discussed above, after the admission control procedure, all the tasks in the urgent set S_u will be scheduled for charging.

First, those urgent tasks whose minimum requirements have not been satisfied

Algorithm 1 MLLF Admission Control Algorithm

Input: Energy state E_i and departure time t_i^d of new task i, Urgent set S_u, Current time slot index t.
Output: Decision of whether to admit the new task.
procedure MLLF(E_i, t_i^d, S_u, t)
    Add the new $\{E_i, t_i^d\}$ and existing tasks S_u to set S_a.
    Get the maximum deadline t_{max}^d for all tasks in S_a.
    for $k = t$ to t_{max}^d **do**
        Compute flexibility $\Phi_j(k)$ for each task $j \in S_a$.
        Get m-th minimum flexibility Φ_m^{min}.
        for Each task $j \in S_a$ **do**
            if $\Phi_j(k) \leq \Phi_m^{min}$ **then**
                Update $E_j(k+1) \leftarrow E_j(k) - 1$.
                if $E_j(k+1) == 0$ **then**
                    Remove task j from set S_a.
                    Set finish time $t_j^f = k$ for task j.
                end if
            else
                $E_j(k+1) \leftarrow E_j(k)$.
            end if
        end for
    end for
    for Each task j in set S_a **do**
        if $t_j^f > t_j^d$ **then**
            return Decline the new task.
        end if
    end for
    return Accept the new task.
end procedure

can be scheduled with the highest priority based on their flexibility. If the number of the urgent tasks is less than the number of chargers, the tasks with flexible charging requirements can be scheduled based on their utilities. The scheduling decision of each time slot is made by

$$I^s(t) = \arg \max_{i \in 1, \cdots, N_t} U_i(t), \tag{2.16}$$

where $I^s(t)$ denotes the task index which is chosen to be charged at time slot t.

The UMP scheduling algorithm is depicted in Algorithm 2. Lines 5 to 9 describe the procedure of scheduling the urgent tasks. Lines 11 to 15 depict the scheduling of the urgent and flexible tasks. The urgent set S_u includes all the tasks admitted but whose minimum requirements have not been satisfied. Those tasks whose minimum requirements have been satisfied but still have time to request extra services will be put inside the flexible set S_f.

2.5 Performance Evaluation

In this section, we implemented our solution and conducted extensive simulations with practical charging settings to evaluate the performance of the proposed admission control and scheduling algorithms. To demonstrate the benefits of the proposed algorithms, we compare the performance with the LLF algorithm [9]. All reported results are simulated and averaged among 500 runs using Monte-Carlo simulation.

2.5.1 Simulation Settings

In our simulation, the charging time is divided into slots with the duration of $\Delta t = 10$ minutes, and each simulation run will last 100 slots. The arrival rate of EVs per time slot is λ. Considering the current EV charging station deployment situation and the EV penetration rate, it is assumed that there are $M = 5$ Level 2 electric vehicle chargers deployed in the charging station. All these chargers use 240 Volt AC outlet and it takes about 3 hours for a continuous full charging for Nissan Leaf which can support a range about 100 miles [22]. According to the statistical data in [23], people in North America typically drives less than 30 miles per day for commute on average. Therefore, it is assumed the inflexible minimum charging requirement for each vehicle follows a uniform distribution between 1 to 5 slots to satisfy their minimum daily usage. For the flexible charging requirements, we assume that it also follows a uniform distribution from 0 to 20 slots.

The staying time of each EV is defined as a redundant time duration plus its total charging requirement. The redundant time duration is set to be a random value between 0 to 20 slots with equal probability. Based on the above information and the utility model introduced in Section III, the per-slot utility function with the unit of cents is set as

$$U_i(t) = \begin{cases} 12, & R_i(t) \leq r_i^{\min} \text{ and } t < t_i^d, \\ -0.5 \times R_i(t) + 12.5, & R_i(t) \geq r_i^{\min} \text{ and } t < t_i^d, \\ 0, & \text{otherwise.} \end{cases}$$

Algorithm 2 UMP Scheduling Algorithm

Input: urgent set S_u, flexible set S_f, number of charger M, current time slot index t.
Output: allocated urgent charging set A_u, and flexible charging set A_f.
procedure UMP(S_u, S_f, M, t)
    Set $N \leftarrow M - |S_u|$.
    if $N \leq 0$ **then**
        Compute flexibility $\Phi_j(t)$ for each task $j \in S_u$.
        Get the M smallest flexibility tasks, add to A_u.
        UpdateUrgentAllocation(A_u).
        Set $A_f \leftarrow \phi$.
    else
        Add all tasks in S_u to A_u.
        Compute utility $U_j(t)$ for each task $j \in S_f$.
        Get the N largest utility tasks, and add to A_f.
        UpdateUrgentAllocation(A_u).
        UpdateFlexibleAllocation(A_f).
    end if
end procedure

procedure UPDATEURGENTALLOCATION(A_u)
    for Each task $j \in A_u$ **do**
        Update $E_j(t+1) \leftarrow E_j(t) - 1$.
        Update $R_j(t+1) \leftarrow R_j(t) + 1$.
        if $E_j(t+1) == 0$ **then**
            Remove task j from S_u.
            if $t + 1 < t_j^d$ **then**
                Add task j to S_f.
            end if
        end if
    end for
end procedure

procedure UPDATEFLEXIBLEALLOCATION(A_f)
    for Each task $j \in A_f$ **do**
        Update $R_j(t+1) \leftarrow R_j(t) + 1$.
        if $R_j(t+1) == r_j^{desired}$ or $t_j^d == t+1$ **then**
            Remove task j from S_f.
        end if
    end for
end procedure

2.5.2 Simulation Results

First the performance of our admission control algorithm is shown in Fig. 2.3. We can see that with the increase of the arrival rate, the task declining probability gradually increases. When the arrival rate is larger than 1 vehicle per time slot, the declining probability increases dramatically. Since the charging capacity is 5 and the average minimum requirement is 5 slots per EV, then the traffic intensity (defined as the arrival rate times the average minimum requirement over the charging capacity) approaches 1 when the arrival rate is 1 per slot. When the arrival rate exceeds 1, there will be more customers being declined. Comparing with the LLF algorithm, our UMP algorithm can achieve the similar declining probability, but a higher utility, which is discussed in the following figures.

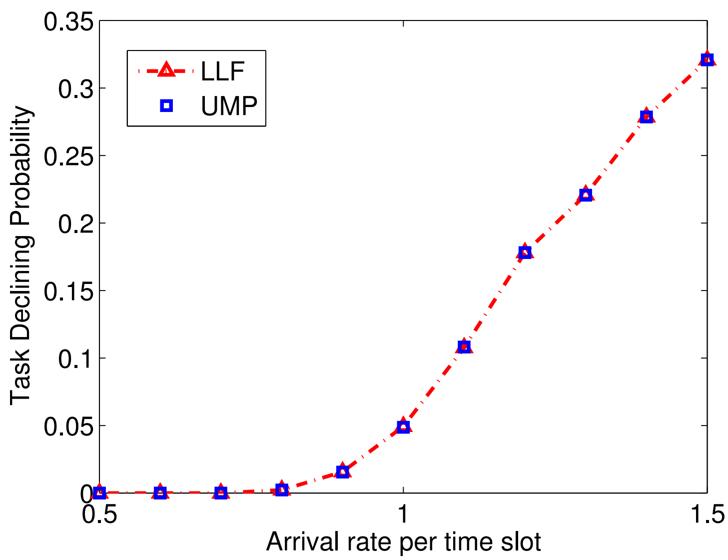


Figure 2.3: Task declining probability with $M = 5$ and avg. $r_{min} = 5$.

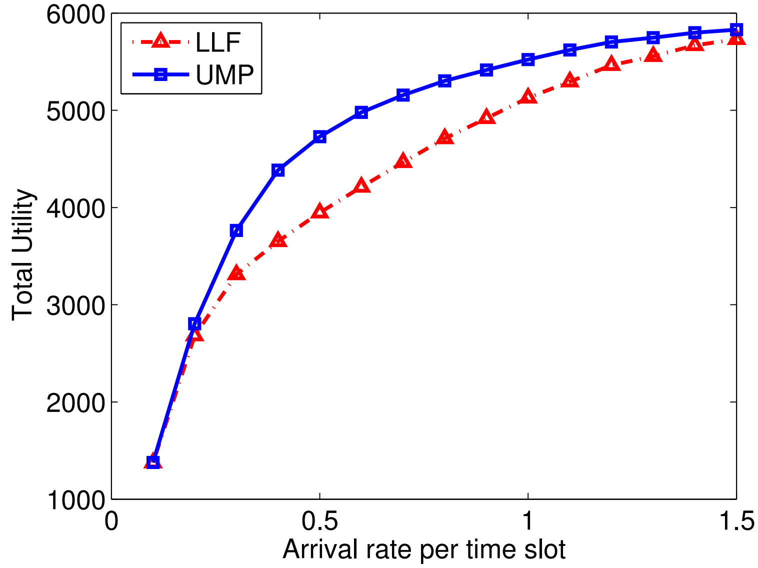
The total accumulated utility of serving all the admitted tasks' requirements is shown in Fig. 2.4a. Both the LLF and UMP algorithms can achieve higher utilities with a larger arrival rate, and the utilities gradually converge when the arrival rate reaches certain value. This is because the chargers have already been saturated with the high arrival rate, and cannot serve more tasks to increase the total utility. Comparing with the LLF algorithm, the proposed UMP algorithm can achieve up to 20% higher total utility, since the LLF algorithm cannot be adaptive to the changing utility for the flexible requirements. Fig. 2.4b shows the utility achieved for serving the extra flexible requirements with different arrival rates. With a low arrival rate, the small number of tasks cannot bring obvious performance difference. While the arrival rate is increasing, the UMP algorithm can beat the LLF algorithm with up to 20% higher utility. But when the arrival rate exceeds certain value, the charger will be saturated, and fewer flexible requirements will get the chance to be served. Thus, the gained flexible requirement utility gradually decreases. In a word, UMP can achieve higher utility, not necessarily serve more requirements.

Fig. 2.5a illustrates the influence of the average inflexible requirements on the total utility. It can be found that with more inflexible requirements, the total utility will increase gradually. This is because these inflexible requirements correspond to a higher price and profit. Obviously, the UMP algorithm always achieves a higher utility than the LLF algorithm. Fig. 2.5b shows the influence of increasing the average inflexible requirements on the achieved utility of serving flexible requirement. The UMP algorithm can achieve around 20% performance gain over the LLF algorithm.

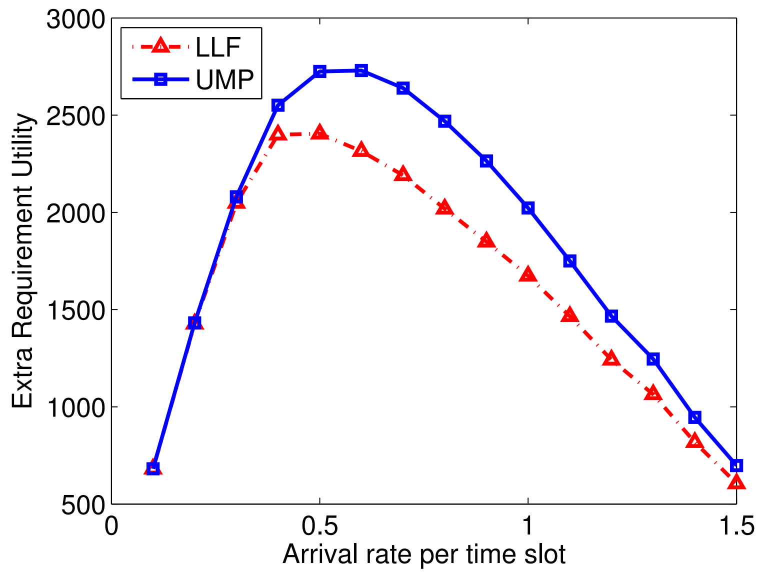
The influence of the average inflexible requirement and arrival rate on the average cost (i.e., average payment for per slot charging) the customers paid for their charged electricity are shown in Figs. 2.6a and 2.6b, respectively. Since most existing works treated the customer's requirement as an inflexible demand, the price keeps flat during the whole charging process. From the two figures, it can be found that the customers saved a lot with the proposed framework than the flat price scheme. In addition, we can notice that the cost saved for the customers gradually decreases with the increase of the inflexible requirement and arrival rate.

2.6 Conclusion

In this chapter, we studied the EV charging scheduling problem by jointly considering the revenue of the charging station and the service requirements of customers. We proposed an online admission control algorithm MLLF which guarantees the necessary, inflexible service requirements of all admitted EVs can be satisfied before their departures. Also, a utility based online scheduling algorithm, UMP, has been proposed to maximize the total utility. Through extensive simulations based on the practical EV charging information, it has been shown that, with the proposed solution, the charging station can achieve a higher utility compared with the LLF algorithm.

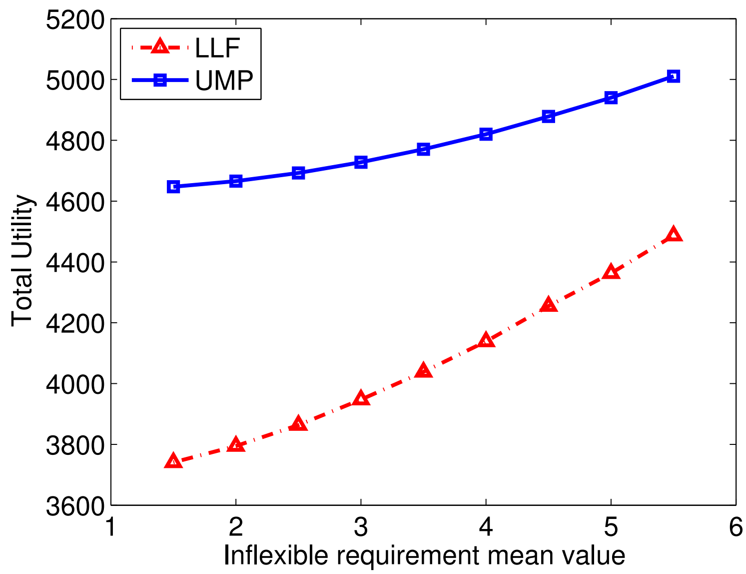


(a) Total utility

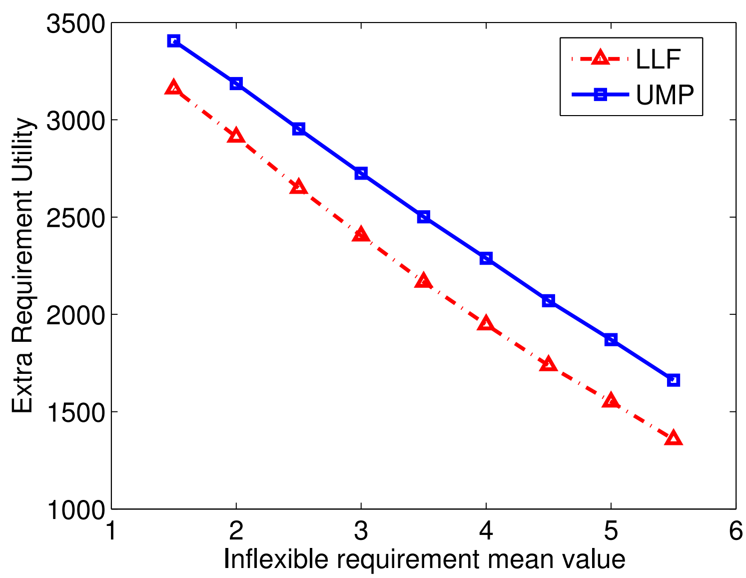


(b) Extra flexible requirement utility

Figure 2.4: The influence of arrival rate on the total and extra utilities.

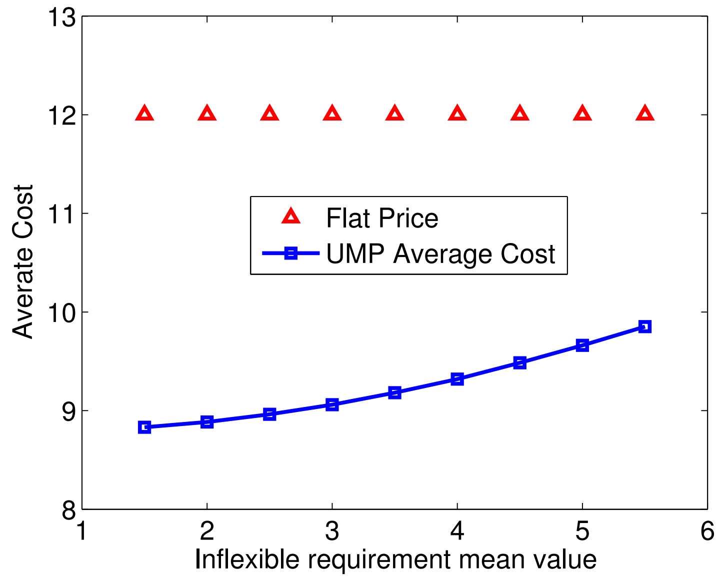


(a) Total utility

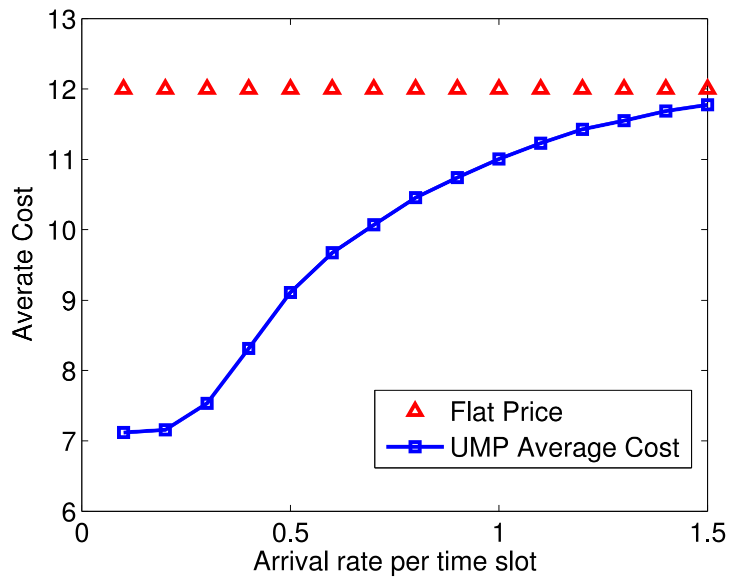


(b) Extra flexible requirement utility

Figure 2.5: The influence of avg. r_{min} on the total and extra utilities.



(a) $\lambda = 0.5$



(b) avg. $r_{min} = 3$

Figure 2.6: The influence of avg. r_{min} and arrival rate on the average cost.

Chapter 3

Intelligent Parking Garage EV Charging Scheduling Considering Battery Charging Characteristic

3.1 Introduction

In chapter 2, we have discussed the EV charging problem under the charging station scenario and achieved the win-win solution for both the charging customers and charging station operator by setting reasonable retail price. In addition, it can be anticipated that more and more parking garages can provide the EV charging services and function as EV charging stations. As time-of-use (TOU) pricing has been widely adopted in current electricity markets [24–26], we also need to consider the impact of wholesale electricity price on the EV charging scheduling activities to keep a profitable operation for the charging operator.

Moreover, the charging efficiency significantly affects the charging duration in the actual charging process. However, for most of the existing works on EV charging scheduling, the charging efficiency variation caused by the battery state of charge (SOC) change has not been thoroughly investigated [24]. Due to the electrochemical characteristic of EV batteries, the charging power decreases substantially for the higher SOCs with the increase of the internal resistance, which causes the charging efficiency significantly reduced along with the charging process [27]. There are two factors affecting the operation of an EV charging station. One is the profit, the most fundamental motive; the other is the service reputation, related to whether the customers' charging requirements can be satisfied before their specified departure time. Typically, the customers pay bills based on the power consumptions. However, providing charging services at the high tariff period is less profitable for the charging operator. Charging the EVs with high SOC is very inefficient, they may occupy the charging facilities for a longer time owing to the low charging efficiency and lead to potential profit reduction. These battery inherent characteristics make the EV charging scheduling a challenging problem. Thus, to keep a profitable operation, it is crucial for the charging operator to well schedule different charging requirements taking the effects of the charging power and electricity price changes into consideration, which is the primary motivation of this chapter.

In this chapter, we investigate the EV charging scheduling problem under a parking garage scenario, aiming to promote the total utility for the charging operator subject to the TOU pricing. First, we develop an intelligent multi-charging system suitable for the garage charging operator to efficiently provide charging service and manage the charging process taking into account the interests of both customers and business. Second, we model the battery charging characteristic change during the actual charging process combined with its intrinsic electrochemical characteristic and analyze its impact on the EV charging scheduling process. Third, we design an efficient adaptive utility oriented scheduling algorithm to maximize the total utility for the charging operator under the premise of customer satisfaction assurance. Fourth, we consider the practical stochastic mobility scenarios and discuss a reservation mechanism for the charging operator to adjust the expected profit and task declining cost, and thus to mitigate the performance degradation caused by the charging information mismatching. Extensive simulations under practical charging settings are conducted to demonstrate the excellent performance of the proposed algorithm compared with other benchmark solutions.

