From both economic and environmental viewpoints, electric vehicles (EVs) provide a promising solution to reduce carbon footprint and save fuel cost compared to the gasoline and diesel vehicles. Therefore, there has been an impetus towards the deployment of EVs, and this trend is further supported by the policy-makers. On the other hand, it is crucial to address and solve the issues of negative impact to the grid, battery limitation, range anxiety and deployment of charging facilities with the growth of EVs.

In this dissertation, we propose a hierarchical system design and charging management in charging stations (CSs), addressing the issues mentioned above. First, we design charging management models in a single CS to provide high quality-of-service (QoS) to EVs and stabilize the grid. In the first part, we present a queuing-based optimization framework in a wired CS, where battery model and different charging strategies are considered to improve the system performance. In the second part, we explore performance modeling in the wireless charging system. The range anxiety issue, physical motion of EVs and reneging behaviors are included in the system design.

Second, we further propose a layered charging management in a network of CSs from traffic and service aspects. To bridge the gap between the current battery technology and the desired charging range, the deployment of a well-planned charging network is crucial. We propose a hierarchical optimization model to optimally locate a given number of fast CSs in a region with the following objectives. In the first layer, we identify the locations of CSs. In the second layer, we use a queuing-based model and introduce a resource allocation framework to provision the limited resources. Further, in the third layer, we consider the battery charging dynamics and develop a station policy to maximize the revenue by setting maximum charging levels.

Third, we propose cloud-based control and charging mechanism in a network of CSs, where both power and communication are included. More specifically, we develop a novel algorithm to
interplay among EVs, system operator (SO), CSs, and two levels of clouds. Toward this end, we present two strategies for profit models, aiming to improve the system performance and gain high profit, where customers’ charging preferences, end-to-end communication delay and limited grid resource are included.

Fourth, we introduce smart EV charging management in Internet of Vehicles (IoV) and blockchain. To fully materialize the potential promise of the emerging IoV, the number of underlying technologies that will play a crucial role in the implementation, have been growing faster. We present three important trends and enabling technologies: blockchain, behavioral economics, and artificial intelligence (AI), which are beyond the traditional power and communications disciplines and will require collaborative and sustained efforts from these areas.
System Design and Modeling in the Electric Vehicle Charging Networks

by
Cuiyu Kong

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North Carolina State University
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Doctor of Philosophy

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DEDICATION

This dissertation is dedicated to my beloved family.
BIOGRAPHY

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INTRODUCTION

The transportation sector has been one of the main sources of greenhouse gas (GHG) emissions and the primary driver of energy consumption. Pushing electric vehicles (EVs) on the road is a potential way to reduce the GHG emissions and to lower the dependency on oil as the main energy source. However, the charging activities of a large scale of EVs may bring potential issues to the charging facilities and the grid. Hence, the smart charging management of EVs needs the support of the well-designed charging facilities and the coordination of the power grid. This work addresses the issues of EV charging activities and proposes charging management models in charging stations (CSs) to coordinate EVs and improve the system performance. The roadmap of this dissertation is introduced in Fig. 1.1. First, in Chapter 1, the current status of EVs and public charging facilities, the challenges and motivation, related work, the contributions of this dissertation are introduced. Then, we present the charging models in a single CS in Chapter 2 and Chapter 3. Further, we propose a hierarchical optimization model for a network of CSs in Chapter 4. We present the cloud-based
charging management in CSs from the viewpoints of power and communication in Chapter 5. Toward this end, we present the smart EV charging management in the era of Internet of Vehicles (IoV) and blockchains in Chapter 6. Then the conclusions are drawn in Chapter 7.

1.1 Current Status of Electric Vehicles and Public Charging Infrastructures

EVs have emerged as an attractive and viable solution to decrease GHG emissions and reduce reliance on fossil fuels. Over the last seven years, we have witnessed a gradual popularity of EVs.
The adoption of EVs surged to a record; the new EV sales is expected to exceed one million in 2017 globally and aggregated sales has exceeded three million since the first introduction of EVs in 2010 [Blo17]. It is also projected that EVs’ stock will reach at least 40 million and EVs would occupy up to 90% of all vehicles sales by 2025 [Age17; Sta17].

This trend is further supported by the policy-makers and expected to grow well into the next decades, as electrifying transportation systems strengthens energy security and independence since electricity can be generated through a diverse set of domestic sources [Age17]. In parallel, The usage of EVs plays a role in the energy sustainability and money saving, compared to gasoline and diesel cars [Ene]. Therefore, the governments in the United Kingdom and France have announced to ban the new sale of gasoline and diesel cars by 2030 and more countries including China, India, Netherlands, and Norway have committed to phase out such vehicles in the near future and promote the deployment of EVs. In addition, major auto manufacturers are investing in multi-billion dollar in EV business to improve energy storage technology and introduce more variety in vehicle models [BT17]. Some automakers, for example, Volvo Cars and Jaguar Land Rover, are targeting to manufacture EVs and bring them to market in the coming years.

On the other hand, reaching such penetration rates necessities widespread presence of public charging facilities such as level 2 chargers (6-7 kW) at parking lots and fast DC chargers (40-50 kW) at places similar to gas stations. In 2016, the number of publicly available slow charging outlets (SCOs) has reached 212,000, while the number of public fast charging outlets (FCOs) has reached 110,000[Age17]. Specifically, China occupied 81% of the FCOs worldwide. It is also projected that the number of FCOs will reach 200 million worldwide in 2020 [Por17]. Undoubtedly the growth of public charging facilities also has a great impetus on the bigger market share of EVs. However, currently their number is not sufficient to satisfy all the EVs. Globally an average of 15 EVs shared one publicly available SCO, and approximately 130 EVs shared one publicly available FCO in 2016.

Table. 1.1 displays the projections of the deployments of EV stocks and COs up to 2030. It is projected that at least 4 million public COs will be deployed in 2030. Compared to SCOs, the number of FCOs is relatively small, and the range will be increased to [0.2, 0.7] million by 2030.
Table 1.1 The projections of the deployments of EV stocks and charging outlets (estimate in millions)

<table>
<thead>
<tr>
<th>Source</th>
<th>Projections</th>
<th>EVs</th>
<th>SCO</th>
<th>FCO</th>
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<tr>
<td></td>
<td>(year)2025</td>
<td>2030</td>
<td>2025</td>
<td>2030</td>
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<tr>
<td>Paris Declaration [CCa15]</td>
<td>55</td>
<td>115</td>
<td>4</td>
<td>7.5</td>
</tr>
<tr>
<td>IEA-2DS [Age17]</td>
<td>70</td>
<td>158</td>
<td>4.9</td>
<td>0.3</td>
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<tr>
<td>IEA-B2DS [Age17]</td>
<td>90</td>
<td>202</td>
<td>6</td>
<td>0.6</td>
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In order to provide a good environment for the charging of EVs, national and local governments have introduced policies to speed up the development of charging infrastructures. In the United States, the government announced a series of new actions to expedite the deployment of EVs and the charging facilities in 2016 [Hou16].