3.2 Related Work

EV charging problems have been studied mainly from three different perspectives, smart grid oriented, aggregator oriented and customer oriented [28]. In this work we concentrate on the aggregator oriented perspective. For this category, there have been extensive research works conducted on the profitable operations for the charging operator [24, 29–37]. In [30], a real-time power allocation strategy was proposed to improve the self-consumption of PV energy and reduce the charging cost for a commercial building micro-grids containing EVs and PV system. Including the mismatching risk between the predicted and actual charging loads, a risk-aware day ahead scheduling was proposed in [33] to minimize the cost for the charging operator. However, the power allocation results are greatly affected by the prediction accuracy. An online coordinated charging decision algorithm was proposed in [34] to minimize the energy cost without knowing the future charging information. The designed algorithm achieved the best known competitive ratio, but the service capacity of the charging station was not taken into consideration. In [2, 24, 35], the scheduling for EV charging with TOU pricing was investigated. The load management technique was developed to shift the deferrable load to the low price time to minimize the peak load and reduce the charging cost. However, the EV's charging duration and demand constraints were not investigated in these works.

Other groups of work utilized the control, scheduling and optimization methods to improve the quality of service during the charging process [6, 10, 38–44]. In [40], optimal power allocation and EV arrival rate adjustment strategies were investigated to reduce the blocking probability of the EV charging requirements. An admission control algorithm was developed in [10], [42] to achieve the maximum profit. However, the charging requirement of each customer cannot be guaranteed under the designed schemes. In [6], the minimization of EV charging waiting time via scheduling charging activities spatially and temporally in a large-scale road network was investigated. A DC fast charging model was incorporated into the queuing analysis as well as the revenue model in [43]. By limiting the requested SOC in an overload condition, the revenue was increased, and the blocking probability of the arriving EVs was decreased. But how to choose the best requested SOC and its corresponding effect on the performance was not fully investigated. Consequently, how to achieve a profitable charging operation under the premise of customer charging QoS assurance has not been well addressed in most existing works, which motivates the study in this chapter.

3.3 System Model and Design Objective

Fig. 3.1 shows the scheme of an intelligent multi-charging system in a parking garage. When an EV arrives at the parking garage, it reports its charging information, i.e., the arrival time, preferred departure time, current and requested battery SOCs, to the garage's charging management system (CMS). The CMS decides whether to admit or to decline the customers' charging requirements and manages the power supply to activate or deactivate the in-facility EVs' charging activities based on the utilized electricity pricing scheme and its scheduling mechanism. The whole charging procedure is controlled by an intelligent charging network. Each admitted vehicle is parked in the charging area and is connected to the charging network. The power dispatching is controlled by the CMS. All the charging activities are automatically switched. Those charging service declined EVs are parked in the non-charging area.

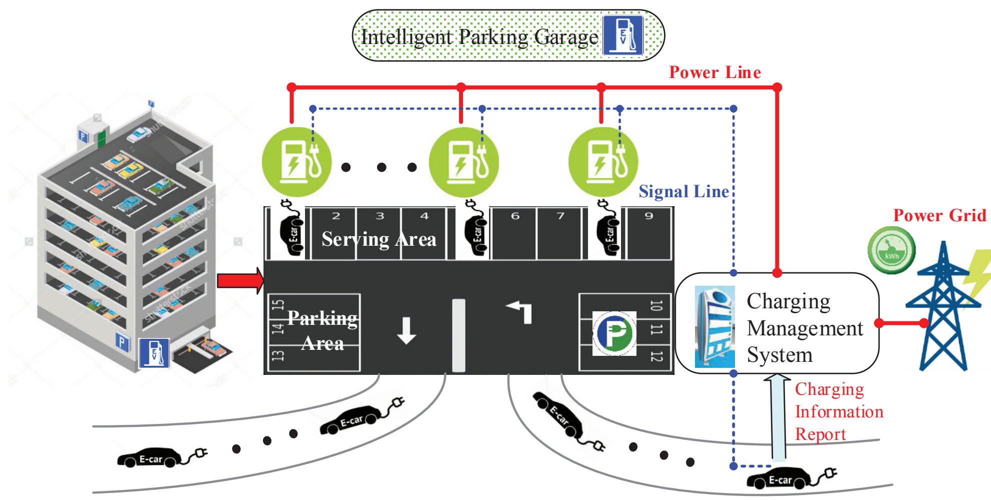


Figure 3.1: Intelligent parking garage EV charging system.

3.3.1 System Model

According to the traffic data collected from the Canton of Zrich [45], we model the EV mobility/parking activity in a workplace parking garage as follows. Suppose the parking garage charging service hours per day is equally divided into T time slots with each slot duration as Δt. Each arrived EV is sequentially indexed. Denote the arrival time and customer anticipated departure time of the ith arrived EV as t_i^a and t_i^d, where $t_i^a < t_i^d \leq T$. The arrivals of EVs follow a Poisson process [6, 46, 47]. According to the vehicular mobility/parking pattern in real life, the arrival rates of the incoming EVs at different periods of the day are different. Thus, the T time slots a day are divided into K periods with each period duration as D_k. For each period, it has different arrival rates denoted as $\lambda_k, k = 1, 2, \cdots, K$. Considering the feature of a workplace parking garage, the departure time of the EVs are assumed to follow a truncated Gaussian distribution [48] $\mathcal{N}(t_d, \sigma_d^2)$, where t_d is the mean of the leaving time and σ_d is the standard deviation.

The charging requirement of an EV is determined by both of its initial battery SOC, S_i^{ini}, when it arrives at the parking garage, where $0 \leq S^{ini} < 1$, and the requested SOC, S_i^{req}, the objective SOC the customer wants the battery to reach at the departure, where $S^{ini} < S^{req} \leq 1$. Most users typically charge their EVs at the levels that were associated with the battery warnings [49]. Consequently, the initial EV battery SOC of a recharge cycle is assumed to follow a truncated Gaussian distribution [48] $\mathcal{N}(\mu_S, \sigma_S^2)$, where μ_S is the battery warning SOC, and σ_S is the standard deviation. The requested SOC of each EV depends on many issues like the customer's preferred departure time, the charging rate and the electricity price, etc. Each EV's charging requirement can be regarded as a *Task*, defined as

$$\mathcal{T}_i = (t_i^a,\ t_i^d,\ S_i^{ini},\ S_i^{req}). \tag{3.1}$$

The charging operator purchases electricity from the utility company subject to a time-varying wholesale price. The wholesale price at different time slots a day is defined as a vector $\mathbf{Pr}_w = [Pr_w^1, Pr_w^2, \cdots, Pr_w^T]$. Currently, most utility companies adopt the TOU pricing to regulate the market. They establish the price based on historical usage data. The price are fixed at different times and pre-known to the users, encouraging them to shift the loads to lower price periods voluntarily to reduce the total load on the power grid at peak hours. In this work, the two step high-low TOU pricing of the Ontario hydro (Canada) [26] is adopted as the wholesale price. Similar to the business model of a gas station, the charging operator charges the customers at a retail price, $\mathbf{Pr}_r = [Pr_r^1, Pr_r^2, \cdots, Pr_r^T]$. Normally, the retail price keeps flat during a business day.

3.3.2 Design Objective

As the charging operator, the objective is to maximize the profit meanwhile to provide satisfactory services to the charging customers. In practical charging situations, owing to the constraints of charging service capability of the parking garage, vehicles' dynamic arrival and departure, and electricity price variation, it is inevitable to decline some customers' charging requirements. Without a proper scheduling of the charging activities, it may lead to a high task declining probability, thus severely affect the customers satisfaction and cause potential profit loss for the charging operator, which is unfavorable for both parties.

Denote N_t as the accumulative total number of EVs arrived at the parking garage until time slot t. Each arrived vehicle is sequentially indexed. For the ith arrived EV, there is a binary decision variable $a_i(t)$ indicating its charging status at each time slot. Obviously, before the EV's arrival time t_i^a, after its departure time t_i^d, or in the case of its being rejected by the admission control mechanism, the decision variable $a_i(t)$ is 0. During the EV's sojourn time, the decision is made by the corresponding scheduling scheme of the CMS.

Considering the charging network service capability, at most M EVs can be charged concurrently at the parking garage. Therefore, during each time slot the total number of EVs being charged should satisfy the following constraint

$$\sum_{i=1}^{N_t} a_i(t) \leq M. \tag{3.2}$$

According to the admission control mechanism, not all the arrived EVs can be admitted for charging. However, for all the admitted ones, they must be guaranteed to reach their requested battery SOC before departure. Thus, for each of these admitted EVs, the accumulative charging duration Δ_i of charging the battery from S_i^{ini} to S_i^{obj} should satisfy the following constraint

$$\Delta_i \leq t_i^d - t_i^a. \tag{3.3}$$

Detailed analysis of Δ_i is introduced in the battery charging characteristic analysis section.

Assume there are N tasks arrived during the whole T time slots. The task set of these N tasks is denoted as $\boldsymbol{\mathcal{T}} = [\mathcal{T}_1, \cdots, \mathcal{T}_N]$. Based on the admission control mechanism, assume there are N_d tasks declined for charging. Then, the task declining probability under the task $\boldsymbol{\mathcal{T}}$ scenario can be expressed as

$$P_d(\boldsymbol{\mathcal{T}}) = \frac{N_d}{N}. \tag{3.4}$$

The obtained profit for the charging operator is depended on the specific scheduling results, which can be further expressed as follows

$$P_{rf}(\boldsymbol{\mathcal{T}}) = \sum_{t=1}^{T} \sum_{i=1}^{N} \mathscr{P}\left(S_i\left(t\right)\right) \cdot \Delta t \cdot \left(Pr_r(t) - Pr_w(t)\right) \cdot a_i\left(t\right), \tag{3.5}$$

where $\mathscr{P}(S(t))$ is the charging power function following the battery charging characteristic. Therefore, the battery SOC of the charging EV can be updated as

$$S_i(t+1) = S_i(t) + \mathscr{P}(S_i(t)) \cdot \Delta t \cdot a_i(t)/B. \tag{3.6}$$

Taking the interests of both the charging operator and the customers into account, a metric, utility, is proposed for the charging operator to comprehensively evaluate the charging scheduling performance. The utility function is expressed as

$$U(\boldsymbol{\mathcal{T}}) = P_{rf}(\boldsymbol{\mathcal{T}}) - \mathbb{C}(P_d(\boldsymbol{\mathcal{T}})), \tag{3.7}$$

where $P_{rf}(\boldsymbol{\mathcal{T}})$ and $P_d(\boldsymbol{\mathcal{T}})$ are the produced profit and task declining probability by a certain scheduling algorithm under the task set $\boldsymbol{\mathcal{T}}$ scenario. $\mathbb{C}(\cdot)$ is the cost function, describing the incurred profit loss for declining the customers' charging requirements. The parameters are set by the charging operator beforehand with the consideration of the maximum tolerated task declining probability. The ultimate objective for the charging operator is to achieve the maximum utility. Thus, one utility maximization problem is formulated as follows

$$\begin{aligned} \max_{a_i(t)} \quad & U(\boldsymbol{\mathcal{T}}) \\ \text{s.t.} \quad & \sum_{i=1}^{N_t} a_i(t) \leq M, \quad \forall t, \\ & \Delta_i \leq t_i^d - t_i^a, \quad \forall i, \\ & S_i(t+1) = S_i(t) + \mathscr{P}(S_i(t)) \cdot \Delta t \cdot a_i(t)/B, \quad \forall i, t. \end{aligned} \tag{3.8}$$

3.4 Battery charging characteristic analysis

Most EVs on current market employ the Li-ion batteries, which have good performance on capacity, safety, life, and cost. Constant current-constant voltage (CC-CV) charging is the commonly used method for Li-ion battery charging [50]. However, due to the electrochemical characteristic of the EV battery, the charging current dramatically decreases along with the increase of battery SOC, which results in significant reduction of the charging power. This phenomenon also leads to a remarkable increase of the charging time to reach a higher SOC. All these unfavorable effects further impact the profitability of the charging operator.

We apply a simplified model to describe the relationship between the maximum allowable battery charging power and the battery SOC based on the Citroen C-Zero electric vehicle charging experimental measurements [51]. We consider all EVs equipped with the same kind of batteries with the same SOC change function $S(t)$. By applying the experimental results, a typical charging power function is expressed as

$$\mathscr{P}(S) = \begin{cases} P_0, & 0 \leq S \leq S^{th}, \\ \dfrac{1-S}{1-S^{th}} P_0, & S^{th} < S \leq 1, \end{cases} \tag{3.9}$$

where S is the current battery SOC and S^{th} is the threshold invoking a shift from the CC period to CV period. Since the voltage does not change much during the CC period, the charging power is simplified as a constant P_0. For the CV period, the charging power is simplified linearly decreasing with the growth of battery SOC.

The required charging duration for a particular task i is mainly determined by its initial and requested battery SOCs, and the charging power. Based on the experimental measurements, to simplify the analysis, the initial battery SOC of each task directly determines the beginning charging power. Then, the charging duration for task i can be obtained by the following Lemma:

Lemma 1. *For any task i, given its initial and requested battery SOCs S_i^{ini} and S_i^{req}, its required charging duration Δ_i can be obtained as*

$$\Delta_i = \begin{cases} \frac{(S_i^{req} - S_i^{ini})B}{P_0}, & S_i^{ini} < S_i^{req} \leq S_i^{th}, \\ \frac{(S^{th} - S_i^{ini})B}{P_0} + \beta \ln(\frac{1-S^{th}}{1-S_i^{req}}), & S_i^{ini} \leq S^{th} < S_i^{req}, \\ \beta \ln(\frac{1-S_i^{ini}}{1-S_i^{req}}), & S^{th} \leq S_i^{ini} < S_i^{req}, \end{cases} \tag{3.10}$$

where $\beta = \frac{(1-S^{th})B}{P_0}$.

Proof. We consider all tasks follow the same SOC change function $S(t)$. For the CC period, as the charging power is a constant, the charging duration is determined by its initial battery SOC S^{ini} and the CC-CV transition threshold S^{th}, which can be calculated as

$$\Delta^{cc} = \frac{\left(S^{th} - S^{ini}\right) \cdot B}{P_0}, \tag{3.11}$$

where B is the rated battery capacity. Then, the battery SOC changes with the CC period accumulative charging time can be expressed as

$$S^{cc}(t) = S^{ini} + \frac{P_0 t}{B}. \tag{3.12}$$

For the CV period, the charging power linearly decreases with the increase of battery SOC. Assume that δ is a very small period, the SOC with the CV period accumulative charging time can be updated by

$$\begin{aligned} S^{cv}(t) &= S^{cv}(t-\delta) + P(t-\delta)\cdot\delta/B \\ &= S^{cv}(t-\delta) + (m - nS^{cv}(t-\delta))\cdot\delta, \end{aligned} \tag{3.13}$$

where $m = n = \frac{P_0}{(1-S^{th})B}$. Then, a differential equation of S can be obtained as

$$\dot{S^{cv}}(t) + nS^{cv}(t) - m = 0. \tag{3.14}$$

By solving this differential equation, we can obtain a general solution for the change of battery SOC with the CV period accumulative charging time as

$$S^{cv}(t) = Ce^{-\frac{P_0}{(1-S^{th})B}t} + 1, \tag{3.15}$$

where C is a constant. By applying the initial condition $S(0) = S^{th}$, the constant C is determined as $C = S^{th} - 1$. Thus, we can obtain

$$S^{cv}(t) = (S^{th} - 1)e^{-\frac{P_0}{(1-S^{th})B}t} + 1. \tag{3.16}$$

Given each individual task's initial and requested battery SOCs, we can map these states to the SOC change function $S(t)$ and obtain its corresponding charging duration from S^{ini} to S^{req}. The initial battery SOC of each task directly determines which charging period it begins. Then, for each individual task its battery charging characteristic can be analyzed as follows.

Case 1: $S^{ini} < S_i^{req} \leq S^{th}$.

This kind of tasks' initial battery SOCs are very low and only require very few charging amount. The charging process only goes through the CC period. The battery charging power maintains at the maximum level, and the task's total charging duration can be expressed as $\Delta_i = \frac{(S_i^{req} - S_i^{ini})B}{P_0}$. Its battery SOC is linearly increasing as $S_i(t) = S_i^{ini} + \frac{P_0 t}{B}$.

Case 2: $S_i^{int} \leq S^{th} < S_i^{req}$.

The charging process needs to go through both the CC and CV periods. For the CC period, the battery is charged from S_i^{ini} to S^{th}. For the CV period, the battery is charged from S^{th} to S_i^{req}. By mapping these states to the SOC change function $S(t)$, we can obtain this task's total charging duration, which is the summation of these two periods. Thus, it can be expressed as follows

$$\begin{aligned}\Delta_i &= \Delta_i^{cc} + \Delta_i^{cv} \\ &= \frac{\left(S^{th} - S_i^{ini}\right) \cdot B}{P_0} + \frac{\left(1 - S^{th}\right) B}{P_0} \ln\left(\frac{1 - S^{th}}{1 - S_i^{req}}\right).\end{aligned} \tag{3.17}$$

Then, for this kind of tasks their battery SOCs at any accumulative charging time t can be expressed as

$$S_i(t) = \begin{cases} S_i^{ini} + \frac{P_0 t}{B}, & t \le t_i^{cc}, \\ (S^{th} - 1)e^{-\frac{P_0}{(1-S^{th})B}(t - t_i^{cc})} + 1, & t > t_i^{cc}, \end{cases} \tag{3.18}$$

where $t_i^{cc} = \frac{(S^{th} - S_i^{ini})B}{P_0}$ is the task's charging duration for the CC period.

Case 3: $S^{th} \le S_i^{int} < S_i^{req}$.

The charging process is deemed as only taking the CV period. Then, we can map its two battery SOC states S_i^{ini} and S_i^{req} to the SOC change function expressed in (3.16), and the charging duration is the time difference between these two states, which is expressed as

$$\Delta_i = \Delta_i^{cv} = \frac{\left(1 - S^{th}\right) B}{P_0} \ln\left(\frac{1 - S_i^{ini}}{1 - S_i^{req}}\right). \tag{3.19}$$

Then, for this kind of tasks their battery SOCs at any accumulative charging time t can be expressed as

$$S_i(t) = (S^{th} - 1)e^{-\frac{P_0}{(1-S^{th})B}(t + t_i^{cv})} + 1, \tag{3.20}$$

where $t_i^{cv} = \frac{(1-S^{th})B}{P_0} \ln(\frac{1-S^{th}}{1-S_i^{ini}})$ is the duration following the SOC change function $S(t)$ with the SOC changing from S^{th} to S_i^{ini}. □

According to Lemma 1, the charging amount $E_i(t)$ at each individual charging slot t can be obtained by the SOC difference at the corresponding charging time. Given the required charging duration Δ_i of each task, its charging sequence $\mathbf{E_i}$ thus can be obtained. For different tasks their charging sequences are heterogeneous. The charging activity at each slot cannot be treated equally and scheduled interchangeably.

One toy example to illustrate the impact of the battery charging characteristic on the scheduling is shown in Fig. 3.2. Assume the system capacity is 6 time slots, the first 2 time slots are within the high price (low profit) period, and the following 4 time slots belong to the low price (high profit) period. There are two tasks requiring charging services. Task 1 and 2 arrive at the beginning of the 1st time slot, and depart at the 6th and the 4th time slots, respectively. The charging sequences of these two tasks are denoted as $\mathbf{E}_1 = \{5, 4, 3\}$, and $\mathbf{E}_2 = \{8, 7, 6\}$. Each number is the amount of energy that can be charged to the EV in the particular slot given its initial SOC and follows the battery charging characteristic. For instance, the number "5" denotes that 5 kWh energy will be charged to EV 1 during its first charging time slot. The objective for the charging operator is to charge more energy at the low price period to earn more profit, meanwhile try its best to accommodate more tasks' charging requirements. To maximize the profit while satisfying all tasks charging requirements, we need to consider the issues of electricity price variations, all tasks' deadline restrictions and each task's charging power sequence decreasing trend. It can be noted that the new problem is more challenging than the counterpart with no battery charging characteristic consideration. Consequently, the charging operator must design efficient scheduling algorithm to achieve the desirable utility, which is discussed in detail in the subsequent sections.

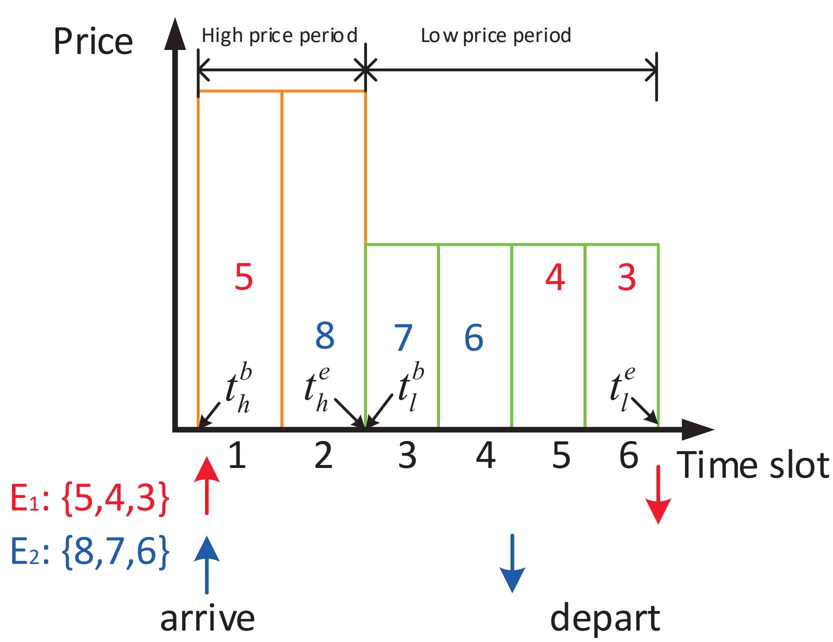


Figure 3.2: Toy example.

3.5 Admission Control and Scheduling Algorithms

In this section, the admission control mechanism is introduced to guarantee the service quality for all the EV charging customers. Then, the scheduling algorithms are designed to optimize the utility for the parking garage charging operator.