1.2 Challenges and Motivation

While EVs are gradually gaining acceptance, it is noteworthy that some challenges and problems exist, which need to be addressed and solved. The challenges and problems are summarized as follows:

- **Impact to Power Grid:** The uncontrolled and concurrent charging of EVs could have disruptive effects on the power grid such as transformer and line overloading, power quality deterioration, and supply-demand imbalances [CN10; SO14] and [Had06]. In Belgium, it is estimated the electricity consumption of EVs can reach to 5% of the total electricity consumption by 2030, which has potential impact on the power grid [CN10]. In peak hours, when lots of EVs charge at the same time, the charging power demand from EVs fluctuate the load curve. The increasing charging power demand imbalances the power load and power supply, disrupting the grid performance. Moreover, the deployment of the network of CSs is crucial to the power grid since the deployment of locations influences the pattern of the power distribution. The heavy load of specific CSs disrupts the balance of the power distributions and power load, which
has great impact to the grid.

- **Battery Issues:** The performance of an EV is related with the underlying battery technology. For example, specific energy (Wh/kg) and energy density (Wh/Liter) characteristics of the battery determine the additional weight and the space required to install the onboard battery, which also determines the all-electric driving range. Another important battery characteristic is the cycle and calendar life which are primarily affected by the charging/discharging power of the battery. The cost of battery is relatively high, which is the main component of the vehicle cost. Every time the battery is charged/discharged, it incurs battery degradation, which is related to the price of a cell unit in the battery, charge/discharge cycles, the temperature of the batteries, the State of Charge (SoC) and the depth of discharge and so on. Therefore, the battery lifespan has been a concern to many customers.

- **Public Charging Facilities Issues:** As mentioned in Section 1.1, publicly available COs are not sufficient to support all the EVs currently. Since the uneven distribution of COs in the different countries, the ratio between the number of EVs and publicly available COs is very high in some countries, taking the United States, Canada, Norway and France as examples. Currently, the growth of EV adoption rate is speeding, where much more COs will be required to satisfy the needs. Under such circumstances, it is necessary to expedite the efficient deployment of publicly available COs.

- **Range Anxiety:** The capacity and the size of the battery are limited, and the public charging facilities are not deployed sufficiently. It is reported that more than 50% of drivers require an EV to cover 313 miles for the maximum daily mileage, but the driving range of an affordable EV with full battery is less than 140 miles in 2017 [Pea11; Che17a]. As a result, range anxiety exists among EV drivers who are worried that an EV cannot reach the destination [Wik] due to insufficient energy. Therefore, an efficient deployment of charging infrastructures is crucial to both city planners and customers.

- **Communication Requirements:** It has been well-documented that uncontrolled EV charging,
especially during peak hours, threatens the stability of the power grids, hence, economic operation of power grids requiring a careful coordination among EVs and CSs is very critical [CN10]. Such coordination, obviously, requires massive data exchange and processing [He12]. Cloud computing has gained increasing attention for realizing cooperation in the smart grid. However, there are no standards of the interplay among EVs, CSs, clouds and system operators. Therefore, an effective system mechanism is crucial for the cloud-based system design.

1.3 Literature Review

1.3.1 Roadmap of EV Literature

In the EV routing and charging optimization research areas, it can be divided into three categories: EV charging without cord, with cord, and communication. The detail information is shown in Fig.1.2.

In the wireless charging network, two research areas are presented. The first one is from the perspective of system level, where two categories are divided: simulation of the wireless charging network and the revenue maximization/cost minimization. The second one is the efficiency of wireless power transfer from the perspective of power and electronics engineering.

In the wired charging, it can be divided to: grid to vehicle and vehicle to grid according to the power capacity. In the area of deficit capacity, the charging scheduling and congestion management are adopted to alleviate the heavy load of power and balance the load of different CSs.

In the communication area, from the point view of interplay among EVs, CSs and grid, communication is required to enable the data exchange. On the other hand, performance modeling concerning the interactions among different players is investigated from the perspective of system level.

In this dissertation, with the objectives of alleviating the heavy loads in CSs and enabling efficient communication among EVs, CSs and SO, we propose a hierarchical system design in CSs. The addressed issues are shown in orange rectangles in Fig.1.2. First, we propose the system design and modeling in a single CS, where we investigate the characteristics and performance in the wired and
wireless charging in a single CS. Second, we propose the performance modeling in a network of CSs from the perspective of locating and sizing CSs, and congestion control. Third, cloud-based charging management model is proposed to accomplish the interplay about EVs, CS, clouds and SO. Further, we present the smart EV charging management in the era of IoV and blockchains.

Figure 1.2 Roadmap of EV charging literature

In Section 1.3.2, the literature of system design in a single CS is presented, addressing the issues of impact to the grid, range anxiety and deficient charging facilities. Meanwhile, a body of literature studied the wireless charging technologies applied in a single CS, which is also presented in Section 1.3.2.

In the multiple CSs setting, some authors investigated the locating and sizing in a network of CSs, and some other studied the system design and control mechanism, presented in Section 1.3.3. The studies about cost efficiency with battery models are described in Section 1.3.4. Regarding the cloud-based communication, the literature is shown in Section 1.3.5. The discussion about IoV is
presented in Section 1.3.6.

1.3.2 System Design of a Single Charging Station

- **Wired Charging in a CS:** In the system design, it is assumed single or multiple classes of customers that are typically grouped according to the charging rate. For instance, the works presented in [Bay13a; Bay11; Fan15; Kar14] and [EK12] proposed queueing-based single CS models and pricing-based admission control frameworks to control the aggregated demand within the grid operating limits. Another approach to alleviate the stochastic demand is to employ energy storage units which act as energy buffers to smooth the spikes [Bay13a] and [Bay11].

- **Wireless Charging in a CS:** Regarding the topic of wireless charging system on the road, some papers have proposed methods to analyze the dynamic wireless charging performance [Def15; DC15; Ou15]. The work in [Def15; DC15] implemented a traffic simulation model and applied the model to the freight distribution scenario. The authors in [Ou15] presented an analytic model to investigate the impact of wireless charging behaviors on the electricity market.

1.3.3 System Design of a Network of Charging Stations

- **Locating and Sizing in a Network of CSs:** In the flows of networks, traffic flows are coming from origin nodes to destination nodes, and these origin-destination (OD) nodes form a set of OD pairs. For each OD pair, a traffic flow goes through it and can be captured if there is at least one facility located along the path between this OD pair. Some studies have presented models for the optimal locations of the facilities to capture traffic flows [Hod90]-[CZ13]. The authors in [Hod90] proposed a flow-capturing location-allocation model (FCLM) to maximize the captured flow. A gravity spatial interaction model was used to obtain the amount of traffic in every path. The authors in [Upc09] proposed a model for location of alternative-fuel stations, where every station has a limited capacity. In [KL05], a model named flow refilling location model (FRLM) was proposed to maximize the captured flow volume while considering the
range of the vehicles. Later the same group of authors presented an effective formulation to solve the FRLM [CK12]. Applying the FCLM mentioned above, the authors in [CZ13] presented two optimization models of fast CS (FCS) locations and illustrated its effectiveness on a case study of the city of Barcelona.

- **Load Balancing and Control in a Network of CSs:** In the multiple station setting, the idea is to route customers to neighboring stations, so that customers can receive service with a certain level of quality of service (QoS), that is typically the waiting time or the blocking (loss-of-load) probability. The work in [Bay13b] proposed a centralized control framework and assigns customers to idle stations, while the works in [Bay12] and [Bay15] presented decentralized control structures to reduce the load among the stations. From the modeling standpoint, authors in [BK12] proposed a spatial and temporal model in dynamic EV traffic systems by adopting $M/M/s$ queues to formulate the charging demand. In [Ban12], the authors considered the demand response at multiple CSS, and modeled each CS as $M/M/1$ queuing systems. Aiming to minimize the waiting time for EVs, authors in [Ban12] formulated the optimization problem and provided an optimal EV allocation algorithm and pricing mechanism to achieve the goal. On the other hand, the energy storage sizing and management models have gained popularity in the literature. The authors in [Yan15; Zhu16; Zhu17] investigated the energy storage capacity issues while the works [Yan16; Jia16] proposed load forecasting models and methods of monitoring inter-area oscillation in the smart power system.

### 1.3.4 Cost Efficiency with Battery Models

Apart from the system level of the CS design, some studies have addressed the charging coordination from the aspects of battery and charging characteristics. The work in [Ma15] observed the charging coordination from the viewpoint of the customers. To be more precise the goal was to minimize the electricity and battery degradation costs. The study in [KD16] proposed a queuing model on the wireless charging highway to maximize the system profit taking the battery degradation cost into account. The work in [Fan15] and [Kon15] considered the charging characteristics of the Li-ion
batteries in a single FCS design. Specifically, in the DC fast charging technologies, the method of constant current constant voltage (CCCV) is used. Before the charging voltage reaches the threshold, the constant current mode is adopted. When it reaches the threshold, the charging mode is switched to the constant voltage mode. This characteristic and the internal resistance of the battery cause charging current decreases dramatically when the state of charge (SoC) is close to full. As a result, the charging power decreases and the charging duration to charge the same amount of energy increases significantly.

1.3.5 Communication Modeling in Charging Networks

To boost the development of intelligent transportation system (ITS), a growing number of papers have presented models to analyze and improve the performance of V2I communication [Kha14; RT14; Zha13]. The authors in [Kha14] presented the analytical work on the multichannel the vehicle to infrastructure(V2I) communications and modeled it as a M/G/s queuing system. The authors in [RT14; Zha13] proposed schemes to improve the system performance on the V2I communication.

On the other hand, the stability, flexibility, security, and on-demand performance of cloud computing provide an efficient platform for charging management [Mar13; RL17] among various players. Cloud-based DMS models was presented in [Kim11; Ber15; Che17b]. A demand response algorithm in smart grid, considering the cloud architecture was proposed in [Kim11; Ber15]. The work in [Che17b] modeled the cloud-based charging and discharging management in public CSs for demand response.

1.3.6 Internet of Vehicles

Internet of Vehicles (IoV), where people, fleet of electric vehicles, utility, power grid, distributed renewable energy resources, and communication and computing infrastructures are connected, has emerged as the next big leap in smart grid and smart cities sectors for a sustainable society.

The EV30@30 campaign has set a collective goal for all EVI members of a 30% EV market share by 2030 [Age17]. This is significantly important steps towards the realization of IoV.
It should be noted that Vehicular Ad-Hoc Network (VANET) is just considered as a node to share messages among vehicles. Going beyond this, IoV as an integral part of the Internet of Things (IoT), is about to enable a range of new capabilities and services far beyond today's VANET offerings. As a matter of fact, IoV considers each vehicle as an IoT smart object that enables vehicles not only gathering data based on its sensing capabilities and disseminating message between peers but also allows vehicles to process and compute such information (e.g., roadside information, obstacles, hazardous location notification, congestion, location information). The large-scale deployment of EVs, including commercial trucking (e.g., FedEx, Frito-Lay, Duane Reade have incorporated EVs into their commercial fleets) in IoV will bring many advantages, especially for smart grids and smart cities, and will reduce greenhouse gas emissions by an estimated 48 million metric tons per year by 2030 [Duvch]. Further, IoV is expected to improve traffic efficiency and management and enhance traffic safety via learning capabilities. Besides, IoV may help accelerate the emerging transportation-as-a-service business model (e.g., served by on-demand autonomous EVs) and also improve social equity by creating innovative business models, especially low-income households could participate in P2P energy trading virtual marketplaces and benefit from the value created by IoV technologies.

1.4 Contributions of This Work

- We consider a small-scale fast public CS and propose two optimization frameworks (Frameworks of Single-class and multi-class EVs) to maximize the station revenue. The blocking probability and waiting time are used as the QoS metrics. Furthermore, we present a detailed battery cost model for Li-ion batteries, which are widely used for automotive applications. In addition to the aforementioned revenue model, we propose two charging strategies: shared chargers and dedicated chargers for different classes.