3.5.1 Admission Control Algorithm

To ensure the QoS for the EV charging customers, each admitted EV must be guaranteed to charge its battery to the requested SOC when it leaves the parking garage. The admission control mechanism can be viewed as a virtual scheduling procedure. Whenever a new task i arrives, it will be put into an active scheduling task set $\mathbf{I}$ together with the existing admitted tasks. Then, all the tasks in $\mathbf{I}$ will be scheduled by the corresponding scheduling algorithm. Since each admitted task must achieve the requested SOC while departure, if any existing admitted task or the newly arrived task itself cannot be charged to its requested battery SOC at the departure, the new task should be declined of service; otherwise, it should be admitted. The flow graph of the charging management system is illustrated in Fig. 3.3. As the most important part of the charging management system, the scheduling algorithms are introduced in next subsection in detail.

3.5.2 Scheduling Algorithm

The discussed EV charging scheduling problem is *causal* as the scheduling policy at each time slot t depends only on the current information state $\mathbf{I_t}$. The future charging information is unknown for the charging operator beforehand, they cannot make a globally optimal scheduling. From [52], it can be seen that there does not exist a causal optimal scheduling policy. Since we cannot, in general, construct causal optimal scheduling policies, we must be content to design sub-optimal heuristic scheduling algorithms.

Considering the time urgency and charging demand comprehensively, the most urgent tasks should have the highest priority to be scheduled. A metric, *flexibility* [52], is utilized to describe the urgency of each task, which is defined as follows. **Definition 1.** The difference between the amount of remaining time to complete a task and the remaining unfinished charging requirement L_i is defined as the flexibility of task i,

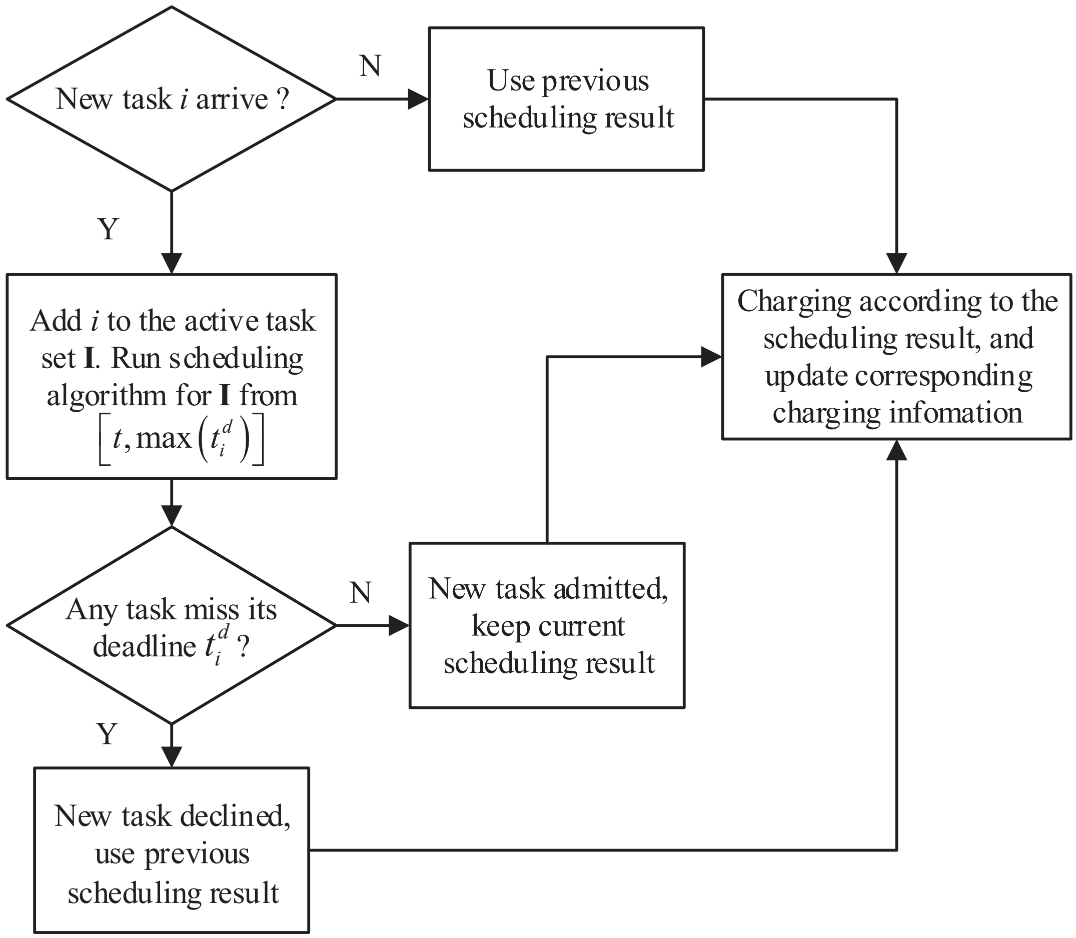


Figure 3.3: Charging management system operation flow graph.

denoted as $\Phi_i(t)$, satisfying

$$\Phi_i(t) = t_i^d - t - L_i(t). \tag{3.21}$$

Obviously, a greedy-based scheduling algorithm (GRD) can be applied to solve the problem. Larger flexibility factors imply greater load deferability. In particular, if a task is not flexible ($\Phi_i(t) = 0$), it must be served immediately to be completed by its deadline. Otherwise, the tasks with the minimum charging amount are sequentially scheduled for charging at each time slot during the high price period; the tasks with the maximum charging amount win the opportunity within the low price period. Apparently, the GRD scheduling algorithm has excellent task admission performance and resource utilization ratio. However, the electricity price variation trend is not taken into consideration. It cannot guarantee as much power as possible to be charged in the low price period. Thus the total profit, the most concerned part for the charging operator, cannot be maximized.

Algorithm 3 Price oriented scheduling algorithm

1: **Input**: M, t, $\mathbf{S} = \{\mathbf{I}, \mathbf{L}, \mathbf{E}, \mathbf{t^d}\}$, t_h^e
2: **Output**: $\mathbf{A}$
3: **procedure** POS(M, t, $\mathbf{S}$, t_h^e)
4:     **if** new task is admitted at t **then**
5:         update $\mathbf{S}$, $t_D = \max(t_i^d), i \in \mathbf{I}$
6:         **if** $t \leq t_l^b$ **then**
7:             **if** $\sum_i L_i(t) \leq M(t_D - t_h^e)$ **then**
8:                 $x = t_l^b$, SCHEDLP(k) for k from $[x, t_D]$
9:             **else**
10:                 $\delta = \sum_i L_i(t) - M(t_D - t_h^e)$
11:                 SCHEDHP(k) for the δ requirements
12:                 $x = t_l^b$, SCHEDLP(k) for k from $[x, t_D]$
13:             **end if**
14:         **else**
15:             $x = t$, SCHEDLP(k) for k from $[x, t_D]$
16:         **end if**
17:     **end if**
18: **end procedure**
19: **procedure** SCHEDHP(t) / SCHEDLP(t)
20:     **if** $\exists \Phi_j(t) = 0, j \in J$ **then**
21:         schedule all tasks in J immediately
22:         update $\mathbf{S}$, $\mathbf{A}$
23:     **else**
24:         $N = \min\{|I|, M, M - |J|\}$
25:         SCHEDHP: schedule the N tasks with min $E(t)$
26:         SCHEDLP: schedule the N tasks with max $E(t)$
27:         update $\mathbf{S}$, $\mathbf{A}$
28:     **end if**
29: **end procedure**

To mitigate the price insensibility of the GRD scheduling, a price oriented scheduling algorithm (POS), as depicted in Algorithm 3, is designed to improve the profit. The key process of POS algorithm is to schedule more high-power tasks in the low price period following the charging power causal decreasing characteristic. If the current time is within the low price period or the estimated total charging requirements is smaller than the low price period capacity, as shown in lines 8 and 15 of Algorithm 3, each round the task with the most charging energy amount wins the scheduling opportunity. Otherwise, as depicted in lines 9 to 13, it preferentially schedules the charging requirements to the high-profit region until the high-profit region reaches its capacity limit. After this stage, it schedules the remaining charging requirements within the available low-profit region. The task with the least charging energy amount has the highest priority during this process. The POS algorithm is aggressive in increasing the profit. However, there is a drawback of it, i.e., the task declining probability cannot be guaranteed, especially for the high traffic intensity scenarios. Since the early arrived tasks always take up the lowest price slot in advance, the later arrived tasks may be blocked due to insufficient charging slots available to them. It can be noticed the two metrics, profit and task declining probability, cannot be guaranteed optimal at the same time.

Therefore, considering the effects of electricity price variation, charging power causal decreasing, and deadline constraints in a comprehensive manner, we propose an adaptive utility oriented scheduling algorithm (AUS) to achieve the desirable total utility for the charging operator. The AUS algorithm, as described in Algorithm 4, adaptively makes the decision on when to invoke each procedure based on the estimated incoming charging requirements. The estimation of the average total charging requirement $\bar{R}$ during a specified period α can be expressed as follows

$$\bar{R} = \bar{\lambda} \cdot \alpha \cdot \bar{L}, \tag{3.22}$$

where $\bar{\lambda}$ is the average arrival rate during the specified period α, and $\bar{L}$ is the average charging slot number per EV. All the information can be estimated by historical data collected by the charging operator.

Depending on the TOU electricity pricing model, the service capacity of the two price periods can be expressed as

$$C_h = M \cdot (t_h^e - t_h^b), \tag{3.23}$$

$$C_l = M \cdot (t_d - t_l^b), \tag{3.24}$$

where the high price period ending time t_h^e and the low price period beginning time t_l^b are equal. It is possible that the price may change a few times during the day, and with a small extension of our proposed AUS algorithm, i.e., comparing the total charging requirements and the low price period capacity and adjust the scheduling sequence, we can still handle the changed price model effectively.

Algorithm 4 Adaptive utility oriented scheduling algorithm

Input: $M, \mathbf{S}, t_h^b, t_h^e, t_d$
Output: $\mathbf{A}$
procedure AUS(M, $\mathbf{S}$, t_h^b, t_h^e, t_d)
    estimate $\bar{R}$ for $[t_h^b, t_d]$ with (3.22)
    calculate C_l with (3.24)
    $\Theta = \max\{\bar{R} - C_l + \theta, 0\}$
    schedule with GRD for the first Θ requirements
    schedule with POS for all the remaining requirements
end procedure

3.5.3 Discussion

For the proposed AUS algorithm, utilizing the GRD scheduling at the beginning guarantees a low task declining probability, and the subsequent POS scheduling guarantees the desirable profit. Since the arrivals of the tasks are random in real scenarios, the actual arrived vehicle number has some deviation from the estimated arrived vehicle number. For the underestimation case, i.e., $\sum_i L_i > \bar{R}$, the underestimation of the total incoming requirements may cause a high task declining probability and then decrease the total utility for the charging operator. To avoid the performance degradation, the robustness issue of the algorithm is considered by incorporating the reservation mechanism. The charging operator can reserve θ extra high-price slots to achieve a relatively small task declining probability and meanwhile a satisfactory profit to guarantee a desirable utility. The extra reservation amount θ can be set as $\theta = k\sigma\bar{L}$, and $\theta \leq C_s - \bar{R}$, where σ is the standard deviation of the arrived vehicle number, k is a tuning parameter, and C_s is the system capacity. Increasing θ makes the scheduling more conservative and secure, so the task declining probability can be substantially decreased. Whereas, the profit is probably affected. Because more user will be charged in the high price period and less user can be selected in the low price period, sometimes even cannot fully utilize the low price period. By analyzing the AUS algorithm, we can find that it converges to the GRD algorithm when the estimated average total charging requirement reaches the system capacity. Consequently, the specific average traffic intensity ρ at which the AUS algorithm converges to the GRD algorithm with given reservation amount θ can be estimated by the following equation

$$\rho = 1 - \frac{\theta}{C_s}. \tag{3.25}$$

Thus, the charging operator can obtain the desired task declining probability by adjusting the reservation amount.

3.6 Case Studies

3.6.1 Simulation Settings

Take a workplace parking garage charging station as an instance to study the charging strategy. With each slot duration $\Delta t = 1$ min, one business day (7am-5pm) is equally divided into $T = 600$ time slots. Considering the current EV penetration rate, traffic pattern and typical power configuration in a workplace parking garage, 8 EVs can be charged concurrently [53]. The whole T time slots are divided into three periods with different arrival rates (7am-9am, 10λ; 9am-12pm, 2λ; 12pm-4pm, 0.5λ). Two charging cases are considered as examples: Case 1, by the default setting of the charging station all EVs depart at the end of the business day; Case 2, the EVs depart randomly around the peak off-work hours following a truncated Gaussian distribution $\mathcal{N}(4:30\text{pm}, \sqrt{30}\text{mins})$, and $t_i^a < t_i^d \leq 5\text{pm}$. The Citroen C-Zero with 16kWh battery is investigated. Based on the study of the EV user charging behavior [49], the initial EV battery SOC of a recharge cycle is assumed to follow the truncated Gaussian distribution $\mathcal{N}(0.1, 0.2)$, and $0 \leq S_i^{ini} < 0.9$. The battery CC-CV stage transition threshold is 0.6. The required SOCs of all charged batteries are preferred as 0.9. The flat retail charging price for the customers is 20 cents/kWh, and the wholesale price adopts the 2015 winter TOU price of Ontario Hydro [26] with high price as 17.5 cents/kWh and low price as 12.8 cents/kWh.

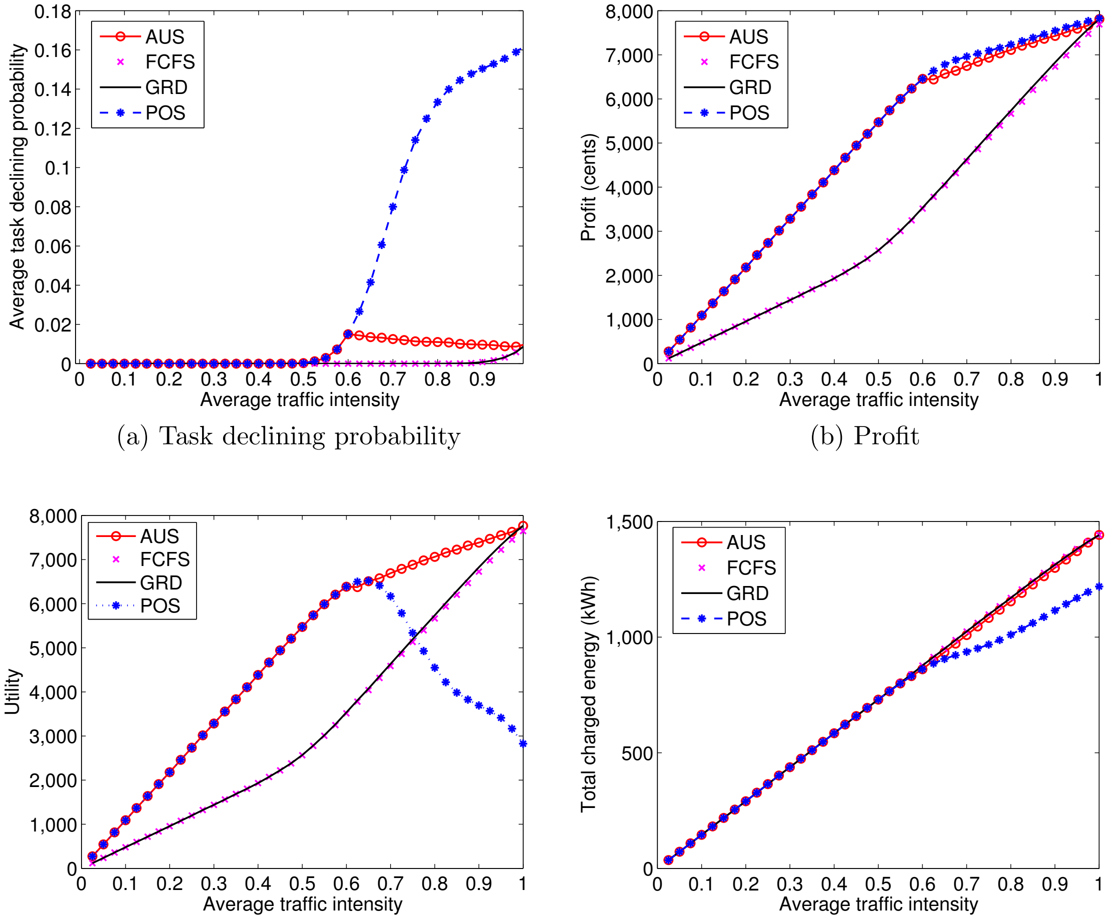
3.6.2 Analysis and Comparison of Results

To better analyze the performance of the proposed adaptive utility oriented scheduling (AUS), the greedy scheduling (GRD), profit oriented scheduling (POS), and most EV charging stations currently adopted first come first serve scheduling (FCFS) are taken for comparisons under 1000 Monte Carlo simulations. For Case 2 another widely utilized charging strategy earliest deadline first (EDF) is considered as well.

Two key performance indexes profit and task declining probability are first investigated for Case 1 under the different traffic intensity scenarios as shown in Fig. 3.4a and Fig. 3.4b, respectively. Task declining probability affects the customer satisfaction, and profit is the motivation for the charging operator. However, it can be seen that the two performance indexes cannot be guaranteed optimal at the same time for any scheduling strategy. Although the main objective for the charging operator is to obtain the maximum profit. It is quite undesirable for the charging station to have a large task declining probability, which severely affects its service reputation and leads to great potential profit loss. Thus, by taking the interests of both parties into account we compare the utility of each algorithm to comprehensively evaluate the scheduling performance in Fig. 3.4c. The cost function here is set as $\mathbb{C}(P_d) = a \cdot (e^{b \cdot P_d} - 1)$ by the charging operator, where $a = 200$, and $b = 20$. The aggregated power demands of the charging station during the whole business day are compared in Fig. 3.4d as well to reflect the energy utilization.

From the simulation results, it can be noted that the GRD algorithm achieves the lowest task declining probability among all algorithms, but losses a lot of profit. The POS algorithm aggressively increases the profit, but the task declining probability is quite unacceptable. By contrast, the proposed AUS charging strategy is sophisticated to achieve the maximum utility with considerable profit under the premise of a relatively low task declining probability. In addition, the AUS algorithm can obtain more profit compared with the high resource utilization algorithms GRD and FCFS, and meanwhile ensure a low task declining probability compared with the POS algorithm. The energy utilization ratio is also promising among all scheduling algorithms, which makes the AUS algorithm the best choice for the parking garage charging operator.

The charging operator can also adopt the introduced reservation mechanism of the AUS algorithm to mitigate the performance degradation caused by the charging information mismatching with vehicle stochastic arrivals. Take the simplest single charger case as illustration. The effects on the scheduling performance with different reservation amounts are compared in Fig. 3.5. Same as the previous analysis, reserving more high-price period resources could effectively decrease the task declining probability under different traffic intensity cases. With the increase of average traffic intensity the AUS algorithm gradually converges to the GRD algorithm, the converging points obtained from the simulation results are in good match with the theoretical results as shown in Fig. 3.5a. Fig. 3.5b shows the profit comparison under different reservation amount cases, and it can be observed that reserving more high-price period resources results in some profit loss. However, choosing the proper reserva-



(a) Task declining probability (b) Profit

(c) Utility (d) Aggregated power demand

Figure 3.4: Performance comparisons for Case 1.

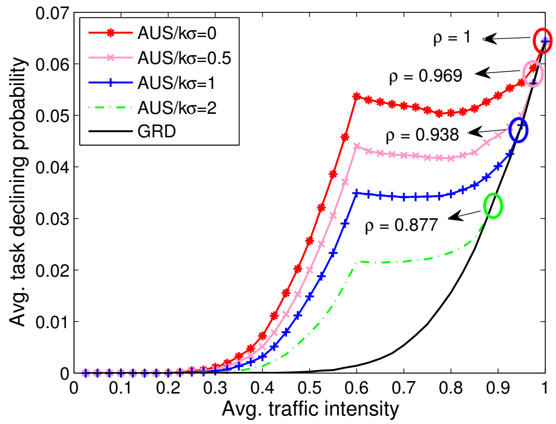
tion amount can achieve a desirable utility, as shown in Fig. 3.5c. With $k\sigma = 1$, it effectively decreases the task declining probability and also obtains the best utility, which is promising for both the customers and the charging operator. Consequently, the garage charging operator can always achieve the desirable utility by choosing a proper reservation amount under different cases.

For Case 2, the vehicles' mobility pattern is more complicated. Deadline restricted scheduling is considered in this case. We also evaluate the different performance to demonstrate the effectiveness of the proposed AUS algorithm. As depicted in Fig. 3.6, we can find that the proposed AUS algorithm is robust to achieve the best utility under the dynamic departure scenario. The task declining probability is properly controlled under different traffic intensity cases, which well guarantees the interests of customers. Meanwhile, the promising profit for the charging operator can also be obtained. Thus, it can provide effective guidance for the garage charging operator to make proper scheduling for the incoming charging requirements, thereby to achieve the desirable utility. The reservation mechanism is also applied under this scenario. Due to the page limit detailed discussions are omitted here.