- We propose an optimization framework in a wireless charging system. Considering the reneging characteristics of EVs before getting served, we model the wireless charging system as $M/M/1$ loss queuing system. We consider the power consumption based on the resistance to
motion, the degradation model for Li-ion batteries, an admission fee model and the velocity behavior in the proposed model. Furthermore, we introduce the scenario of V2I communication on the wireless charging highway to enable the data exchange between EVs and the infrastructure.

- We develop a hierarchical system model from the perspectives of both the traffic and queuing network. Specifically, we consider the characteristics of traffic flows, resource allocation and a profit model in a network of FCSs. In the first layer, the locations of FCSs is determined in a way to maximize the captured traffic flow. In the second layer, COs allocation is proposed meet the QoS targets. In the third layer, considering the battery degradation cost and battery charging characteristics, a profit optimization model is proposed by reasonably limiting the requested SoC (SoCr).

- Facing the issues of limited energy and a very large scale of EVs, we present a cloud-based charging management framework in a network of CSs and propose a profit maximization model. We take into account price incentives, and different QoS provided to customers, whereby two levels of cloud computing are considered. Two classes of EVs are considered: EVs in CS in highway exits (CSH) and in parking lots (CSp). The different communication latency requirements and willingness to delay charging are considered in the model design.

- We present a two-tier cloud-based electric vehicle charging framework to tackle issues of high charging demand in CSs during peak hours and communications among large-scale electric vehicles in a network of CSs and system operator. The obtained results demonstrated that the proposed concept is feasible. Further, to shed light on the emerging technologies for the smart and connected EVs in IoV, we focus on three major trends: blockchain, behavioral economics and artificial intelligence (AI).
2.1 Introduction

Chapter 2 analyzes the system design and architectures in a single CS, which provides fundamental mechanism in this dissertation.

The charging power of EV decreases significantly when the SoC gets closer to the fully charged state, which leads to a longer charging duration. Each time when the battery is charged at high rates, it incurs a significant degradation cost that shortens the battery life. Furthermore, the differences between demand preferences, battery types, and charging technologies make the operation of the
CSs a complex problem.

Even though some of these issues have been addressed in the literature, the CS modeling with battery models and different customer preferences have been neglected.

To that end, this Chapter proposes two queuing-based optimization frameworks. In the first one, the goal is to maximize the system revenue for single class customers by limiting the SoCr targets. The EV cost function is composed of battery degradation cost, the waiting cost in the queue, and the admission fee. Under this framework, the CS is modeled as a $M/G/s/k$ queue, and the system performance is assessed based on the numerical and simulation results. In the second framework, we describe an optimal revenue model for multi-class EVs, building upon the approach utilized in the first framework. Two charging strategies are proposed: a dedicated charger model and a shared charger model for the multi-class EVs.

We evaluate and compare these strategies. Results show that the proposed frameworks improve both the station performance and QoS provided to customers. The results show that the system revenue is more than doubled when compared to the baseline scenario which includes no limitations on the SoCr.

### 2.2 Optimal System Revenue Framework for Single-Class Customers

In Section 2.2, we present the optimization framework for the single-class case. The main goal of the proposed framework is to limit the state of charge demand of vehicles at a reasonable level, e.g., 90% SoC, so that the station revenue is maximized by serving more vehicles. The rationale behind this is that charging power duration increases as the battery SoC is getting closer to the full state. Therefore, the core of the framework is the battery charging model and the battery degradation cost which is related to the conventional constant current constant voltage method of the Li-ion batteries. Furthermore, the system revenue depends on the stochastic involved with the customer demand such as mean waiting time and the blocking probability, therefore a queuing analysis is also provided.
2.2.1 Charging Power Model

CCCV method is widely used for Li-ion battery charging, as it protects the battery life. During the charging, the current remains constant until it reaches the threshold value. After the threshold, the voltage (V) is maintained at a fixed value and the charging current (A) decreases exponentially. In terms of charging power (kW), from the empty battery to a threshold energy, the charging power remains constant. Once the energy reaches the threshold, the charging power is decreasing with the increment of SoC. In this Chapter, the charging power function in [Fan15] is adopted, which is:

\[
P(E) = \begin{cases} 
  P_{\text{max}} & E < E_c \\
  m_1 - n_1 \cdot E & \text{otherwise}
\end{cases}, \quad (2.1)
\]

where \( E \) is the energy in the battery and \( E_c \) is the threshold energy for the mode from constant power to the decreasing power. \( m_1 \) and \( n_1 \) are the constant parameters in [Fan15], and \( P_{\text{max}} \) is the maximum charging power for an EV, as shown in Fig. 2.1.

The charging times are related to the initial (\( E_i \)) and requested energy (\( E_r \)) levels and the charging power. We assume the SoC distribution is obtained via historical data and known by the station operator. Then, for a given SoC distribution, an example presented in Fig. 2.2, the charging duration distribution can be obtained by the following,

\[
t = \begin{cases} 
  \frac{E_c - E_i}{P_{\text{max}}} + \frac{1}{n_1} \log \left( \frac{m_1 - n_1 \cdot E_i}{m_1 - n_1 \cdot E_r} \right), & E_i \leq E_c \\
  \frac{1}{n_1} \log \left( \frac{m_1 - n_1 \cdot E_i}{m_1 - n_1 \cdot E_r} \right), & E_i > E_c
\end{cases}, \quad (2.2)
\]

Notice that the first component represents the time it takes to charge the vehicle, which is the amount of energy transfer from the initial SoC to the threshold value divided by the constant charging power. While the natural logarithmic component represents the energy transfer after the threshold value. Of note, the SoC is assumed to be bounded between 0—100%.

As given in [Fan15; Luo13] and [Dai11], the initial state of charge SoC\(_i\) distribution follows a normal distribution and it is set to be \( \mathcal{N}(30, 15) \), where the mean is 30 and standard variation is 15.
And it is truncated to target SoC internal of $[5, SoC_r - 10\%]$. The example illustrated in Fig.2.2 shows the distribution of $SoC_i$ when $SoC_r$ is set to 85%. Thus, knowing the distribution of $SoC_i$ and (2.2), the distribution of charging times can be obtained. For the given settings, the results are shown in Fig.2.3.

Moreover, from the charging time distribution, the mean charging time $\mathbb{E}(t_{ch})$ is known. Then the mean charging power $\mathbb{E}(P_{ow})$ can be obtained as

$$\mathbb{E}(P_{ow}) = \frac{E_r - \mathbb{E}(E_i)}{\mathbb{E}(t_{ch})},$$

where $\mathbb{E}(E_i)$ is the mean value for $E_i$. It is noteworthy that the charging time and the charging power are a function of the requested state of charge level $SoC_r$. For higher $SoC_r$, the required charging time increases and the charging power decreases.
2.2.2 Battery Degradation Cost

As the vast majority of car manufacturers employ Li-ion batteries, we choose to analyze them in our battery model. Each time the battery is charged, there is an associated degradation cost, which is a function of the charging power and the charging duration [Ma15]. The battery degradation becomes a critical element under the high charging regime, as it shortens the life cycle of the battery. Therefore, we include battery degradation cost in our optimization framework as a function of the charging power and the battery characteristics [Ma15]. The expected battery degradation cost can be represented by,

$$\mathbb{E}(c_{batt}) = a \cdot (\mathbb{E}(P_{ow}))^2 + b \cdot \mathbb{E}(P_{ow}) + c,$$

(2.4)
where $P_{ow}$ is the mean charging power of an EV. The remaining parameters represent a typical Li-ion battery characteristics and selected as $a = (10^6/M) \cdot V_{norm} \cdot \Delta T \cdot P_{cell} \cdot \alpha$, $b = 10^3 \cdot V_{norm} \cdot \Delta T \cdot P_{cell} \cdot \beta$ and $c = M \cdot V_{norm} \cdot \Delta T \cdot P_{cell} \cdot \gamma$ [Ma15]. Here $M$, $V_{norm}$, $\Delta T$ and $P_{cell}$ are denoted as the number of cell units in an EV, open circuit voltage of a Li-ion cell unit, the length of charging interval $t$, and price of single energy unit in a battery cell. $\alpha$, $\beta$, and $\gamma$ are defined in [Ma15], which are functions of $V_{norm}$. Once the battery type of an EV is known, the values of $a$, $b$ and $c$ can be calculated. Thus from mean charging power $\mathbb{E}(P_{ow})$ during mean charging time $\mathbb{E}(t_{ch})$, the cost of an EV incurs is $\mathbb{E}(c_{batt}) \cdot \mathbb{E}(t_{ch})$.

2.2.3 Admission Fee

A customer who joins the system gains reward $R$ after completing the service. When the $SoC_r$ is higher, EV is more satisfied, and earns a higher reward. We adopt a linear reward function, that is

**Figure 2.3** Charging time distribution $SoC_r=85\%$
\[ R = m \cdot SoC_r + n, \]  

where \( m \) and \( n \) are the constant positive parameters. An EV pays the admission fee \( p \) to join the system. On the other hand, there is a waiting cost due to delayed service, and a battery degradation cost upon charging the battery. Therefore, the total cost for an EV is

\[ C_{total} = p + c_w \cdot E(t_w) + E(c_{batt}) \cdot E(t_{ch}), \]  

where \( c_w \) is a constant representing the waiting cost per time unit and \( E(t_w) \) is the mean waiting time of an EV in the queue.

The system owner can increase the admission fee to get more system profit [Has15], while the users accept to join the system only if the reward \( R \) is larger than the total cost \( C_{total} \), that is \( R \geq p + c_w \cdot E(t_w) + E(c_{batt}) \cdot E(t_{ch}) \). In other words, the reward should be equal or larger than the cost of an admission fee, waiting cost, and battery degradation cost. Hence, the maximum admission fee paid by an EV can be calculated by

\[ p = R - c_w \cdot E(t_w) - E(c_{batt}) \cdot E(t_{ch}). \]  

The revenue of system operator is composed by the admission fee paid by EVs and the number of arrivals in each time unit. Thus, it’s necessary to know the arrival rate of EVs. The following subsection presents the system revenue model.

### 2.2.4 System Revenue model

In the \( M/G/s/k \) queue system, there are \( S \) chargers and \( r \) waiting spaces, where \( r = K - S \). The EVs arrive according to the exponential distribution with arrival rate \( \lambda \). The charging time follows a general distribution, which is a function of \( SoC_r \) and charging power \( P_{aw} \). Notice that, due to limited service space, if there are \( K \) customers in the system, the new arrivals will not be able to join the system, hence will be blocked. Let \( P_K \) denote the blocking probability of the system for a given
arrival rates, customer demand, and charge rates. Then the system revenue $R_e$ can be calculated by

$$R_e = \lambda \cdot (1 - P_K) \cdot p.$$ (2.8)

Substituting $p$ in (2.7), we get

$$R_e = \lambda \cdot (1 - P_K) \cdot (R - c_w \cdot \mathbb{E}(t_w) - \mathbb{E}(c_{batt}) \cdot \mathbb{E}(t_{ch})).$$ (2.9)

In the above equation, $P_K$, $R$, $\mathbb{E}(t_w)$, $\mathbb{E}(c_{batt})$ and $\mathbb{E}(t_{ch})$ are functions of $SoC_r$. When $SoC_r$ is higher, on one hand, the reward for customers $R$ is higher. On the other hand, this translates into higher mean charging time $\mathbb{E}(t_{ch})$, which leads to higher blocking rate, higher mean waiting time, and less revenue for the station. Hence, the proposed method aims to determine the optimal $SoC_r$ to gain the optimal system revenue. In the following subsection, relationships between charging power, charging time and $SoC_r$ are illustrated.

2.2.5 $M/G/s/k$ queuing model in charging system

We start our analysis by deriving an expression for the blocking probability $P_K$. The customers will be blocked when there are $K$ customers in system because of the limited service space, which is given by

$$P_K = \frac{(S \rho)^S}{S!} \zeta^{K-S} P_0.$$ (2.10)

The procedures to find $P_K$, $\zeta$ and $P_0$ are given in Appendix A. Once we know the arrival rate $\lambda$, the number of servers $S$, and the mean service rate $\mu = 1/\mathbb{E}(t_{ch})$, the blocking probability of $M/G/s/k$ can be approximated. Notice that the blocking probability is also a function of $SoC_r$, since service rate $\mu$ is determined by the target state of charge level. For the better evaluation of system performance, the approximation of mean waiting time is derived, which is also given in Appendix A.
2.2.6 Performance Analysis in Single Class Customers

In this subsection, a case study for a DC FCS is presented to determine the optimal SoC for the optimal system revenue. The proposed method is compared to the case when SoC is not limited, which serves as a baseline scenario.