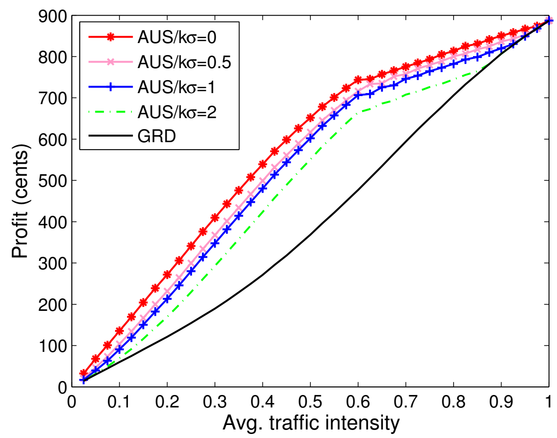
To demonstrate the vehicle mobility pattern independence of our proposed AUS scheduling algorithm, we consider the scenarios where EVs uniformly arrive at the parking garage for a simple two-charger scenario. The performance of task declining probability, obtained profit and achieved total utility with different scheduling algorithms under different traffic scenarios are compared in Fig. 3.7. From the simulation results, it can be seen the proposed AUS algorithm still achieves the maximum utility with considerable profit gain under the premise of a relatively low task declining probability. Consequently, our proposed scheduling algorithm is applicable under different stochastic vehicle mobility models.

3.7 Conclusion

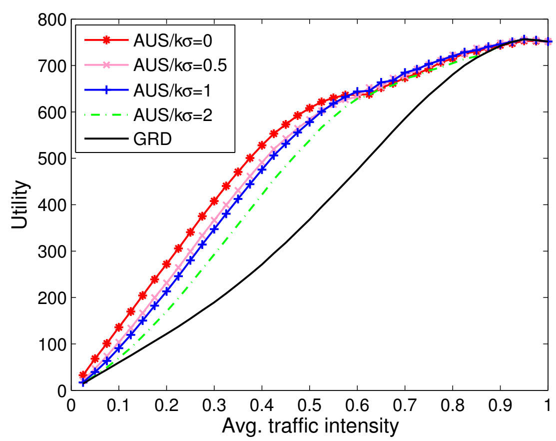
In this chapter, we investigated the EV charging problem at an intelligent parking garage subject to the real TOU electricity pricing. We designed a multi-charging system for the garage charging operator to effectively provide charging services by jointly considering the charging station profit and customer satisfaction. Besides, we analyzed the battery charging characteristic change during the actual charging process and applied it into the EV charging problem. Furthermore, we proposed an adaptive utility oriented scheduling algorithm to effectively achieve the maximum total utility for the charging operator under the dynamic traffic pattern scenario. We also discussed the reservation mechanism for the charging operator to mitigate the performance degradation caused by the charging information mismatching with vehicles' stochastic arrivals. Through extensive simulations, it has been shown that the proposed AUS algorithm is applicable under different stochastic vehicle mobility processes. With it the charging operator can achieve the best performance compared with other existing algorithms, which is promising for the parking garage charging service proliferation.



(a) Task declining probability

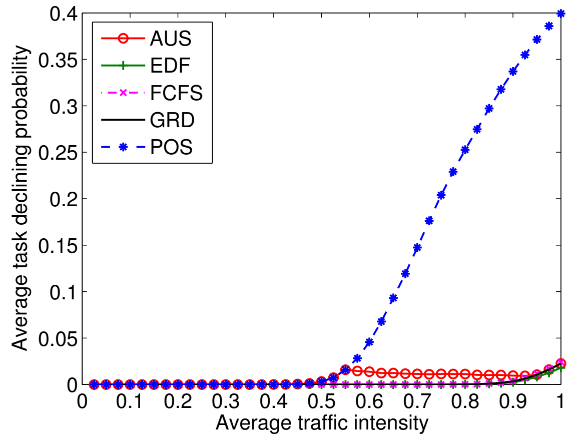


(b) Profit

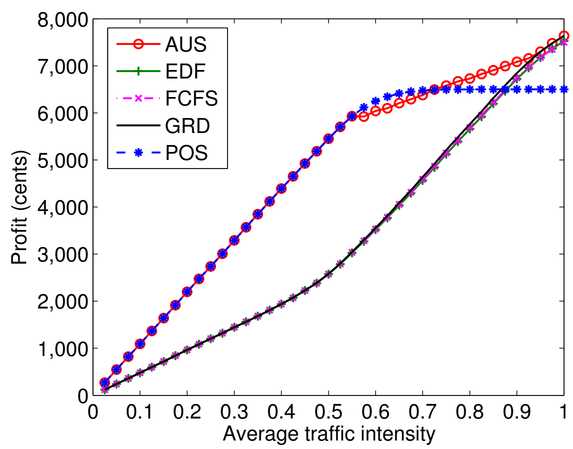


(c) Utility

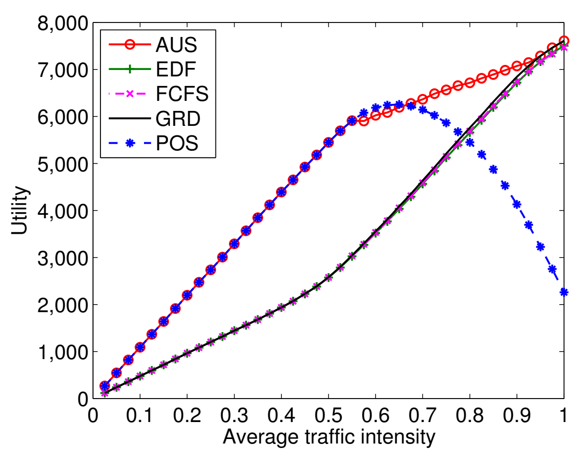
Figure 3.5: Performance comparisons with different reservation amount



(a) Task declining probability

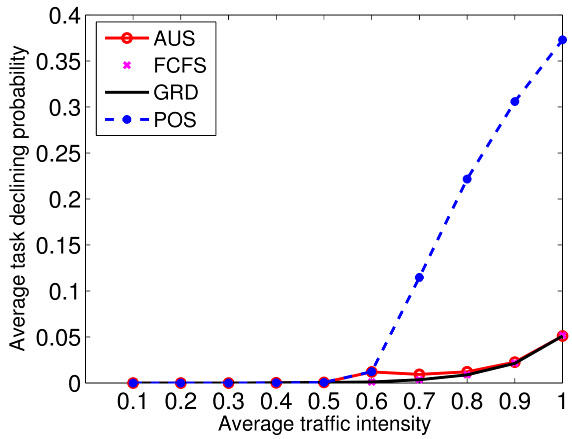


(b) Profit

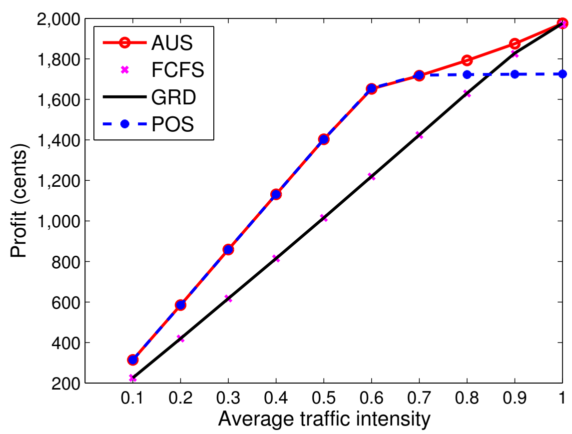


(c) Utility

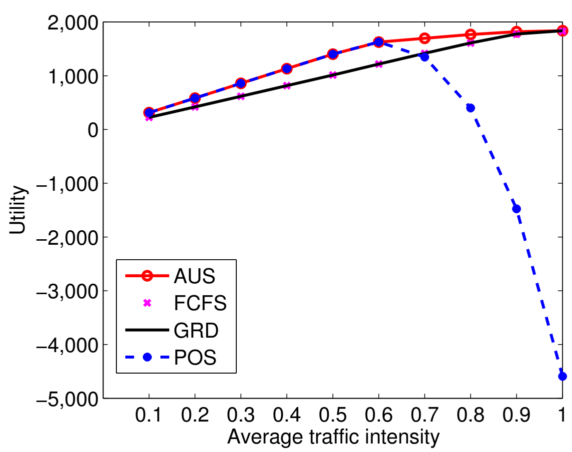
Figure 3.6: Performance comparisons for Case 2.



(a) Task declining probability



(b) Profit



(c) Utility

Figure 3.7: Performance comparisons for vehicle stochastic arrivals.

Chapter 4

Electric Vehicle Charging Scheme for a Park-and-Charge System Considering Battery Degradation Costs

4.1 Introduction

In the previous chapters, we have discussed the EV charging problem from different perspectives. However, one of the core problems for EV charging has not been fully addressed is how to ensure the EV batteries operating healthily and efficiently during the charging process. As EV's market share is increasing, more and more public charging facilities are required to provide charging services for EV customers. Recently, one promising operation mode, named park-and-charge system [54, 55], has been proposed for electric vehicle charging. The parking garage equips several charging points and provides both the parking and charging services. EVs can be charged during the parking period. Some projects have been carried out to explore the feasibility of this mode [56,57]. Several European universities led by ETH have conducted the V-charge project to design automated valet parking and charging system to implement this operation mode [57]. An important step to promote this charging mode to large scale is to develop effective and efficient charging load scheduling scheme.

In this chapter, we investigate the EV charging scheduling problem of a park-and-charge system with the objective to minimize the EV battery charging degradation cost while satisfying the battery charging characteristic. First, we design the operation mode of the park-and-charge system suitable for the charging operator to provide charging service and manage the charging process taking into account the interests of both customers and parking garage. Subsequently, a battery degradation cost model is devised to capture the characteristic of battery performance degradation during the charging process. Taking into account the developed battery degradation cost model, EV charging scheduling problem is explored and a cost minimization problem is formulated. To make the problem tractable, we investigate the features of the problem and decompose the problem into two sub-problems. A vacant charging resource allocation algorithm and a dynamic power adjustment algorithm are proposed to obtain the optimal solution of cost minimization. Several simulations based on realistic EV charging settings are conducted to evaluate the effectiveness and applicability of the proposed methods in discussed charging scenarios. Simulation results exhibit the superior performance of the proposed algorithms in achieving the most degradation cost reduction and the lowest peak power load compared with other benchmark solutions, which is beneficial for both customers and charging operators.

4.2 Related Work

Many research works have been conducted on designing effective charging scheduling algorithms for EV charging operation. Some efforts have been put on the power grid oriented issues, i.e., how to mitigate the potential impact on the power grid associated with large scale EV charging [58–61]. In [59], a decentralized algorithm is proposed to schedule the electric vehicle charging with the objective of flattening the grid load. A two-stage optimization method is proposed in [60] to minimize the network energy loss using smart charging and discharging of PHEVs. Other group of works utilized the control, scheduling, and optimization methods to focus on the EV user oriented issues, i.e., improve the EV user quality of service during the charging process. Optimal power allocation and EV arrival rate adjustment strategies are investigated in [62] to reduce the EV charging requirement blocking probability. In [6], the minimization of EV charging waiting time via scheduling charging activities spatially and temporally in a large-scale road network was investigated.

Although the EV charging scheduling problems have been discussed from different aspects in these works, one of the core problems for electric vehicle has not been fully addressed yet. A major factor preventing the proliferation of electric vehicle in current auto market is the high cost of EV batteries [63]. Ensuring the healthy and efficient operation of the battery and extending the battery lifetime is one of the most concerned points for each EV owner, also a very important issue valued greatly from the charging operating business's perspective. Many internal and external factors affect the battery performance [27, 64–70]. One important factor is the battery capacity fading, which has significant effects on the battery lifetime [68]. Several research works have investigated the factors affecting the battery capacity fading. One important contributing factor is temperature. A genetic algorithm based PHEV charging profile optimization has been addressed in [69] to find the optimal energy cost and battery resistance growth. A capacity fading model for $LiFePO_4$ based on real operating conditions in electric vehicles was proposed in [65] and concluded that preventing the high temperature of the battery was important to optimize the battery lifetime. The cost of EV battery wear due to V2G application in power system was analyzed in [70]. The effect of ambient temperature on the battery degradation was considered in this work. Without a good control of the battery charging process, a larger charging power will generate more heat and thus increase the battery temperature, which deteriorates the EV battery capacity and lifetime. An intelligent charging system capable of estimating and minimizing these effects can potentially extend the battery lifetime and reduce the battery degradation. Therefore, to achieve the best operating mode, it is crucial for the system to develop effective charging scheduling scheme to minimize the battery degradation cost and reduce the system peak power load, which is the primary motivation of this chapter.

4.3 Park-and-charge system

In this section, we first propose a framework for the park-and-charge system and then further introduce the operating model of the designed system. The detailed implementation of the control strategy is introduced afterwards.

4.3.1 System Design

As illustrated in Fig. 4.1, in a large parking garage, every parking spot is equipped with a charging outlet and connected to the charging network. People drive to the parking garage, park their EVs, connect the vehicles to the charging outlets, and leave for their personal affairs, such as working, shopping and etc. During the parking period, the charging system can charge electricity to the connected EVs according to customer specified charging requirements. The park-and-charge system includes three participants: the utility company, the charging operator and the charging customers. The charging operator purchases electricity from the utility company and provide charging services to the customers. When an EV arrives at the parking garage, the driver reports the charging information, i.e., the arrival time, estimated departure time, current battery SOC and objective battery SOC, to the parking garage's charging management system (CMS). The CMS then makes a decision on whether to admit the customer's charging requirement based on its admission control mechanism. Each admitted vehicle's charging requirement must be satisfied before its departure time. All admitted vehicles are connected to the charging network to receive charging services. Those EVs with charging requirement rejected can park in the non-charging area or travel to other charging places for service. With the collected charging information of all admitted EVs, the CMS then distributes the optimal control strategy to schedule the charging activities of all admitted EVs to achieve the EV battery degradation cost minimization while ensuring all the admitted service requirements.

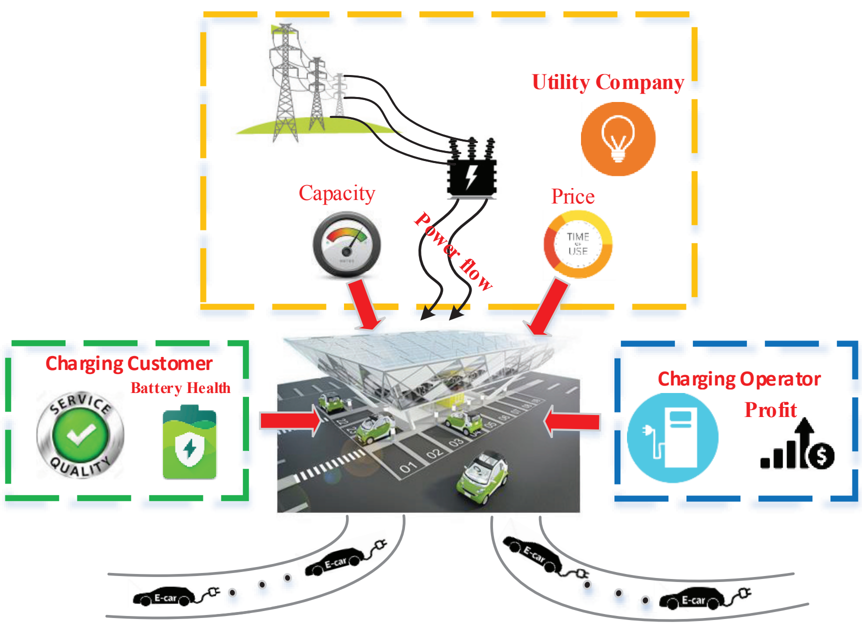


Figure 4.1: Illustration of the park-and-charge system.

4.3.2 System Implementation

The designed park-and-charge system is operated in a top-down three-level structure as shown in Fig. 4.2. The top level implements the charging tasks admission control. It has the highest priority to guarantee the quality of service (QoS) for the arrived charging customers, i.e. the service opportunity and charging requirement fulfillment. Based on the customer reported charging information, the CMS can obtain the necessary required charging slot number and the corresponding charging sequence for each requested customer subject to the battery charging characteristics. Then, the CMS makes a decision on admitting or rejecting the charging requirement based on its admission control mechanism. After collecting the charging information of all admitted customers, the charging operator compares current total number of charging slots required with that are available. If they are equal, the charging operator determines the charging scheduling strategy directly based on the obtained charging sequences. Otherwise, the charging operator may use the vacant charging resources and adjust the charging power sequence for each customer to minimize the total battery degradation cost of all the charging customers and alleviate the system's peak power load at the same time. Then, the charging operator schedules the charging activities of all the active tasks based on their determined charging sequences.

4.4 System Models

In this section, we present the detailed system model applied to our designed park-and-charge system.

4.4.1 EV Mobility Model

Workplace parking garage is a typical implementation for a park-and-charge system. The employees can park their cars for charging during their normal working hours. After work they pick up their cars and drive back home. The charging service is usually provided during the working hours. The total charging service time per day is equally divided into T time slots with each slot duration as Δt. EVs dynamically arrive at the parking garage and are sequentially indexed according to their arrival time. Denote the ith EV's arrival time as t_i^a. The arrivals of EVs follow a Poisson process [6, 46, 47]. Considering the feature of a workplace parking garage, the EV departure time can be assumed following a truncated Gaussian distribution [48] with

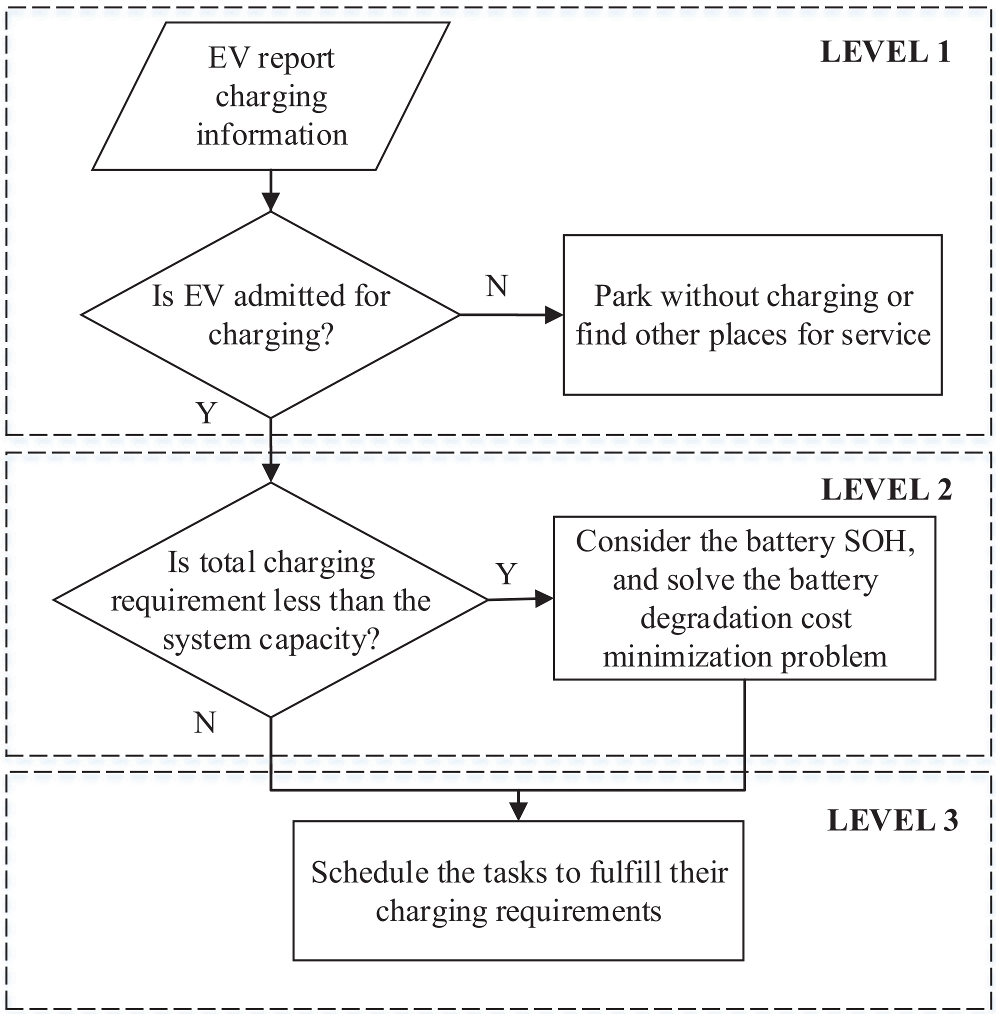


Figure 4.2: Operation flow graph of the park-and-charge system.

the mean value as the peak leaving time. The dynamic departure case can be treated as a deadline restricted problem. Detailed discussion for the dynamic departure case can be referred to our previous work [3]. To make the problem simpler, all vehicles are assumed to arrive at the beginning of each time slot, and to depart at the end of the business day, i.e., time slot T.

4.4.2 Charging Requirement Model

When each EV arrives at the parking garage and requests the charging service, the driver reports the EV's initial battery SOC S_i^{int} and the objective battery SOC S_i^{obj} expected at the departure time to the CMS. Most users typically charge their EVs at the levels that were associated with the battery warnings [49]. The objective SOC of each EV depends on many factors such as the customer's expected staying time, charging rate and electricity price, etc. Accordingly, each EV's charging requirement can be regarded as a four-tuple task $\mathcal{T}_i = (t_i^a,\ T,\ S_i^{int},\ S_i^{obj})$.

4.4.3 Battery Charging Model

As the battery charging characteristic has been detailedly analyzed in Section 3.4, we employ the same CC-CV charging model in this chapter.