From the relation between charging power and SoC, if the battery is charged to be 100% SoC, the charging time will be large when compared to lower SoC targets. Hence, the proposed method aims to limit the demand of EVs, which is SoC, to maximize system revenue in (2.9). The assumed range of SoC is between 60 to 95% in the proposed method. Starting from SoC = 60%, each time the value is increasing by 5% until reaching 95%. After the finite iterations, the optimal system revenue among these enumerations is selected.

A Matlab script was used to model the numerical portion, while Java was used to simulate the model. The simulation model is run for 100,000 EVs, and the system input parameters in Table 2.1 are given by λ = 10, S = 7, and r = 3. In the first simulation setting, the target SoC is varied from 60% to 95% with an increment of 5%. The case when target SoC is 99% is also simulated and compared. The initial state of charge distribution SoC is chosen as \( N(30, 15) \), truncated to \([5, SoC - 10]\)%.

Function input parameters are shown in Table 2.2. DC fast charging model is chosen for evaluation. Hence, the maximum charging power \( P_{max} \), the battery capacity, and the threshold energy \( E_c \) are assumed to be 45 kWh, 15 kWh, and 5 kWh respectively. Combined with (2.1), \( m_1 \) and \( n_1 \) are calculated to be 67.5 and 4.5 respectively. \( a, b \) and \( c \) values are adapted from \([Ma15]\) for Li-ion batteries. The waiting cost per hour \( c_w \) is assumed to be 20. When there's no waiting cost and no battery degradation cost, an EV pays 10 units for admission fee \( p \) in simulation based on \([KA05]\). So the maximum reward \( R \) is set to be 10 units. Hence combined with (2.5), \( m \) and \( n \) are calculated to be 9 and 1 unit respectively.

In Fig.2.4a, we show the relationship between the mean charging time and the SoC levels. It can be seen that the charging duration from SoC = 30% to SoC = 85% takes about 20 minutes. However, the charging duration raises exponentially when the SoC is set to 95%, and it takes 14.7 more minutes to charge the next 10% SoC. In Fig.2.4b, the mean charging power is presented. As shown
Table 2.1 System input parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>10/hour</td>
</tr>
<tr>
<td>$SoC_i$</td>
<td>$\mathcal{N}(30, 15)$, truncated to $[5, SoC_r - 10]$(%))</td>
</tr>
<tr>
<td>$SoC_r$</td>
<td>60:99(%)</td>
</tr>
<tr>
<td>$s$</td>
<td>7</td>
</tr>
<tr>
<td>$r$</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 2.2 Function input parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{max}$</td>
<td>45</td>
</tr>
<tr>
<td>$m_1$</td>
<td>67.5</td>
</tr>
<tr>
<td>$n_1$</td>
<td>4.5</td>
</tr>
<tr>
<td>$a$</td>
<td>0.004</td>
</tr>
<tr>
<td>$b$</td>
<td>0.075</td>
</tr>
<tr>
<td>$c$</td>
<td>0.003</td>
</tr>
<tr>
<td>$c_w$</td>
<td>20 ($/\text{hour}$)</td>
</tr>
<tr>
<td>$m$</td>
<td>9 ($)</td>
</tr>
<tr>
<td>$n$</td>
<td>1 ($)</td>
</tr>
</tbody>
</table>

in the figure, when the $SoC_r$ is set to higher values the mean charging power drops, due to the charging characteristics presented in Fig.2.1. Similarly, Fig.2.4c shows that the traffic intensity, $\rho$, increases with $SoC_r$, because the mean charging duration also grows as shown in Fig.2.4a.

Fig.2.4d and Fig.2.4e depict results for blocking probability and mean waiting time respectively. Similar to previous findings, higher $SoC_r$ targets leads to undesired system performance, higher blocking rates and long waiting times. In Fig.2.4d and Fig.2.4e, numerical results are almost the same as the simulation results except for the case when $SoC_r=99\%$. The reason for the difference
between these two results when $SoC_r = 99\%$ is that the traffic intensity $\rho$ goes to infinity and system becomes unstable.

One of the main findings of this section is presented in Fig. 2.4f, which depicts the system revenue under different $SoC_r$. By varying the $SoC_r$ from 60 to 99\%, the station revenue is calculated. It is shown that for the given simulation parameters, setting $SoC_r$ to 90\% maximizes the system revenue, which is calculated as $R_e^*$ is 74.8. The proposed framework is compared with the baseline scenario where the target $SoC_r$ is not limited. The results presented in Fig. 2.5 shows that the proposed method can significantly improve the system performance and more vehicles can be served with the same amount of grid resources.
2.3 Optimal System Revenue Framework for Multi-Class Customers

In this section, we extend the previous framework for the multi-class setting. Similar to the single-class case, the CS is modeled with a $M/G/s/k$ queue, but this time $J$ classes of EVs can be served. The customer classes are differentiated by charging technology, customer preferences, and the
amount of battery cell units. Therefore, the parameters in charging power function in (2.1) are
different among different customer types \( j \in \{1, 2, ..., J\} \).

In addition to the computation of optimal \( SoC_r \) levels for each class, we propose two different
resource allocation methods. The first one is the dedicated charger model, in which charging
resources are allocated to different customer classes. The second method, on the other hand, does
not physically divide the resources and the demand is met by the shared resource pool. The allocation
methods are depicted in Fig.2.6, which simply assumes that there are two classes of EVs. The primary
goal is to choose the strategy that maximizes system revenue under different traffic loads.

2.3.1 Dedicated Charger Model

In the dedicated charger model, the primary goal is to compute the optimal composition of chargers
and the \( SoC_r \) targets for each customer type. The arrival rate of type \( j \) is denoted by \( \lambda_j = \theta_j \lambda \), where
\( \theta_j \) is the proportion of total arrival rate of system \( \lambda \) for type \( j \). Similarly, the waiting space for class \( j \)
is denoted by \( r_j \). From (2.9), the class \( j \) revenue in dedicated chargers model is :

\[
R^j_{e,d} = \theta_j \lambda \cdot (1 - P_{ro}^j) \cdot (R - c_w \cdot \mathbb{E}(t_w) - c_{batt} \cdot \mathbb{E}(t_{ch}))
\]

(2.11)

where \( P_{ro}^j, \mathbb{E}(t_w), \mathbb{E}(c_{batt}), \) and \( \mathbb{E}(t_{ch}) \) are the blocking probability, the mean waiting time, the mean
battery degradation cost in time unit, and the mean charging time of customer type \( j \) respectively.

The number of chargers allocated to type \( j \) is denoted by \( s_j \). Since there a group of chargers are
dedicated to each charger type the system acts as \( J \) different queues and from the analysis presented
in the previous section, optimal \( SoC^*_r,j \) for each class revenue \( R^j_{e,d} \) can be calculated.

Specifically, the proposed method aims to find the optimal \( s^*_j \in \{1, 2, ..., S\} \) and optimal \( SoC^*_r,j \)
to optimize the total system revenue \( \sum_{j \in \{1, 2, ..., S\}} R^j_{e,d} \). Therefore, the optimal system revenue in dedicated
charger method can be calculated from

\[
\sum_{j \in \{1, 2, ..., S\}} R^j_{e,d}
\]
arg max \sum_{j \in J} R_{e, d}^j(\theta_j \lambda, s_j, SoC^j_r) \\
subject to \sum_{j \in J} s_j = S \\
\theta_j, \lambda, S, J are given

Given \( \theta_j, \lambda, S \) and \( J \), optimal combination of \( \{s_1^*, s_2^*, ..., s_J^*\} \) and optimal system revenue can be gained from the model above.

### 2.3.2 Shared Charger Model

In the shared charger model, the same resource pool is shared by all customer types. The arrival rate of type \( j \) is \( \lambda_j = \theta_j \lambda \), where \( \theta_j \) denotes the proportion of total arrival rate of system \( \lambda \) for type \( j \). The shared waiting space is denoted by \( r \). Since all customer classes share the same chargers and waiting space, the blocking probability for each class is the same. Let \( P^o \) be the blocking probability for each class in shared charger model, \( P^o = P^1_{ro} = P^2_{ro} = ... = P^J_{ro} \). And the mean waiting time for each class is also the same because of shared waiting spaces, which is denoted by \( \mathbb{E}(t_w) \). And \( \mathbb{E}(t_w) = \mathbb{E}(t_w^1) = \mathbb{E}(t_w^2) = ... = \mathbb{E}(t_w^J) \). From (2.9), the class \( j \) revenue in shared charger model is:

\[
R_{e,s}^j = \theta_j \lambda \cdot (1 - P^o) \cdot (R - c_w \cdot \mathbb{E}(t_w) - \mathbb{E}(c_{bat}^j) \cdot \mathbb{E}(t_{ch}^j))
\]

(2.13)

Hence, the system revenue becomes \( \sum_{j \in J} R_{e,s}^j(\theta_j \lambda, SoC^j_r, S) \). Given \( \theta_j, \lambda, SoC^j_r \) and \( S \), the system revenue in shared charger model is determined.

### 2.3.3 Toy Examples for the Dedicated Charger Model

In our case study, enumeration method is used to determine the optimal combination of chargers \( \{s_1^*, s_2^*, ..., s_J^*\} \). The main procedure is as follows. First, for each value of \( s_j \), optimal \( SoC^*_r \) method is executed to determine the optimal class revenue \( R_{e, s}^j(s_j) \). Then, find the optimal combination \( \{s_1^*, s_2^*, ..., s_J^*\} \) by calculating \( \sum_{j \in J} R_{e,s}^j \) and select the highest system revenue to be optimal.

The following case study is presented to clarify the matters. Assume there are two customer
Table 2.3 Toy example I – system input parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>total ( \lambda )</td>
<td>8/hour</td>
</tr>
<tr>
<td>( SoC_i )</td>
<td>( \mathcal{N}(30, 15) ), truncated to ([5, SoC_r - 10] )%</td>
</tr>
<tr>
<td>( SoC_r )</td>
<td>60:95%</td>
</tr>
<tr>
<td>( S )</td>
<td>10</td>
</tr>
<tr>
<td>( r_{1,2} )</td>
<td>3</td>
</tr>
<tr>
<td>class1 ( P_{max,1} )</td>
<td>45 kW</td>
</tr>
<tr>
<td>class2 ( P_{max,2} )</td>
<td>22 kW</td>
</tr>
<tr>
<td>( m_2 )</td>
<td>33</td>
</tr>
<tr>
<td>( n_2 )</td>
<td>2.2</td>
</tr>
</tbody>
</table>

classes. Class 1 of EVs uses DC fast charging power, with a maximum power of 45 kW. Class 2, on the other hand, prefers Level II, three-phase chargers, with a maximum power of 22 kW. The threshold energy, \( E_c \) for fast charger customers remains the same, while the threshold for the second class is determined as 5 kWh. Combined with (2.1), parameters in charging power model of Class 2 are \( m_2 = 33 \) and \( n_2 = 2.2 \). The system input parameters in Table 2.3 are given by \( \lambda = 8 \), \( S = 10 \), and \( r_1 = r_2 = 3 \). The target \( SoC_r \) is varied from 60% to 95% and the \( SoC_i \) distribution is selected as \( \mathcal{N}(30, 15) \), truncated to \([5, SoC_r - 10] \)%.

We analyze the system for three population compositions, \((\theta_1, \theta_2)\) = \{(75\%, 25\%),(50\%, 50\%),(25\%, 75\%)\}. The numerical results and simulation results are shown in Table 2.4 and TABLE 2.5, respectively. On one hand, when population of one class of EVs is relatively large, for example, class 2, the system is prone to allocate more chargers to class 2 to decrease the blocking probability and achieve higher system revenue. On the other hand, if fewer chargers are dedicated to class 2, the system is prone to decrease the \( SoC_r \) to shorten the charging time, since the average charging time of class 2 is long.

Next, we present the second toy example to evaluate the influence of different traffic loads on
the dedicated charger model. Assume $SoC_r$ is set as 90%, and the EV composition is selected as $(\theta_1, \theta_2) = (50\%, 50\%)$. Arrival rates of each class is varied from 1 to 7. Moreover, the total number of chargers and the waiting space for each class are chosen to be 10 and 3, respectively. The rest of the simulation parameters are given in Table 2.6.

For the numerical and simulation results, the optimal number of chargers for each customer class is chosen as $(4, 6)$, and the arrival rate for each class is varied from $\lambda_j = 1 \cdots 7$. The average numerical service rates for class 1 and class 2 are 2.354 and 1.151 customers/hour respectively. We further present the traffic intensity in Fig2.7a. The results show that simulation results support the numerical findings. It is also noteworthy that, when the arrival rate of the class 2 customers approaches to $\lambda_2 = 7$, the system becomes unstable as the traffic intensity $\rho > 1$.