Given the time slot duration Δt, with each individual task's initial and objective battery SOCs S_i^{int} and S_i^{obj}, its necessary required charging slot number L_i and the corresponding charging energy sequence $\mathbf{E}_i$ can be obtained by the SOC difference at each corresponding charging time slot, where $\mathbf{E}_i = (E_i(1), E_i(2), \cdots, E_i(L_i))$, $E_i(k)$ is the energy charging amount at time slot k, which is expressed as

$$E_i(k) = (\mathcal{S}_i(k\Delta t) - \mathcal{S}_i((k-1)\Delta t)) \cdot B_i = \int_{(k-1)\Delta t}^{k\Delta t} \mathcal{P}\,(t)dt, \tag{4.1}$$

where B_i is the rated battery capacity of EV i. Although the charging power varies continuously over time, while Δt is relatively small, the energy charging amount can be approximated as follows

$$E_i(k) \approx \mathcal{P}\left((k-1)\,\Delta t\right) \cdot \Delta t. \tag{4.2}$$

Thus, we can obtain the charging power sequence $\mathbf{P}_i = (P_i(1), \cdots, P_i(L_i))$ as well, where $P_i(k) = \mathcal{P}(k\Delta t)$ is the charging power at the beginning of the kth time slot .

4.4.4 Battery Degradation Model

Capacity fading is an important manifestation of battery degradation. Experimental results [71] have shown that high temperature is a stress factor to accelerate the battery capacity fading. The temperature dependence of capacity fading rate can be analyzed based on the Arrhenius relationship [72]:

$$r = Ae^{-E_a/(RT)}, \tag{4.3}$$

where r is the battery capacity fading rate under the absolute temperature T (in kelvins), A is the proportionality constant, E_a is the activation energy, and R is the universal gas constant.

According to the Arrhenius relationship, it is noticeable that battery capacity fading rate increases exponentially as the temperature rises. During the EV charging process, with large charging power, more heat is generated at the battery side. These generated heat will cause the battery temperature to rise, and then increase the battery capacity fading rate, which is unfavorable for the battery lifetime. According to the model proposed in [73], the temperature change produced by a given charging profile is approximated as a linear function of charging power expressed as

$$T(P) = T_{amb} + R_{th} \cdot P, \tag{4.4}$$

where R_{th} is the thermal resistance of the battery pack and T_{amb} is the ambient temperature. Therefore, the relationship between the capacity fading rate and the charging power can be expressed as

$$r(P) = Ae^{-\frac{E_a}{R} \cdot \frac{1}{T_{amb}+R_{th} \cdot P}}. \tag{4.5}$$

It can be noted that the larger the charging power the higher the battery temperature will be, and then it is more harmful to the battery healthiness and lifetime.

Consequently, in order to optimize the charging profile and prolong the battery lifetime, estimated equivalent costs of battery degradation are defined here in terms of battery capacity fading, which is expressed as follows

$$\mathcal{C}(\mathbf{P}) = \frac{Q}{B} C_{bat} = \frac{\sum_{i=1}^{L} r(P(i))\Delta t}{B} C_{bat} = \beta \sum_{i=1}^{L} r\left(P(i)\right), \tag{4.6}$$

where Q is the total capacity fading of the charging process, B is the rated battery capacity, C_{bat} is the cost of replacing the battery pack, L is the task's necessary required charging slot number, $P(k)$ is the charging power at the kth charging time slot and $\beta = \frac{\Delta t \cdot C_{bat}}{B}$ is a positive coefficient.

4.5 Problem Formulation

As introduced in the previous system implementation part, the park-and-charge system is operated in an event-driven manner. The system schedules the EV charging activities in real-time. Detailed operation of the system is formulated as follows.

4.5.1 Task Admission Control

Whenever a new EV arrives at the parking garage and asks for charging, the CMS of the parking garage triggers the task admission control mechanism to determine if the charging requirement can be admitted for service. Considering current EV penetration rate and the service capability of the charging network, it is assumed that at most M EVs can be charged concurrently in the parking garage. For the newly arrived task $\mathcal{T}_j = (t_j^a,\ T,\ S_j^{int},\ S_j^{obj})$, with knowing its charging information its necessary required charging slot number L_j and the corresponding charging power sequence $\mathbf{P}_j$ can be obtained accordingly. Then, the admission control mechanism compares current total number of charging slots required with that are available and makes the decision. The new task will be accepted for charging if the following constraint is satisfied,

$$\sum_{i \in \mathbf{I}\left(t_j^a\right)} L_i^{t_j^a} + L_j^{t_j^a} \leq M\left(T - t_j^a + 1\right), \tag{4.7}$$

where $\mathbf{I}\left(t_j^a\right)$ is the existing admitted active task set at time slot t_j^a, and $L_i^{t_j^a}$ is the necessary required charging slot number for each task in $\mathbf{I}$ at time slot t_j^a.

4.5.2 Battery Degradation Cost Minimization Problem

The admission control mechanism guarantees as many tasks as possible to get the charging opportunity under their acceptable maximum charging power conditions. While in most cases, especially under the low traffic scenarios, there are some vacant charging resources not being fully utilized if the vehicles are charged under their maximum acceptable charging powers. Under these circumstances the charging operator can adjust the tasks' charging power and fully utilize all the vacant resources to minimize the battery degradation cost and meanwhile relieve the system's peak power load. Thus, a battery degradation cost minimization problem can be formulated as follows

$$\begin{aligned}
\mathbf{P_0}: \quad \min_{\mathbf{P}_i^t} \quad & \sum_{i=1}^{N_t} \mathcal{C}\left(\mathbf{P}_i^t\right) \\
\text{s.t.} \quad & P_i(1) \leq \mathscr{P}\left(\mathcal{S}_i(t)\right), \\
& P_i(k) \leq \mathscr{P}\left(\mathcal{S}_i(t) + \frac{1}{B_i}\sum_{j=1}^{k-1} P_i(j)\cdot\Delta t\right), k > 1 \\
& \sum_{k=1}^{L_i} P_i(k)\cdot\Delta t = \left(S_i^{obj} - \mathcal{S}_i(t)\right)\cdot B_i, \\
& \sum_{i} \mathbf{1}_{P_i(k)>0} \leq M, \quad \forall k.
\end{aligned} \tag{4.8}$$

The optimization problem is implemented in an event-driven manner, it is executed whenever a new task is admitted for charging. The charging operator adjusts the charging power sequence to minimize the total battery degradation cost of all the active tasks, where N_t in the objective function is the number of currently active tasks, $\mathbf{P}_i^t$ is the charging power sequence of task i at current time slot t. The first two constraints ensure that the active tasks' charging power at each charging time slot is smaller than their maximum allowable charging power following the battery charging characteristic, where $\mathcal{S}_i(t)$ is the battery SOC at the beginning of current time slot t. The third constraint guarantees the charging requirement fulfillment of each admitted task after its whole charging process. The fourth constraint ensures that the number of EVs charged simultaneously cannot exceed the system maximum service capability, where $\mathbf{1}_{P_i(k)>0}$ is an indicator function.

4.6 Battery Degradation Cost Minimized EV Charging Scheme

By analyzing the feature of the above battery degradation cost minimization problem, it can be observed that we only need to adjust the task's charging power sequence under the situation that the total necessary required charging slot number is smaller than the available system service capacity.

According to the capacity fading rate function, we can obtain the following Lemma.

Lemma 2. *Within the feasible charging power range, the capacity fading rate function is convex.*

Proof. According to (4.5), the capacity fading rate function can be written as $r(P) = ae^{-\alpha \cdot \frac{1}{kP+b}}$, where $a = A$, $\alpha = \frac{E_a}{R}$, $k = R_{th}$, $b = T_{amb}$ are all positive coefficients. Then we can obtain

$$\frac{\partial r}{\partial P} = a\alpha k \cdot \frac{1}{(kP+b)^2} \cdot e^{-\frac{\alpha}{kP+b}} > 0, \tag{4.9}$$

$$\frac{\partial^2 r}{\partial P^2} = a\alpha k^2 \cdot e^{-\frac{\alpha}{kP+b}} \cdot \left[\frac{\alpha}{(kP+b)^4} - \frac{2}{(kP+b)^3}\right]. \tag{4.10}$$

It can be seen that the convexity of $r(P)$ depends on the relationship between P and $\frac{(\alpha/2-b)}{k}$. When $P < \frac{(\alpha/2-b)}{k}$, the capacity fading rate function is convex. According to the measurement data by Sandia National Laboratories, the Li-ion battery has an activation energy on the order of 50 kJ/mol [74]. The universal gas constant $R = 8.3144598$ $J/mol/K$. Thus, $\alpha = E_a/R = 6013.6$ K. The thermal resistant $R_{th} = 0.002$ $°C/W$, and the ambient temperature is 25 $°C$ [73]. According to the current charging technology, the maximum charging power P is around 120 kW [75], which is far smaller than $\frac{(\alpha/2-b)}{k}$. Then, we can see $\frac{\partial^2 r}{\partial P^2} > 0$. Thus, within the feasible charging power range the capacity fading rate function is convex. □

Based on the property introduced by Lemma 1, we can further obtain the following theorem,

Theorem 1. *For any active task, given its total charging requirement expanding the charging power sequence is beneficial to decrease the battery degradation cost.*

Proof. Assume that the task's original charging power sequence is $\mathbf{X} = (x_1, x_2, \cdots, x_L)$. By expanding the charging power sequence for one time slot while following the battery charging model, the new charging power sequence is updated as $\mathbf{Y} = (y_1, y_2, \cdots, y_{L+1})$.

Meanwhile, it has the relationship of $\sum_{i=1}^{L} x_i = \sum_{i=1}^{L+1} y_i$, and $x_i \geq y_i, \forall i \in [1, L]$. Since $r(P)$ is a convex function, according to (4.6) we have

$$\begin{aligned} \mathcal{C}(\mathbf{X}) &= \beta \sum_{i=1}^{L} r(x_i) = \beta \sum_{i=1}^{L} r(y_i + x_i - y_i) \\ &\geq \beta \left(\sum_{i=1}^{L} r(y_i) + r'(y_i)(x_i - y_i) \right). \end{aligned} \tag{4.11}$$

Given the following relationships

$$\sum_{i=1}^{L} (x_i - y_i) = y_{L+1}, \tag{4.12}$$

$$r(y_{L+1}) \leq r'(y_{L+1}) \cdot y_{L+1}, \tag{4.13}$$

and

$$r'(y_1) > r'(y_2) > \cdots > r'(y_{L+1}), \tag{4.14}$$

we have

$$\begin{aligned} r(y_{L+1}) &\leq r'(y_{L+1}) \cdot y_{L+1} = r'(y_{L+1}) \cdot \sum_{i=1}^{L} (x_i - y_i) \\ &\leq \sum_{i=1}^{L} r'(y_i) \cdot (x_i - y_i). \end{aligned} \tag{4.15}$$

Then, we have

$$\begin{aligned} \mathcal{C}(\mathbf{X}) &\geq \beta \left(\sum_{i=1}^{L} r(y_i) + r'(y_i)(x_i - y_i) \right) \\ &\geq \beta \left(\sum_{i=1}^{L} r(y_i) + r(y_{L+1}) \right) = \beta \sum_{i=1}^{L+1} r(y_i) = \mathcal{C}(\mathbf{Y}). \end{aligned} \tag{4.16}$$

Thus, given the total charging requirement expanding the charging power sequence can effectively decrease the battery degradation cost. □

According to Theorem 1, it is beneficial to make full use of all the available charging resources to reduce the total battery degradation cost. Given the updated total charging slot number K for each specific task, we need to determine its charging power sequence accordingly to minimize the cost and meanwhile to satisfy all charging constraints. Thus, the problem can be expressed as

$$\begin{aligned}
\mathbf{P_1}: \quad & \min_{P(k)} \quad \sum_{k=1}^{K} r\left(P(k)\right) \\
& \text{s.t.} \quad P(1) \leq \mathscr{P}\left(\mathcal{S}\left(t\right)\right) \\
& \qquad P(k) \leq \mathscr{P}\left(\mathcal{S}\left(t\right) + \frac{1}{B}\sum_{j=1}^{k-1} P(j) \cdot \Delta t\right), k > 1 \\
& \qquad \sum_{k=1}^{K} P(k) \cdot \Delta t = \left(S^{obj} - \mathcal{S}\left(t\right)\right) \cdot B
\end{aligned} \tag{4.17}$$

where $K = \min(L + v, T)$, L is the task's necessary required charging slot number at current time slot t, and v is the extra available vacant charging slot number which can be allocated to the task for charging. The first two constraints in the optimization problem restricts the charging power at each time slot not exceeding the maximum allowable charging power as per the battery charging characteristic. The third constraint restricts the task's charging requirement being satisfied after the whole charging duration.

To solve the above problem $\mathbf{P_1}$, given the extra available vacant charging slot number v, we propose a dynamic power adjustment algorithm (DPA) to minimize the battery degradation cost by optimizing the task's charging power sequence and fully utilizing all the available charging resources. The detailed description of the DPA algorithm is depicted in Algorithm 5. For that kind of tasks whose objective SOC is smaller than S^{th}, by expanding the charging sequence, the power is evenly distributed throughout the whole charging process. Otherwise, we first set a base charging power P_1 evenly distributed among all available charging slots as step 5 shows. Since the battery maximum allowable charging power gradually decreases with the battery SOC increase, if the EV is always charged in accordance with the base charging power, it will break the maximum allowable charging power constraint in the later charging phases. In other words, in real charging process the charging activity still follows the physical maximum charging power constraint. However, due to the small charging power allocated at the beginning of the charging process, the customer specified charging requirement cannot be fully satisfied at the end of the charging process. Thus, the charging power needs to be adjusted similar to the way when we pour certain amount of water into a container. The charging power needs

Algorithm 5 Dynamic power adjustment algorithm

Input: S^{int}, S^{obj}, L, v, ϵ

1: $K = \min\left(L + v, T\right)$
2: **if** $S^{obj} \leq S^{th}$ **then**
3: $\quad P'(k) = \frac{\left(S^{obj} - S^{ini}\right)B}{K\Delta t}$
4: **else**
5: $\quad P_0 = \mathscr{P}(S^{int})$
6: $\quad$ Get the task's charging power curve $\mathcal{P}(t)$ by P_0, S^{int}
7: $\quad$ Set $i = 1$
8: $\quad$ Obtain the initial charging power $P_i = \frac{\left(S^{obj} - S^{\text{int}}\right)B}{K\Delta t}$
9: $\quad$ Get $t_i = \mathcal{P}^{-1}\left(P_i\right)$
10: $\quad$ Get $\Delta_i = P_i \cdot \left(K\Delta t - t_i\right) - \int\limits_{t_i}^{K\Delta t} \mathcal{P}\left(t\right)dt$
11: $\quad$ **while** $\Delta_i > \epsilon$ **do**
12: $\quad\quad i = i + 1$
13: $\quad\quad P_i = P_{i-1} + \frac{\Delta_{i-1}}{t_{i-1}}$
14: $\quad\quad t_i = \mathcal{P}^{-1}(P_i)$
15: $\quad\quad \Delta_i = P_i \cdot \left(t_{i-1} - t_i\right) - \int\limits_{t_i}^{t_{i-1}} \mathcal{P}\left(t\right)dt$
16: $\quad$ **end while**
17: $\quad$ Get $t' = \mathcal{P}^{-1}\left(P_i\right)$
18: $\quad P(t) = P_i$, for $t \in [0, t']$
19: $\quad P(t) = \mathcal{P}(t)$, for $t \in [t', K\Delta t]$
20: $\quad P'\left(k\right) = P(k\Delta t)$
21: **end if**

Output: Updated charging power sequence $\mathbf{P'}$

to be gradually increased. This procedure is iterated until the task's total charging requirement being satisfied. The detailed power adjustment procedure is shown from steps 9 to 17. At last, we can obtain the updated charging power sequence $\mathbf{P'}$, which guarantees to achieve the minimized battery degradation cost for the given task and meanwhile satisfying all the charging constraints.

The problem $\mathbf{P_1}$ achieves the cost minimization for each individual task given its total available charging slot number K. However, for the whole charging system we need to determine how to allocate all the vacant resources to the corresponding tasks so as to minimize the total battery degradation cost of the system as the problem indicated in $\mathbf{P_0}$. According to Theorem 1, it can be noted that expanding the charging sequence can effectively reduce the battery degradation cost $\mathcal{C}$. On the other hand, for each individual task how the cost reduction amount $\Delta\mathcal{C}$ changes by successively expanding the charging sequence over one more vacant charging resource is of our great interests.

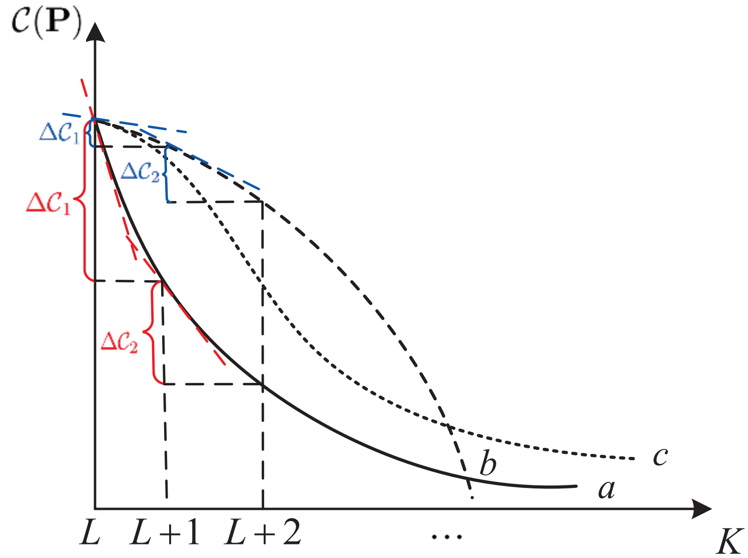


Figure 4.3: Illustration of the cost function.

As illustrated in Fig. 4.3, there are three possibilities for the cost reduction trend by expanding the charging sequence, i.e., convexly decreases as indicated in curve a, concavely decreases as indicated in curve b, and convexity undetermined decreases as indicated in curve c. For the convex case, the cost reduction amount $\Delta\mathcal{C}$ by successively expanding the charging sequence over one more time slot is gradually decreasing. Thus, the vacant charging resources can be allocated individually to the task which produces the most cost reduction to achieve the maximum cost saving for the system. While for the concave case, the cost reduction amount $\Delta\mathcal{C}$ by successively expanding the charging sequence over one more time slot is gradually increasing. Therefore, the vacant charging resources can be preferentially allocated to the task which makes the most cost reduction to the maximum extent, so on so forth until all vacant charging resources have been allocated. For the convexity undetermined case, since how the cost reduction amount $\Delta\mathcal{C}$ exactly changes is uncertain, it is difficult to obtain the optimal allocation solution directly.

Owing to the unavailability of the explicit expression of the charging power sequence, it's hard to determine the trend of above cost reduction difference $\Delta\mathcal{C}$ directly from mathematical derivations. Thus, we conduct 5000 Monte-Carlo simulations to evaluate the average cost reduction decreasing probability with different values of the battery degradation cost parameter α, i.e., the probability of $\Delta\mathcal{C}_{i+1} < \Delta\mathcal{C}_i$. Simulation result is shown in Fig. 4.4. We can see the trend of cost reduction $\Delta\mathcal{C}$ does not necessarily increase or decrease with the allocation of more vacant charging resources. It depends on the specific value of the battery degradation cost parameter α, which determines the convexity or concavity of the cost function. For our previously discussed battery degradation model, under practical scenario the parameter $\alpha = 6013.6\ K = 5740°C$, it can be seen within the feasible charging power range the cost reduction amount $\Delta\mathcal{C}$ of expanding the charging sequence successively over one more vacant charging resources is determined decreasing. In other words, the cost function $\mathcal{C}(\mathbf{P})$ is convexly decreasing with the increase of charging sequence number like the curve a illustrated in Fig. 4.3.

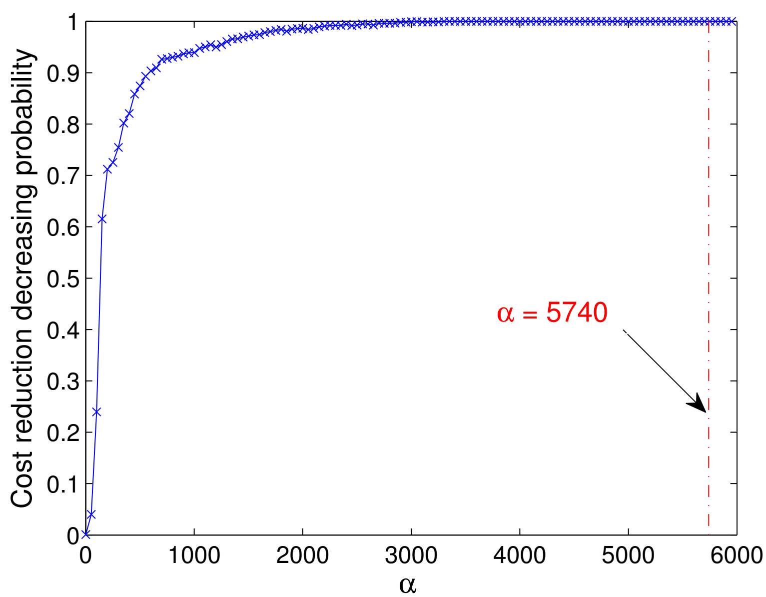


Figure 4.4: Average cost reduction decreasing probability vs. α.

According to the above discussed battery degradation cost variation trend after expanding the charging sequence, we propose an optimal vacant resource allocation algorithm (VRA), as described in Algorithm 6, to allocate all these vacant charging resources to the best candidate tasks to minimize the total battery degradation cost of the system. Assuming there are V available vacant charging resources besides all tasks' necessary required charging requirements. The vacant charging resources are allocated individually. We hypothetically expand each task's charging sequence for one time slot and obtain its updated charging power sequence by solving problem

$\mathbf{P}_1$. Then, the cost reduction $\Delta\mathcal{C}$ of each task after expanding the charging sequence can be obtained. By comparing the potential cost reductions of all the tasks, we can find the one which produces the maximum cost reduction. Then, this vacant charging resource is allocated to this task and its charging sequence is updated correspondingly. This procedure is iteratively executed until all vacant charging resources have been allocated. For each specific task its maximum charging sequence length cannot be larger than the total available slot number from current time to the end of the business day. If any task reaches this limit, it will not be engaged in the allocation any more.

Algorithm 6 Vacant resource allocation algorithm

Input: t, $\mathbf{I}$, $\mathbf{S^t}$, $\mathbf{S^{obj}}$, ϵ, V

Obtain each task's current charging power sequence $\mathbf{P}_i$ and the sequence length $L_i^0 = \|\mathbf{P}_i\|_{\ell_0}$, $i \in \mathbf{I}$
while $V > 0$ **do**
    for $i = 1 : \|\mathbf{I}\|_{\ell_0}$ **do**
        $L_i = \|\mathbf{P}_i\|_{\ell_0}$
        if $0 < L_i < T - t + 1$ **then**
            $\mathbf{P'}_i = \mathrm{DPA}(S_i^t, S_i^{obj}, L_i^0, L_i + 1 - L_i^0, \epsilon)$
            $\Delta\mathcal{C}_i = \mathcal{C}(\mathbf{P}_i) - \mathcal{C}(\mathbf{P'}_i)$
        else $\Delta\mathcal{C}_i = 0$
        end if
    end for
    if $\max(\Delta\mathcal{C}) = 0$ **then**
        break
    end if
    $[\Delta\mathcal{C}_k, k] = \arg\max \Delta\mathcal{C}$
    $\mathbf{P}_k = \mathbf{P'}_k$
    $V = V - 1$
end while

Output: The updated charging power sequence $\mathbf{P}_i$, $i \in \mathbf{I}$

Based on the battery degradation cost variation trend and the feature of our proposed greedy based vacant resource allocation algorithm, we can obtain the following theorem,

Theorem 2. *The proposed vacant resource allocation algorithm is optimal to achieve the minimum battery degradation cost for the system.*

Proof. By successively expanding the charging power sequences, different tasks' battery degradation cost reduction sequences are denoted as $x_1 \geq x_2 \geq \cdots$, $y_1 \geq y_2 \geq \cdots$, $z_1 \geq z_2 \geq \cdots$, and $\cdots$, respectively.

According to the greedy algorithm, suppose we first choose x_1, where $x_1 = \max\{x_1, y_1, z_1, \cdots\}$. Then, we should choose $\max\{x_2, y_1, z_1, \cdots\}$. If the greedy algorithm is not optimal, if and only if we have the following conditions $y_2 \geq \max\{x_2, y_1, z_1, \cdots\}$, or $z_2 \geq \max\{x_2, y_1, z_1, \cdots\}$, or $\cdots$. Apparently, this relation is contradicted with the fact that $y_2 < y_1$, or $z_2 < z_1$, or $\cdots$. Consequently, we can see the greedy algorithm is definitely optimal to achieve the most battery degradation cost reduction. $\square$

Ultimately, according to the determined charging power sequence of each active task, the charging operator makes the scheduling decision for each time slot. As the system is operated in an event-driven manner, whenever a new task arrives, it needs to reallocate the charging resources and update each task's charging profile. Thus, it's better to schedule the larger charging power task first to save more charging resources and leave more flexibility to serve the future arrived charging requirements.

4.7 Performance Evaluation

In this section, we conduct extensive simulations to evaluate the performance of the proposed battery degradation cost minimized charging scheme by comparing it with some benchmark algorithms.

4.7.1 Simulation Settings

We take a regular workplace parking garage as the object. The whole working hours (9am-5pm) are equally divided into $T = 800$ time slots, with each slot duration as $\Delta t = 0.01$ hrs. Considering the current EV penetration rate and the grid configuration in a workplace parking garage, we assume at most 8 EVs can be charged simultaneously [75] in the garage. According to different EV mobility patterns, two main charging scenarios are studied here: Case 1, all EVs arrive before work and depart after work. This case can be treated as an offline case, all tasks' charging information are known to the charging operator. Case 2, the EVs dynamically arrive at the parking garage before the middle of the day following a Poisson process with an arrival rate λ and depart after work. This case can be treated as an online case, the task's charging information reveals to the charging operator only when it arrives at the parking garage. All EVs are equipped with a 60 kWh battery. The maximum charging power during the CC stage is 40 kW. The battery CC-CV stage transition threshold is 0.6. Considering the charging behaviors of most customers, the initial EV battery SOCs are assumed following a uniform distribution from 0.1 to 0.5. The required battery SOCs are assumed following a uniform distribution from 0.8 to 0.9.

4.7.2 Simulation Results

To analyze the performance of the proposed battery degradation cost minimized charging scheme, Round-Robin and Random allocation strategies are also taken for comparisons. All results are carried out over 100 Monte Carlo simulations.

For Case 1 the offline scenario, the performance of battery degradation cost reduction gain over the original unexpanded case under different arrived vehicle numbers is first demonstrated in Fig. 4.5. From the figure, we can see by utilizing the vacant charging resources the battery degradation cost are significantly reduced. With more vehicles arriving there are less vacant charging resources can be utilized, thus the cost reduction gain is correspondingly decreased. Even so, our proposed VRA algorithm can always achieve the best cost reduction gain compared with the other two strategies.

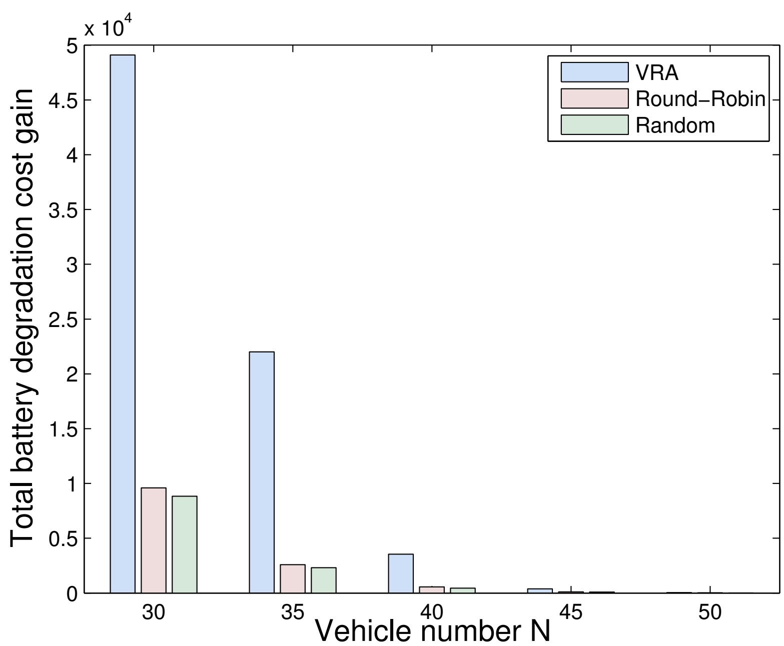


Figure 4.5: Total battery degradation cost reduction gain.

In order to evaluate the fairness issue among all the charging customers under different allocation strategies, we employ the Jain's fairness index [76], which is defined as follows

$$\mathcal{J}\left(C_1, C_2, \cdots, C_N\right) = \frac{\left(\sum\limits_{i=1}^{N} C_i\right)^2}{N \cdot \sum\limits_{i=1}^{N} C_i^2}, \tag{4.18}$$

where N is the total charging customer number, $C_i = C(\mathbf{P}_i)$ is the battery degradation cost of the ith customer. The fairness comparison is shown in Fig. 4.6. It can be noticed that VRA algorithm achieves the best fairness for all customers to reduce their battery degradation cost.

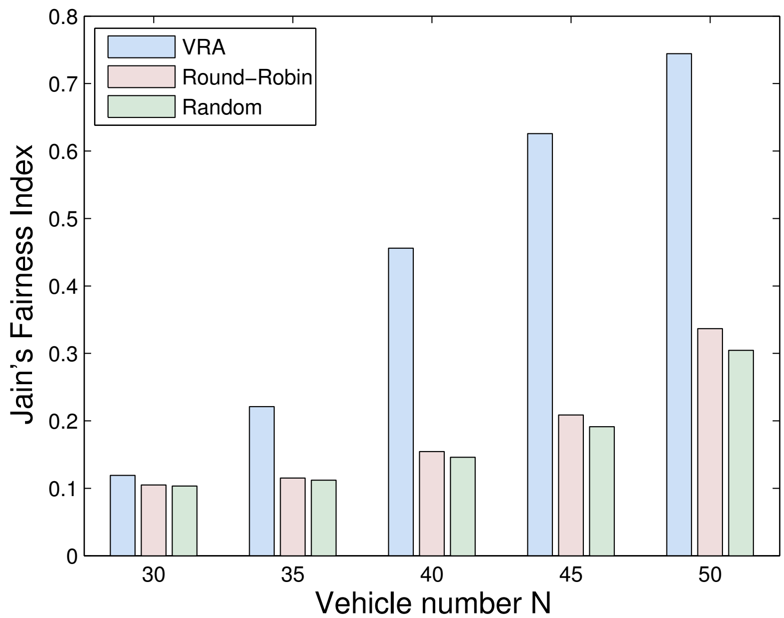


Figure 4.6: Jain's fairness index.

As we discussed before, expanding the charging sequence can not only reduce the battery degradation cost, which is beneficial for the customers to prolong the battery lifetime, it is also effective to relieve the peak load for the charging system. The peak charging power load comparison under 40 arriving vehicles case is shown in Fig. 4.7. It can be noted that with using the VRA algorithm the system peak charging power load reduces the most 15% among all the algorithms under the discussed scenario, which is very promising for the charging system operation.

For Case 2 the online scenario, all EVs dynamically arrive at the parking garage. To verify the effectiveness and robustness of the proposed charging scheme, we evaluate the performance under different arrival rate scenarios. The battery degradation

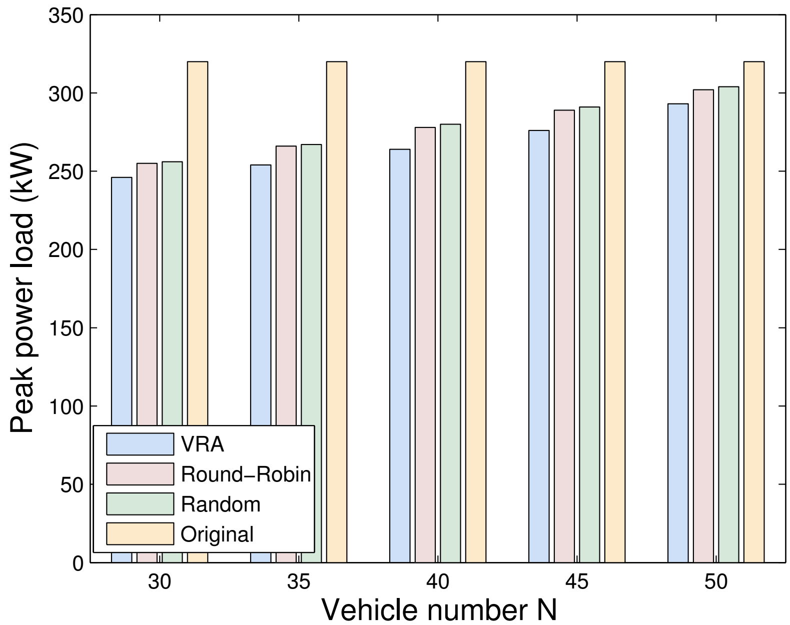


Figure 4.7: Peak charging power load.

cost reduction gain over the original unexpanded case is compared in Fig. 4.8. From the figure, we can see the proposed VRA algorithm can always achieve the most battery degradation cost reduction among all the strategies. Another important performance index, system peak power load, is demonstrated in Fig. 4.9. With increasing the arrival rate, there are higher probability more vehicles are charged simultaneously, which will make the system peak load rise. By utilizing our proposed VRA algorithm, it can be noted that the system power load can be always effectively decreased. Under some scenarios, the system peak power can be reduced over 50 % compared with the original unexpanded case, which is quite promising for the charging system operation.

4.8 Conclusion

In this chapter, we investigated the EV charging problem under a park-and-charge system. We designed the operating model for the system to provide charging service by jointly considering the interests of both customers and business. A practical charging scheme was proposed for integrating the effects of battery degradation into EV charging scheduling problem. We devised a battery degradation cost model to capture the characteristic of battery performance degradation during the charging

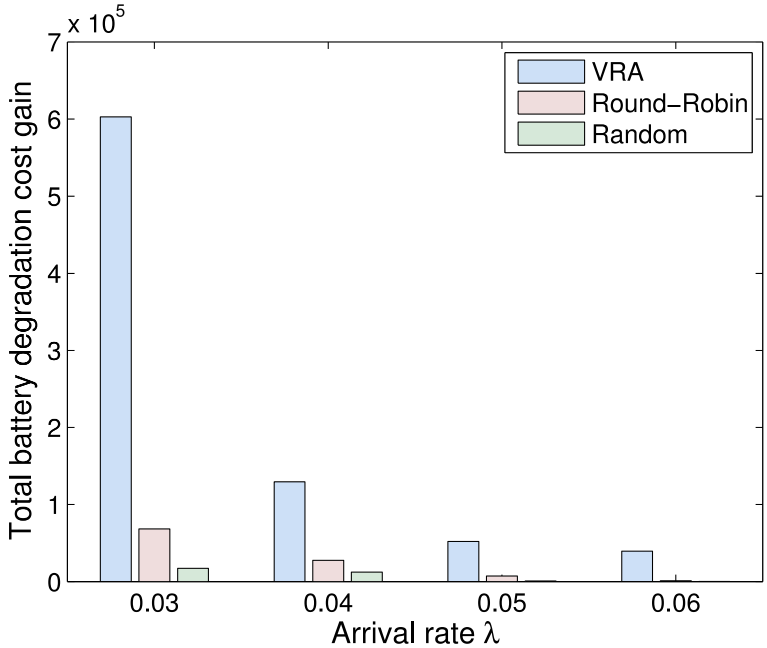


Figure 4.8: Online case total battery degradation cost reduction gain.

process. The developed battery degradation cost model was incorporated into the optimal EV charging scheduling scheme design to minimize the system total battery degradation cost. By investigating the feature of the cost minimization problem, we decomposed the problem into two sub-problems and proposed vacant resource allocation algorithm and dynamic power adjusting algorithm to solve the associated optimization problem. The applicability and effectiveness of the proposed methods were demonstrated through several case studies. The obtained results exhibited the superior performance of the proposed method in achieving both battery degradation cost minimization and system peak power load reduction, which benefits both the customers and charging operator.

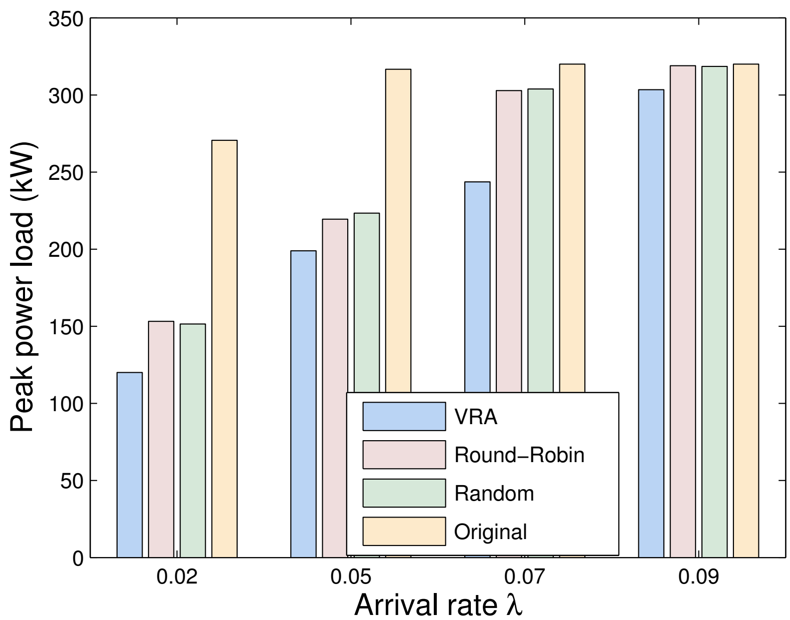


Figure 4.9: Online case peak charging power load.

Chapter 5

Maximum Utility Scheduling for Residential Community Electric Vehicle Charging

5.1 Introduction

In the previous chapters, we have discussed the EV charging problem mainly under the charging station scenario. When possible, EV owners prefer to charge their EVs at home. Compared with other conventional loads, EVs typically have a high energy requirement and require a large charging power. They thus can place considerable stress on the existing power grid [77]. Within a residential community, it is beneficial to have a charging aggregator to control the EVs' charging activities to avoid the situation that large number of EVs are charged simultaneously causing the peak load increase abruptly happening, which may cause severe damages to both the power grid and community residents [78,79]. The charging process itself has some impacts on the battery performance [70]. How to effectively reduce the impacts under the premise of ensuring the expected charging energy is a very important and challenging topic.

Motived by the above issues, in this chapter, we focus on the residential community charging scenario with the objective to maximize the total utility of the community charging network, in which the charging aggregator controls the EVs' charging activities to cover their necessary daily travel requirements while meeting the other corresponding constraints. First, we extend the battery charging characteristic analysis to a general non-linear case. To comprehensively evaluate the gain of the whole charging network, we propose a utility optimization problem by jointly considering the charging energy and battery performance degradation during the charging process. Second, we prove that the utility maximization problem is a convex optimization problem and propose a utility maximized charging scheme to achieve the maximum utility for the community charging network. Finally, we conduct extensive simulations to evaluate the performance of the proposed scheme under the underload and overload scenarios, respectively. The results demonstrate that the proposed utility maximized charging scheme can substantially outperform the benchmark solutions in terms of higher utility and task service rate.

5.2 Related Work

Recently, many studies have been conducted on the EV charging control problem. In general, the EV charging problem can be classified into two main categories: supply side oriented and demand side oriented problems. The supply side problem mainly studied on how to control the impact of EV charging activities on the power grid [15, 80–85]. A valley filling algorithm was proposed in [83] to schedule the EV charging with the objective of flattening the grid load. In [15], a distributed random access framework was proposed to coordinate the PHEV charging to protect the distribution grid from bus congestion and voltage drop. A Lagrangian based partial decomposition method was proposed in [84] to reduce the total generation cost and alleviate the transmission grid congestion in transmission-constrained power systems. While the demand side oriented works mainly focused on the issues related to the EV charging users [86–90]. EV charging user convenience was considered as the main objective of the scheduling problem in [87]. A distributed coordinated algorithm was correspondingly proposed to maximize the user convenience under the power constraints imposed by the power utility. In the case of limited charging resources, fairness issue becomes quite critical. A physical fair-queuingg framework was established in [88] to achieve the best scheduling fairness. To minimize the charging cost for the customers, a moving horizon based real-time charging scheme was proposed in [89] to the dynamic coordination of vehicles.

Although the EV charging scheduling problems have been studied from different perspectives. One important issue, i.e., battery performance degradation, should be considered during the charging process. Several research works have investigated the factors affecting the battery performance degradation [64, 65, 73, 91, 92]. The health model for $LiFePO_4$ cell units was specified in [91]. The impact of temperature and discharging rate on the lithium-ion battery aging was investigated in [92] and concluded that high temperature is a killer of the battery lifetime. Based on real operating conditions of electric vehicle, a capacity fading model for $LiFePO_4$ battery was proposed in [73]. Given all these findings, it is critical for the charging aggregator to develop effective charging schemes not only providing necessary energy required by the charging customer but also protecting the EV battery health, which is the primary motivation of this chapter.

5.3 System Models

We consider a residential community charging scenario. As illustrated in Fig. 5.1, people come back home, plug in their EVs, set the charging requirements, leave the EVs for charging during the midnight, and unplug their EVs the next morning. When each EV sets its charging requirement, it reports the current battery SOC, target battery SOC and the minimum charging amount to the charging aggregator. During the predetermined service period, the community charging aggregator controls the charging activities with the objective of utility maximization for the entire charging network in the community. Depending on the total charging requirements and service capacity the charging aggregator executes the task admission mechanism first to determine which tasks can be served. Then, it determines the optimal charging duration of each active task to maximize the total utility of the charging network.

5.3.1 Charging Requirement Model

EV owners' charging behavior depends to a large extent on the daily driving pattern and the electricity tariff structure. Most EV owners drive the vehicles to and from work for commuting purpose. According to the statistics of daily traffic versus time of day in U.K, two peaks, the morning peak (7am-9am) and the afternoon peak (4pm-6pm), are observed for both commuting and business uses [93]. In addition, the electricity pricing off-peak hours normally sit between 7pm to 7am [94]. Consequently, most EV owners plug in their EVs for charging after coming back home and unplug the EVs for driving before leaving home. As introduced in the charging scenario part, the charging aggregator normally schedules the EVs' charging demands during the off-peak hours to alleviate the load to the power grid. Thus, according to the EV

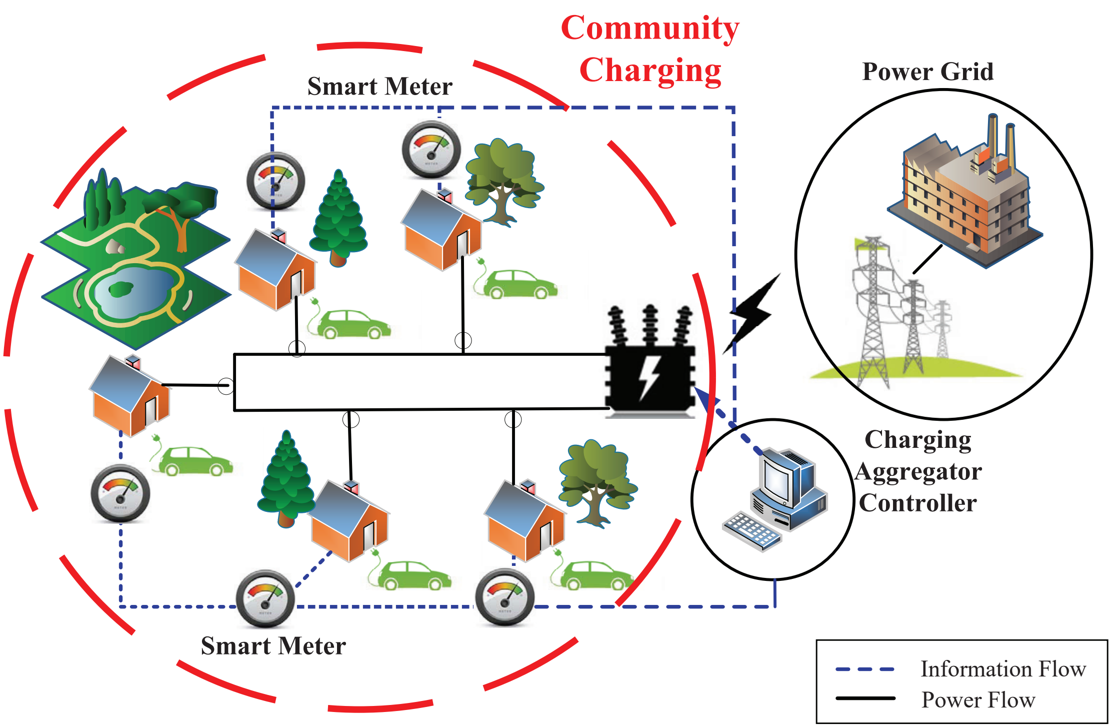


Figure 5.1: System model.

user charging behavior and the grid load cycle all the EVs are assumed plugged in before the charging service beginning time, and unplugged after the charging service ending time. All the EVs are sequentially indexed by their plug-in time. The total charging service duration is denoted as T^s.

For the EV owners, when they plug in their EVs for charging, they have expected minimum and maximum charging requirements. The minimum charging requirement guarantees their necessary daily usage, while the maximum charging requirement is the desired charging amount of each customer. For instance, some customers prefer to fully charge their batteries, while some expect a 90% capacity charge. Denote each customer's minimum charging requirement as $r^{\min}$ and the maximum expected charging requirement as $r^{\max}$, respectively.

Based on the driving pattern statistics, most people drive less than 53 km per day [95]. It is found that a log normal distribution, with mean μ_d and standard deviation σ_d, can be selected to approximate the probability density function of EV's daily travel distance [96]. The distribution function is expressed as

$$f_d\left(x:\mu_d,\sigma_d\right)=\frac{1}{\sqrt{2\pi}\sigma_d x}e^{-\frac{(\ln x-\mu_d)^2}{2\sigma_d^2}}. \tag{5.1}$$

Given the daily travel distance, the minimum inflexible charging requirement of each customer can be estimated by the following equation

$$r^{\min}=\frac{d}{D}\cdot B, \tag{5.2}$$

where D is the full capacity range of the EV, and B is the rated battery capacity.

The maximum expected charging requirement of each customer depends on the initial battery SOC S^i when the customer plans to charge the vehicle and the personal preference of the target batty SOC S^t. Thus, the maximum charging requirement of each customer can be expressed as follows

$$r^{\max}=(S^t-S^i)\cdot B. \tag{5.3}$$

Accordingly, each EV's charging requirement can be regarded as a four-tuple task defined as $\mathcal{T}=(i,S^i,r^{\min},r^{\max})$.

5.3.2 Battery Charging Characteristic Model

On current market the vast majority of electric vehicles utilize lithium-ion battery as energy storage unit, which has also been applied in many consumer electronics. Compared with the conventional rechargeable lead-acid and nickel metal hydride batteries, Li-ion battery has the advantages in capacity, safety, lifetime, etc. The Li-ion battery is voltage limiting similar to the lead acid battery, but has tighter voltage tolerances and the absence of trickle or float charging at full charge.

As mentioned in Chapter 3, (CC-CV) charging is the main charging approach for Li-ion battery [50, 97]. Different from the previous simplified linear relationship between the battery charging power and the battery SOC, this relationship is depicted more precisely as the following convex decreasing function

$$\mathcal{P}(S) = aS^2 + bS + c, \tag{5.4}$$

where two constraints $\mathcal{P}(0) = P_m$ and $\mathcal{P}(1) = 0$ also apply; P_m is the maximum charging power; a, b, c are coefficients. According to the above constraints, it can be obtained that $b = -a - P_m$, $c = P_m$, and $0 < a < P_m$. The value of a determines the power decreasing speed with the increase of battery SOC. Different batteries may have different characteristics. The detailed value of a can be obtained by fitting the experimental measurement data of different types of batteries.

In order to see how the battery SOC changes with the accumulative charging duration, assume δ is a very short time interval we can obtain the following relationship,

$$S(t) = S(t-\delta) + \frac{\mathcal{P}(t-\delta)\cdot\delta}{B}, \tag{5.5}$$

where B is the rated battery capacity. After some mathematical manipulations, we can obtain the following first order nonlinear ordinary differential equation

$$S'(t) = \frac{a}{B}S^2(t) - \frac{a+P_m}{B}S(t) + \frac{P_m}{B}. \tag{5.6}$$

By solving this differential equation with the initial condition $S(0) = 0$, we can obtain the expression of $S(t)$ as

$$S(t) = \frac{P_m e^{\frac{P_m}{B}t} - P_m e^{\frac{a}{B}t}}{P_m e^{\frac{P_m}{B}t} - a e^{\frac{a}{B}t}}. \tag{5.7}$$

Substitute (5.7) into (5.4), the relationship between charging power and accumulative charging time can be obtained as

$$P(t) = \frac{P_m \left(P_m - a\right)^2 \mathrm{e}^{\frac{(P_m+a)}{B}t}}{\left(P_m \mathrm{e}^{\frac{P_m}{B}t} - a\mathrm{e}^{\frac{a}{B}t}\right)^2}. \tag{5.8}$$

For each charging customer, denote the accumulative charging duration as T^a. Thus, the total charging energy E during this period can be expressed as

$$E = \int_{t=0}^{T^a} P(t)dt, \tag{5.9}$$

where $P(t)$ is the instantaneous battery charging power subject to the battery intrinsic charging characteristic.

As the charging aggregator, it targets on the whole charging network utility maximization while taking into account the interests of both business and customers. Considering each customer's specific charging requirement and the quality of service, the following constraint should always be satisfied

$$r^{\min} \leq E \leq r^{\max}. \tag{5.10}$$

5.3.3 Battery Degradation Model

Battery capacity fading occurs regardless whether the battery is inactive (so-called "calendar life" loss) or active ("cycle life" loss). However, many stressing factors accelerate the battery capacity fading leading to faster battery degradation. Temperature is one important factor. High temperature speeds up the battery active material depletion [71]. Empirically, the temperature dependence capacity fading can be described by the Arrhenius relationship [72]:

$$r(T) = Ae^{-E_a/(RT)}, \tag{5.11}$$

where r is the battery capacity fading rate (% capacity loss) under the absolute temperature T (Kelvin), A is the pre-exponential factor, E_a is the activation energy, and R is the universal gas constant.

During the charging process, ohmic heat is generated. These generated heat will cause the battery temperature rising, which is unfavorable for the battery lifetime.

According to the model proposed in [73], the temperature change produced by a given charging profile is approximated as a linear function of the charging power expressed as

$$T(P) = T_{amb} + R_{th} \cdot P, \tag{5.12}$$

where R_{th} is the thermal resistance of the battery pack and T_{amb} is the ambient temperature. Therefore, the relationship between the capacity fading rate and the charging power can be expressed as

$$r(P) = Ae^{-\frac{E_a}{R} \cdot \frac{1}{T_{amb} + R_{th} \cdot P}}. \tag{5.13}$$

Accordingly, for an accumulated charging period T^a, the total capacity fading can be expressed as

$$C = \int_{t=0}^{T^a} r\left(P\left(t\right)\right) dt. \tag{5.14}$$

5.3.4 Utility Model

Based on the aforementioned models, we consider the effective charging energy to EVs to satisfy their charging requirements. As we can see the more energy provided to the charging customers the closer to their expected maximum charging requirements. However, as we discussed before longer charging time also brings more battery degradation, which is not desirable from the customer's point of view. Thus, to comprehensively evaluate the whole gain for the charging network incorporating the interests of both the business and customers, we propose the following utility model

$$\begin{aligned} \mathcal{U}\left(T^a\right) &= k_1 E - k_2 C \\ &= k_1 \int_{t=0}^{T^a} P(t) dt - k_2 \int_{t=0}^{T^a} r\left(P\left(t\right)\right) dt, \end{aligned} \tag{5.15}$$

where T^a denotes the accumulative charging duration for the EV, which is determined by the charging aggregator; k_1 and k_2 are positive parameters specified by the charging aggregator to reflect the weight of charging energy and battery degradation. By tuning the parameters, the charging aggregator can adjust the weight of each part of the utility function, thus to make different decisions on the charging activities.

5.4 Problem Formulation

As the community charging aggregator the objective is to control all the EVs' charging activities to achieve the maximum utility for the whole charging network. Meanwhile, the EVs' charging activities must also meet the constrains to make the system work effectively. Thus, a utility maximization problem can be formulated as follows

$$
\begin{aligned}
\mathbf{P_0}: \quad & \max_{T_i^a} \quad \sum_{i=1}^{N} \mathcal{U}_i \left(T_i^a\right) \\
& \text{s.t.} \quad r_i^{\min} \leq \int_{t=0}^{T_i^a} P_i(t)dt \leq r_i^{\max}, \\
& \qquad \sum_{i=1}^{N} T_i^a \leq M \cdot T^s, \\
& \qquad T_i^a \leq T^s, \\
& \qquad \sum_{i} \mathbf{1}_{P_i(t)>0} \leq M.
\end{aligned} \tag{5.16}
$$

In the objective function, N is the number of current active tasks requesting charging service. The charging aggregator needs to determine each task's total charging duration T_i^a to maximize the total system's utility. The first constraint ensures that each active task's total charging energy should be larger than its minimum charging requirement to guarantee its necessary daily usage and no larger than its maximum charging requirement to avoid the over charging happening. The second constraint guarantees all active tasks' total charging duration less than the system's total service capacity. The third constraint ensures each task's charging duration less than the system's maximum service duration. The fourth constraint ensures that the number of EVs charged simultaneously cannot exceed the community charging network maximum service capability, where $\mathbf{1}_{P_i(k)>0}$ is an indicator function. M is the maximum number of branches which can be charged concurrently. It is normally restricted by the peak power considering the power gird safe operation [51].

5.5 Utility Maximized Charging Scheme

As introduced in the previous system model part, it can be noticed that the charging aggregator needs to determine which tasks among all the charging requests can be served during the service hours and the corresponding charging duration of each active task as well. Detail operation of the system can be analyzed as follows.

5.5.1 Task Admission Control

Since each active task's minimum charging requirement must be satisfied to guarantee the EV owner's necessary daily usage, moreover to provide more charging opportunities to as many customers as possible, each task's minimum requirement should have higher priority to be served. As discussed in the previous battery charging characteristic part, (5.7) depicts the relationship of battery SOC over accumulative charging duration when the battery SOC changing from 0. Owing to the heterogeneity of different tasks' initial battery SOCs, through this relationship we can map each task's S^i to the corresponding time t^0 of its $S(t)$ function as $t^0 = S^{-1}(S^i)$. Then, the task's corresponding charging power over the accumulative charging duration can be obtained. Similarly, we can obtain each task's corresponding time t^1 of its $S(t)$ function when its minimum charging requirement is completed as $t^1 = S^{-1}(S^i + \frac{r^{\min}}{B})$. Thus, the total charging duration to finish each task's minimum charging requirement can be expressed as follows

$$\Delta = t^1 - t^0 = S^{-1}(S^i + \frac{r^{\min}}{B}) - S^{-1}(S^i). \tag{5.17}$$

According to the system capacity and load conditions, there are two situations: underload condition and overload condition. For the underload scenario, all the tasks' minimum charging requirement can be accommodated, i.e., $\sum_i \Delta_i \leq M \cdot T^s$. For the overload scenario, all the tasks' minimum charging requirement is larger than the system's service capability, i.e., $\sum_i \Delta_i > M \cdot T^s$. The charging aggregator needs to determine which tasks can be served. According to the principle of utility maximization, we proposed a metric, *unit utility*, to describe the potential utility gain of each task, which can be expressed as follows

$$u = \frac{\mathcal{U}(\Delta)}{\Delta}. \tag{5.18}$$

The charging aggregator admits the minimum charging requirements of the tasks based on their unit utilities in a descending order until no more tasks can be accommodated.

5.5.2 Problem Analysis

After meticulously analyzing the original problem $\mathbf{P}_0$, we can see it actually can be decomposed into two sub problems: first, satisfy each task's minimum charging requirement; second, determine each task's subsequent charging duration to achieve the maximum utility for the charging network.

For the overloaded condition, it is straightforward for the charging aggregator to do admission control and scheduling based on the proposed utility based admission control mechanism to achieve the maximum utility for the charging network. However, in most cases the system is operated under the underloaded condition. After satisfying each active task's minimum charging requirement, with the remaining charging resources the charging aggregator needs to determine each task's subsequent charging duration accordingly to achieve the maximum utility for the charging network. Consequently, the new utility maximization problem is expressed as follows

$$
\begin{aligned}
\mathbf{P_1}: \quad \max_{T_i^a} \quad & \sum_{i=1}^{N} \mathcal{U}_i' \left(T_i^a\right) \\
\text{s.t.} \quad & \int\limits_{t=t_i^1}^{t_i^1+T_i^a} P_i(t)dt \leq r_i^{\max} - r_i^{\min}, \\
& \sum_{i=1}^{N} T_i^a \leq M \cdot T^s - \sum_i \Delta_i, \\
& T_i^a \leq T^s - \left\lfloor \sum_i \Delta_i \Big/ M \right\rfloor, \\
& \sum_i \mathbf{1}_{P_i(t)>0} \leq M.
\end{aligned}
\tag{5.19}
$$

where

$$
\mathcal{U}_i'(T_i^a) = k_1 \left(r_i^{\min} + \int\limits_{t=t_i^1}^{t_i^1+T_i^a} P_i(t)dt \right) - k_2 \int\limits_{t=t_i^0}^{t_i^1+T_i^a} r\left(P_i\left(t\right)\right)dt \tag{5.20}
$$

T_i^a is each task's accumulated charging duration after its minimum charging requirement $r_i^{\min}$ being satisfied.

According to the charging energy function and the capacity fading function, we can obtain the following Lemmas.

Lemma 3. *The total charging energy function is concavely increasing with the accumulated charging duration.*

Proof. According to (5.9), we can obtain

$$\begin{aligned}\nabla E\left(T^a\right) &= \frac{\partial \int\limits_{t=t^1}^{t^1+T^a} P(t)dt}{\partial T^a} = P\left(t^1+T^a\right) \\ &= \frac{P_m(P_m-a)^2 \mathrm{e}^{\frac{(P_m+a)}{B}\left(t^1+T^a\right)}}{\left(P_m \mathrm{e}^{\frac{P_m}{B}(t^1+T^a)} - a\mathrm{e}^{\frac{a}{B}(t^1+T^a)}\right)^2}.\end{aligned} \tag{5.21}$$

Since $0 < a < P_m$, $\nabla E\left(T^a\right) > 0$ always holds.

Then, we can obtain

$$\nabla^2 E\left(T^a\right) = -\frac{P_m(P_m-a)^3 \mathrm{X} \mathrm{e}^{\frac{(P_m+a)}{B}\left(t^1+T^a\right)}}{BY^3}, \tag{5.22}$$

where $X = P_m \mathrm{e}^{\frac{P_m}{B}\left(t^1+T^a\right)} + a\mathrm{e}^{\frac{a}{B}\left(t^1+T^a\right)}$ and $Y = P_m \mathrm{e}^{\frac{P_m}{B}\left(t^1+T^a\right)} - a\mathrm{e}^{\frac{a}{B}\left(t^1+T^a\right)}$.

It can be noted that $X > 0$ $Y > 0$, thus $\nabla^2 E\left(T^a\right) < 0$ always holds. Consequently, the total charging energy E is concavely increasing with the increase of the accumulated charging duration T^a. □

Lemma 4. *The total battery capacity fading function is concavely increasing with the accumulated charging duration.*

Proof. According to (5.14), we can obtain

$$\begin{aligned}\nabla C\left(T^a\right) &= \frac{\partial \int\limits_{t=t^1}^{t^1+T^a} r\left(P\left(t\right)\right)dt}{\partial T^a} = r\left(P\left(t^1+T^a\right)\right) \\ &= Ae^{-\frac{E_a/R}{T_{amb}+R_{th}\cdot\frac{P_m(P_m-a)^2 \mathrm{e}^{\frac{(P_m+a)}{B}\left(t^1+T^a\right)}}{\left(P_m \mathrm{e}^{\frac{P_m}{B}(t^1+T^a)} - a\mathrm{e}^{\frac{a}{B}(t^1+T^a)}\right)^2}}}\end{aligned} \tag{5.23}$$

Obviously, $\nabla C\left(T^a\right) > 0$ always holds.

In regards to the second order derivative of C, it is expressed in (5.24), in which X, Y are the same as expressed in Lemma 1, $Z = \frac{P_m\left(T^a+t^1\right)}{B}$ and $W = \frac{a\left(T^a+t^1\right)}{B}$.

It can be noticed that $\nabla^2 C\left(T^a\right) < 0$ always holds. Therefore, the total battery capacity fading C is concavely increasing with the increase of the accumulated charging duration T^a. $\square$

Based on the property introduced by the above two lemmas, we can obtain the following Remark.

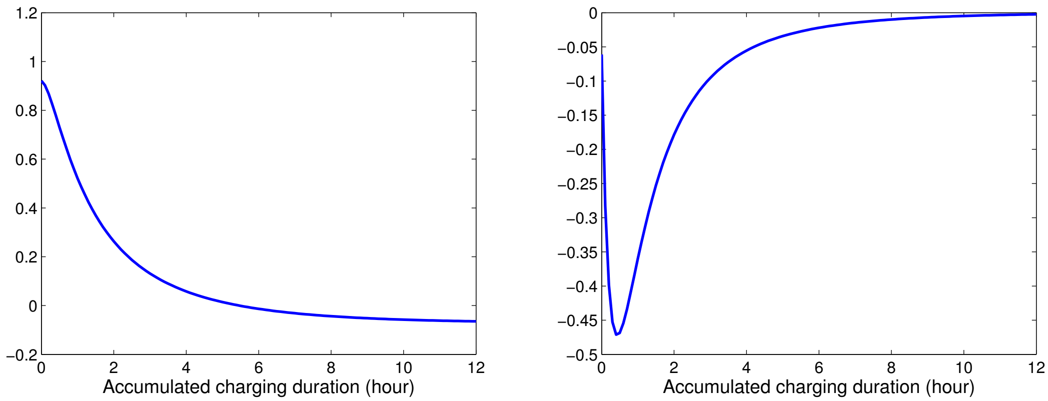
Remark 1. *Since the utility function is the subtraction of two concave functions, the convexity of the utility function is unfixed. It depends on the specific value of the charging parameters and the coefficients k_1 and k_2 specified by the charging aggregator.*

As the parameters of the charging problem have many physical restrictions, we should discuss the problem under the practical parameter settings. According to the measurement data by Sandia National Laboratory, the Li-ion battery has an activation energy on the order of 50 kJ/mol [74]. The universal gas constant is $R = 8.314 J/mol/K$. The thermal resistant is $R_{th} = 2K/kW$, and the ambient temperature is 25 $°C$. According to [98], current Li-ion battery's cycle life is more than 4000 cycles. Thus, the pre-exponential factor is set as 1.5×10^5. Assume the EV is charged by the Level 2 charging mode with peak charging power of 20 kW. We investigate a 2017 model of Nissan Leaf equipped with a 30 kWh battery. k_1 depicts the electricity price, eg. 0.085 CAD according to BC Hydro step 1 price. k_2 depicts the battery degradation cost, eg. 5500/20. According to [99], the replacement cost of a new battery pack of Nissan Leaf is around 5500 CAD. Typically, the battery's end of life is designed to be about 80% of its initial capacity. Thus, $k_2 \cdot C$ is corresponding to the total battery degradation cost of current charging activity. Then, the utility can be interpreted as the gain of the charging network. With all these parameters we can analyze the convexity of the utility function as shown in Fig. 2.

From the figures, we can see within the feasible charging duration the first order derivative of the utility function is changing from positive to negative with the increase of accumulated charging duration. The second order derivative keeps negative within the feasible charging duration. According to this feature, we can obtain the following Remark.

Remark 2. *Under the practical charging parameter setting, within the feasible charging duration range, the utility function is a concave function.*

$$\nabla^2 C\left(T^a\right) = -\frac{A P_m (P_m - a)^3 E_a R_{th} \mathrm{XY} \mathrm{e}^{(W+Z) - \frac{E_a/R}{\left(R_{th}\frac{\partial E}{\partial T^a} + T_{amb}\right)}}}{BR\left(-2aP_m T_{amb}\mathrm{e}^{(W+Z)} + \left(P_m{}^3 - 2aP_m{}^2 + a^2 P_m\right) R_{th}\mathrm{e}^{(W+Z)} + P_m{}^2 T_{amb}\mathrm{e}^{2Z} + a^2 T_{amb}\mathrm{e}^{2W}\right)^2} \tag{5.24}$$



(a) 1st order derivative

(b) 2nd order derivative

Figure 5.2: The utility function convexity analysis.

Based on the concavity of the utility function, each task's optimal charging duration T^{a*} to achieve the maximum utility can be obtained by solving the following equation

$$k_1 \cdot \nabla E\left(T^{a*}\right) - k_2 \cdot \nabla C\left(T^{a*}\right) = 0. \tag{5.25}$$

where $\nabla E\left(\bullet\right)$ and $\nabla C\left(\bullet\right)$ are expressed in (5.21) and (5.23), respectively.

5.5.3 Utility Maximized Charging Scheduling Algorithm

According to the above analysis of the utility function, we propose a utility maximized charging scheduling algorithm (UMS) as described in Algorithm 7, to schedule all active tasks' charging activities to maximize the total system's utility. Since in real charging situation the charging aggregator controller cannot make decisions in a continuous time manner. The whole time horizon is equally divided into several time slots, and the decision is made by time slot. As described in the algorithm, we can obtain the time t when all tasks' minimum charging requirements are satisfied at first. Since there are at most M EVs can be charged concurrently, we need to evaluate if there is any remaining charging resource can be utilized at t as indicated in line 2. For each active task, it has three important time durations. As shown is lines 8 to 11, by solving (5.25) we can obtain each task's optimal charging duration T^{a*} to achieve its maximum utility. T^f is each task's feasible sojourn time from t to its charging ending time. T^r is the minimum charging duration needed for the task to fulfill its maximum charging requirement after its minimum charging requirement being satisfied. Then, each task's feasible charging duration should be the minimum of these three parameters. With time going on, the potential utility increment ΔU of each active task after expanding the charging duration for another time slot can be obtained. If any task's accumulated charging duration is over its feasible charging duration T^u or the current time has exceeded the task's charging ending time, this task becomes inactive and does not continue to be involved in the charging scheduling process. With m' as the maximum allowable charging task number at the scheduling time, the m' tasks with the most ΔU are scheduled for charging. Corresponding information is updated afterwards. This procedure is iteratively executed until all tasks are inactive.

Based on the concavity of the utility function, the proposed algorithm is optimal to achieve the maximum utility for the whole charging network.

5.6 Performance Evaluation

In this section, we implement our solution and conduct extensive simulations with practical charging settings to evaluate the performance of the proposed utility maximized charging scheme by comparing it with some benchmark algorithms.

5.6.1 Simulation Settings

We take a normal residential community of 150 households as investigation object. The charging aggregator provides charging service during the off-peak hours from 7pm to 7am. The total charging duration is equally divided with each slot duration of 1 min. We investigate the model of Nissan Leaf with 30kWh battery and up to 172 km of range on a single full charge. The EVs are charged by Level 2 charging mode with peak charging power of 20 kW. Considering the power grid safety it is assumed that at most 10 EVs can be charged simultaneously. The initial battery SOCs are assumed following a uniform distribution from 0.1 to 0.5. The minimum charging requirement of each EV is assumed to cover its daily travel distance following the log normal distribution with mean travel distance of 53 km. The target battery SOCs are assumed following a uniform distribution from 0.8 to 0.95. According to the total number of EVs requesting for charging and their minimum charging requirements, two main charging scenarios are considered here: underload charging scenario and

Algorithm 7 Utility maximized charging scheduling algorithm

Input: active task index set $\mathbf{I}$, active task information set $\mathcal{T}_i = (i, S^i, r_i^{\min}, r^{\max}), i \in \mathbf{I}$, maximum simultaneous charging tasks number M

Obtain all tasks' $r^{\min}$ finishing time $t = \left\lceil \left\lceil \frac{\sum_i \Delta_i}{\Delta t} \right\rceil \Big/ M \right\rceil$

Obtain the occupied charging resources number n at time t, $n = \mathrm{rem}(\left\lceil \frac{\sum_i \Delta_i}{\Delta t} \right\rceil \Big/ M)$

if $n = 0$ **then**

  $t = t + 1$, $m = M$

else $m = M - n$

end if

for $i = 1 : \|\mathbf{I}\|_{\ell_0}$ **do**

  Obtain T_i^{a*} by solving (5.25)

  $T_i^f = T^s - t$

  $T_i^r = S^{-1}(S^i + \frac{r^{\max}}{B}) - S^{-1}(S^i + \frac{r^{\min}}{B})$

  $T_i^u = \max\{\min\{T_i^{a*}, T_i^f, T_i^r\}, 0\}$

end for

while $t \leq T^s$ **do**

  for $i = 1 : \|\mathbf{I}\|_{\ell_0}$ **do**

    if $T_i^a \leq T_i^u$ & $T_i^u > 0$ **then**

      $\Delta U_i = \mathcal{U}_i(T_i^a + \Delta t) - \mathcal{U}_i(T_i^a)$

    else $\Delta U_i = 0$

    end if

  end for

  if $\max(\Delta U) = 0$ **then**

    break

  end if

  $m' = \min\{m, \|\mathbf{\Delta U}\|_{\ell_0}\}$

  schedule the m' tasks with the most ΔU

  update the scheduled tasks' $T_i^a = T_i^a + \Delta t$

  $m = M$, $t = t + 1$

end while

Output: Each task's accumulated charging duration T_i^a after its $r^{\min}$ being satisfied overload charging scenario.

5.6.2 Simulation Results

To analyze the performance of the proposed utility maximized charging scheme, first come first serve (FCFS) and Round-Robin (RR) charging schemes are also taken for comparisons as the benchmark. All results are carried out over 100 Monte Carlo simulations.

For the underloaded scenario, the performance of total utility under different charging request vehicle numbers is first demonstrated in Fig. 5.3. From the figure, we can see our proposed utility maximized charging scheme can always achieve the most utility compared with the other two schemes. The case of excessive battery performance degradation caused by long time charging can be effectively avoided under the UMS scheme, which is important for the charging network.

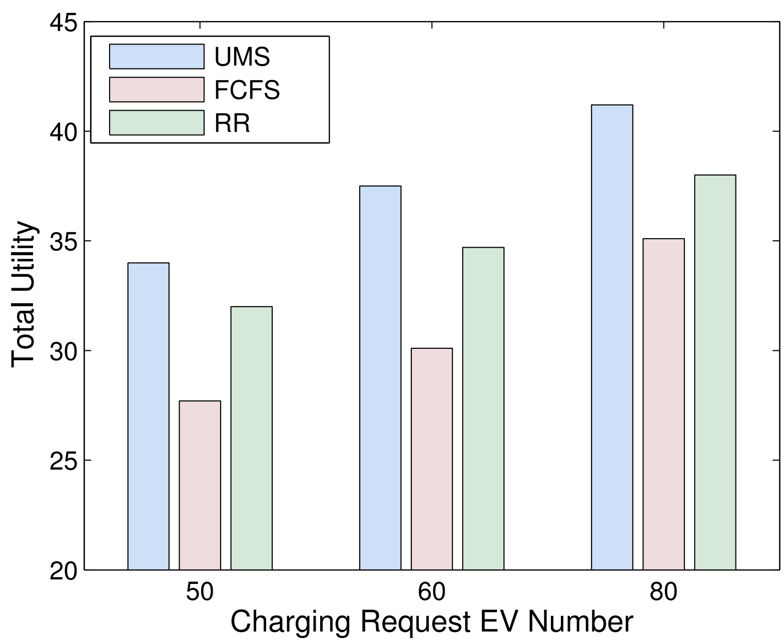


Figure 5.3: Total achieved utility.

In order to evaluate the achieved utility fairness among all the charging customers under different charging strategies, we employ the utility based Jain's fairness index, which is defined as follows

$$\mathcal{J}\left(U_1, U_2, \cdots, U_N\right) = \frac{\left(\sum\limits_{i=1}^{N} U_i\right)^2}{N \cdot \sum\limits_{i=1}^{N} U_i^2}, \tag{5.26}$$

where N is the total charging customer number, U_i is the total achieved utility of the ith customer after the whole charging process. The fairness comparison result is shown in Fig. 5.4. It can be noticed that the UMS scheme has lower fairness index than the Round-Robin scheme, which targets to obtain the best fairness. This is reasonable, because it cannot achieve the most utility under the premise of ensuring every task fairly increase its utility.

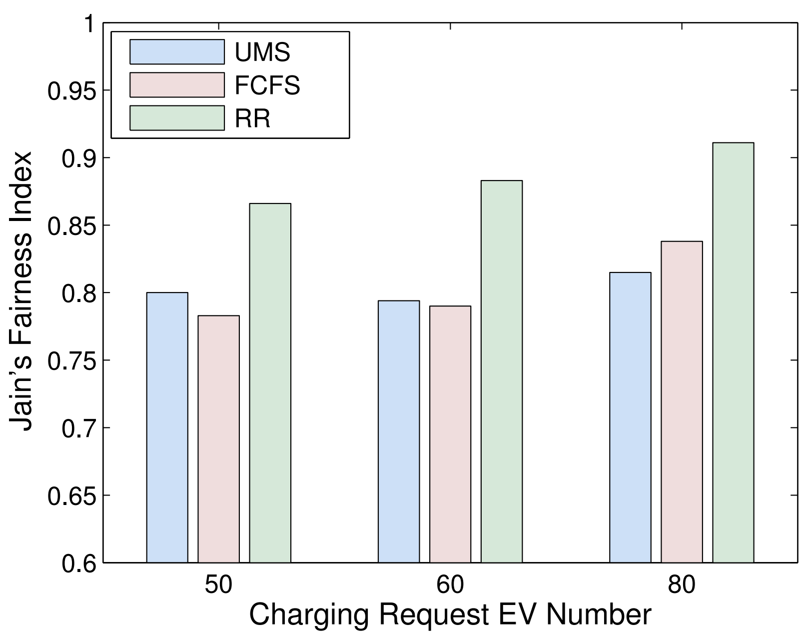


Figure 5.4: Jain's fairness index.

For the overloaded scenario, the summation of all EVs' minimum charging requirements have surplussed the system service capacity. To verify the effectiveness of the proposed charging scheme, we evaluate the performance under different charging request vehicle number scenarios. The total achieved utility is compared in Fig. 5.5. From the figure, we can see the proposed UMS algorithm can always achieve the most utility than the FCFS scheme. Another important performance index, average task service probability, is demonstrated in Fig. 5.6. It can be noticed that the UMS scheme achieves the higher task service probability, which is desirable for more task to get the charging opportunities. Last but not least the fairness issue is also compared as shown in Fig. 5.7. We can see that the UMS scheme achieves slightly better performance than the FCFS scheme. Based on all the achieved performance, the proposed UMS charging scheme is quite promising for the charging network operation.

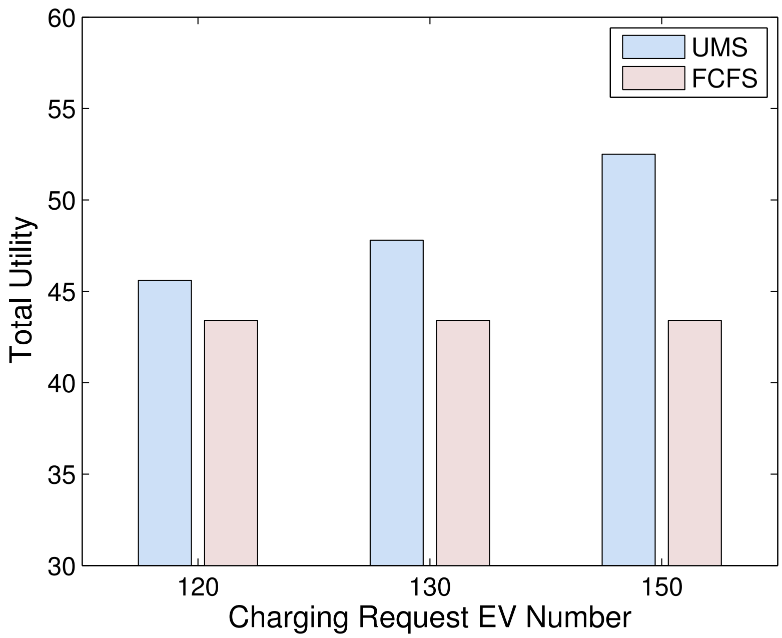


Figure 5.5: Total achieved utility.

5.7 Conclusion

In this chapter, we investigated the EV charging problem under a residential community scenario. By jointly considering the charging energy and battery performance degradation during the charging process, we proposed a utility model to evaluate the gain of the charging process. Then, we formulated the charging scheduling problem as a utility maximization problem, which not only guaranteed the necessary energy to the charging request users to cover their necessary daily travel requirements but also to protect the battery health. By investigating the features of the utility maximization problem, we proved it as a convex optimization problem and proposed a utility maximized charging scheme to achieve the utility optimality of the charging network. The applicability and effectiveness of the proposed charging scheme were

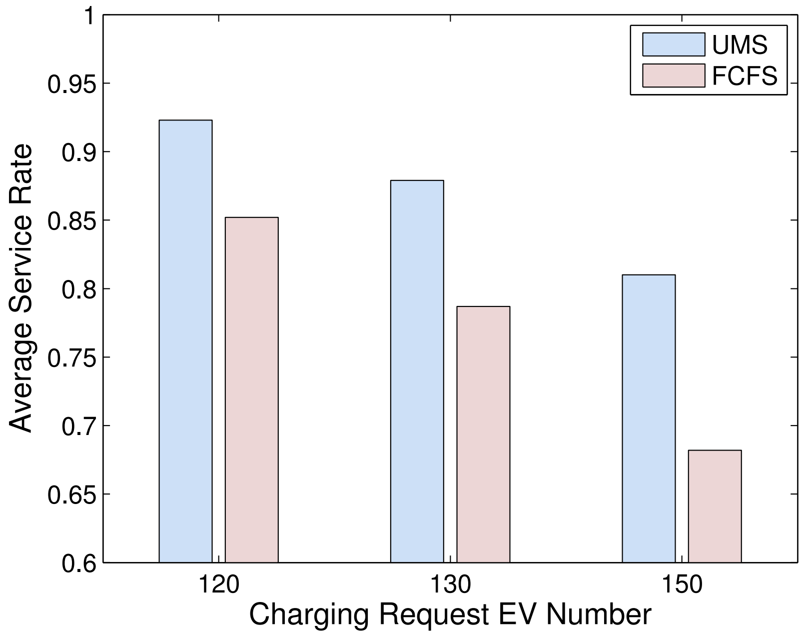


Figure 5.6: Average task service rate.

demonstrated under the underload and overload cases through several simulations based on real EV charging parameters. The obtained results exhibited the superior performance of the proposed charging scheme in achieving the most utility and higher task service rate compared with the other benchmark solutions, which is beneficial for both the charging customers and aggregator.

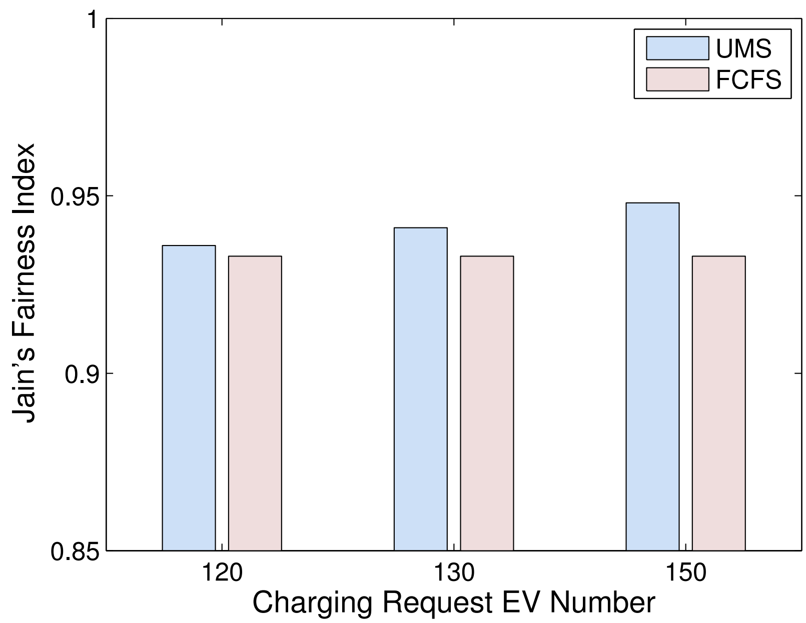


Figure 5.7: Jain's fairness index.

Chapter 6

Conclusions and Future Work

6.1 Conclusion

In this dissertation, we have discussed and analyzed the electric vehicle charging scheduling problem from different perspectives. The following outlines the contribution we have achieved.

- In Chapter 2, we studied the EV charging scheduling problem by jointly considering the revenue of the charging station and the service requirements of customers. We proposed an admission control algorithm which guarantees the necessary inflexible service requirements of all admitted EVs being satisfied before their departures. Also, a utility based scheduling algorithm was proposed to maximize the total utility. Through extensive simulations based on the practical EV charging information, it has been shown that the proposed approach can outperform the state-of-the-art one in terms of total utility, so that the charging station can enjoy a higher profit and the customers can enjoy more cost savings.

- In Chapter 3, we investigated the EV charging problem at an intelligent parking garage subject to the real TOU electricity pricing. We designed a multi-charging system for the garage charging operator to effectively provide charging services by jointly considering the charging station profit and customer satisfaction. Besides, we analyzed the battery charging characteristic change during the actual charging process and applied it into the EV charging problem. Furthermore, we proposed an adaptive utility oriented scheduling algorithm to effectively achieve the maximum total utility for the charging operator under the dynamic traffic pattern scenario. We also discussed the reservation mechanism for the charging operator to mitigate the performance degradation caused by the charging information mismatching with vehicles' stochastic arrivals. Through extensive simulations, it has been shown that the proposed AUS algorithm is applicable under different stochastic vehicle mobility processes. With it the charging operator can achieve the best performance compared with other existing algorithms, which is promising for the parking garage charging service proliferation.

- In Chapter 4, we investigated the EV charging problem under a park-and-charge system. We designed the operating model for the system to provide charging service by jointly considering the interests of both customers and business. A practical charging scheme was proposed for integrating the effects of battery degradation into EV charging scheduling problem. We devised a battery degradation cost model to capture the characteristic of battery performance degradation during the charging process. The developed battery degradation cost model was incorporated into the optimal EV charging scheduling scheme design to minimize the system total battery degradation cost. By investigating the feature of the cost minimization problem, we decomposed the problem into two sub-problems and proposed vacant resource allocation algorithm and dynamic power adjusting algorithm to solve the associated optimization problem. The applicability and effectiveness of the proposed methods were demonstrated through several case studies. The obtained results exhibited the superior performance of the proposed method in achieving both battery degradation cost minimization and system peak power load reduction, which benefits both the customers and charging operator.

- In Chapter 5, we investigated the EV charging problem under a residential community scenario. By jointly considering the charging energy and battery performance degradation during the charging process, we proposed a utility model to evaluate the gain of the charging process. Then, we formulated the charging scheduling problem as a utility maximization problem, which not only guaranteed the necessary energy to the charging request users to cover their necessary daily travel requirements but also to protect the battery health. By investigating the features of the utility maximization problem, we proved it as a convex optimization problem and proposed a utility maximized charging scheme to achieve the utility optimality of the charging network. The applicability and effectiveness of the proposed charging scheme were demonstrated under the underload and overload cases through several simulations based on real EV charging parameters. The obtained results exhibited the superior performance of the proposed charging scheme in achieving the most utility and higher task service rate compared with the other benchmark solutions, which is beneficial for both the charging customers and aggregator.

6.2 Future work

For the future work that plans beyond this dissertation, there are still various open issues of importance.

- For the work in Chapter 2, each customer's flexible and inflexible requirements are predetermined before their arriving at the charging station. In addition, the utility is fixed corresponding to the task's charging requirement. However, in real charging process the customer can adjust their flexible and inflexible charging requirements according to the charging station set price or utility. We need to find a reasonable model to reflect this variation. On the other hand, after the charging station tuning the utility function the customers' charging requirement adjustment will reversely affect the total utility of the charging station, just like the supply and demand relationship in economics. Thus, how to set a suitable utility function to achieve the maximum utility considering the pricing demand relationship is quite an interesting problem deserves our further investigation. In addition, our designed scheduling algorithm is online heuristic, we also need to derive the corresponding approximation ratio of our solution compared with the offline optimal solution.

- For the work in Chapter 3, there are several aspects which can be further investigated. First, we only considered a two-step TOU pricing as current electricity pricing. With more steps price variation even under the real-time pricing (RTP) situation, considering the vehicle's deadline restricted feature and the charging amount heterogeneity determined by the battery charging characteristic, how we can obtain the most profit for the charging station. Otherwise, if it is too hard to achieve the optimality, whether we can achieve some performance bound needs our further exploration. Second, inspiring by the discussion of Markov process in [100, 101], we can consider the Markovian property of the arrival process to further extend our work and utilize the M/G/K queue to analyze the charging process.

- For the work in Chapter 4, our proposed battery degradation model mainly considered the temperature effect during the charging process. However, other factors like the battery SOC and depth of discharge (DOD) also affect the battery performance. Therefore, to have a comprehensive assessment for the battery degradation during the charging process all these factors should be jointly considered. In addition, in our discussed scenario the vehicle mobility issue has not been addressed. With the mobility issue consideration, how to adjust the charging power sequence and allocate the vacant charging resource is an interesting issue to be further studied.

- For the last work in Chapter 5, we considered a centralized control strategy for the EV charging scheduling. This is feasible for a small scale community. However, for a large scale scheduling situation centralized control exposes its drawbacks as follows. It needs accurate information of all the customers which has heavy communication overhead. Besides, it is difficult to solve a large scale optimization problem within a short time and the computation complexity sometimes is too high to be implemented. Consequently, we should design a distributed scheduling approach for supporting a high EV penetration rate scenario. Also, the real time changing base load should be considered together with the EV load in our future research.

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