Moreover, we continue to present the performance metrics, Fig.2.7b depicts the blocking probability for each class, while Fig. 2.7c shows the numerical and simulation results for the revenue calculations in the multi-class setting. Fig.2.7d depicts the system revenue. As the arrival rate in-

### Table 2.4 Toy Example I – numerical results

<table>
<thead>
<tr>
<th>$(\theta_1, \theta_2)$</th>
<th>$s_j^*$</th>
<th>$SoC_r^*$</th>
<th>Optimal system revenue ($/\text{hour}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(75%, 25%)</td>
<td>(7, 3)</td>
<td>(95%, 80%)</td>
<td>62.31</td>
</tr>
<tr>
<td>(50%, 50%)</td>
<td>(5, 5)</td>
<td>(95%, 85%)</td>
<td>60.68</td>
</tr>
<tr>
<td>(25%, 75%)</td>
<td>(3, 7)</td>
<td>(95%, 85%)</td>
<td>59.63</td>
</tr>
</tbody>
</table>

### Table 2.5 Toy Example I – simulation results

<table>
<thead>
<tr>
<th>$(\theta_1, \theta_2)$</th>
<th>$s_j^*$</th>
<th>$SoC_r^*$</th>
<th>Optimal system revenue ($/\text{hour}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(75%, 25%)</td>
<td>(7, 3)</td>
<td>(95%, 80%)</td>
<td>62.22</td>
</tr>
<tr>
<td>(50%, 50%)</td>
<td>(5, 5)</td>
<td>(95%, 85%)</td>
<td>60.14</td>
</tr>
<tr>
<td>(25%, 75%)</td>
<td>(3, 7)</td>
<td>(95%, 85%)</td>
<td>59.44</td>
</tr>
</tbody>
</table>
increase, operator gains higher system revenue since it can serve more customers when the blocking probability is low.

2.4 Performance Analysis for the Multi-class Setting

In Section 2.4, a case study is presented to evaluate the performance of the proposed models. The main goal is to investigate the relation between the traffic intensity and resource usage. The system is simulated for 100,000 EVs in class 1 (fast charging) and 100,000 EVs in class 2 (level-II three phase) for both models. The system parameters are given in Table 2.6. The total waiting spaces in the shared
Table 2.6 Toy example II: system input parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_{1,2}$</td>
<td>1:7</td>
</tr>
<tr>
<td>$SoC_i$</td>
<td>$\mathcal{N}(30, 15)$, truncated to $[5, SoCr-10%]$</td>
</tr>
<tr>
<td>$SoCr$</td>
<td>90%</td>
</tr>
<tr>
<td>$S$</td>
<td>10</td>
</tr>
<tr>
<td>$r_{1,2}$</td>
<td>3</td>
</tr>
<tr>
<td>class1</td>
<td>$P_{max,1}=45$ kW</td>
</tr>
<tr>
<td>class2</td>
<td>$P_{max,2}=22$ kW</td>
</tr>
</tbody>
</table>

![Graph](image1)

(a) Traffic Intensity: Shared and dedicated chargers

![Graph](image2)

(b) Class blocking probability: Shared and dedicated chargers

Figure 2.8 Dedicated and shared charger model: traffic intensity, blocking probability and class revenue

In the shared charger model, the average service rate is 1.545 customers/hour. Hence, from $\rho = \frac{\lambda}{S\mu}$, the traffic density varying arrival rate from 1···14 is calculated and depicted in Fig.2.8a. For example, when arrival rate of each class is 5, the traffic intensity becomes $\rho = \frac{5+5}{10\cdot1.545} = 0.647$. In the dedicated charger model, the optimal composition of chargers allocated to each class are not equal to each other, thus, the traffic intensity varies under different traffic regimes. The results are depicted in Fig.2.8a. Furthermore, the mean charging time of these two classes in dedicated charger
model is not the same, hence, their traffic intensities are plotted separately.

![Graph showing system revenue vs arrival rate for shared and dedicated chargers]

**Figure 2.9** Dedicated and shared charger model: system revenue

Fig.2.8b depicts the blocking probability of each class for the proposed models. In the shared charger model, since each EV class share the same chargers and the waiting spaces, their blocking probabilities are the same. In dedicated charging model, the blocking probability of class 2 increases faster than that in class 1. This is because the charging duration of class 2 is longer and this is reflected in the blocking performance. Furthermore, as the arrival rate increases, the blocking probabilities of dedicated chargers model is higher than those in shared chargers model. Hence, if the station operates under high traffic regime, system operator should choose shared charger model for better performance.

In Fig.2.9, when arrival rate of each class is low, the system revenues of two models are close. When traffic intensity becomes larger, shared charger model outperforms dedicated charger model because utilization of chargers is larger in shared charger model with increasing arrival rate. When arrival rate for each class is 6, system gains highest revenue in shared charger model. Then revenue begins to decrease in shared charger model because of heavy traffic load. From Fig.2.8a, when arrival
rate for each class is $8, \rho > 1$. This time, system revenue in dedicated charger model becomes larger than that in shared charger model. The reason is for the very heavy traffic load, in dedicated charger, the system allocates more chargers to fast charging class of EVs to keep its blocking probability small. However, in shared charger model, when traffic load is very heavy, EVs are easy to be blocked since level-II three phase charging of EVs occupy the chargers for long time. Hence, the blocking probability is very high and system revenue decreases dramatically.

Hence, the strategy for maximizing system revenue is that: when traffic intensity $\rho < 1$, shared charger model should be used; when $\rho \geq 1$, dedicated charger model works better.

### 2.5 Conclusion

In this Chapter, we propose two revenue maximization frameworks for CS. The first framework corresponded to a revenue model for stations with single customer class. The CCCV method decreases the charging power dramatically when the SoC gets close to fully state, which also results in a long charging duration. Therefore, the main thrust of this work is to limit the SoCr for customers, so that more customers could be served. The system is modeled as a $M/G/s/k$ queue, where we also provide a method to generate a general charging time distributions. In this system revenue model, the EV’s cost components includes battery degradation cost, the cost of waiting time, and admission fee. Then, we determined the optimal SoC$_r$ that maximizes the system revenue.

The second framework, on the other hand, built upon the first one and proposed a revenue model for multi-class EVs. For this case, we proposed two different operating strategies which were shared and dedicated charger models. The system performance of each case was compared and analyzed. Our results indicated that the proposed frameworks have improved the system performance.
OPTIMAL CHARGING FRAMEWORK FOR ELECTRIC VEHICLES ON THE WIRELESS CHARGING HIGHWAY

3.1 Introduction

Chapter 3 presents a single CS system design on wireless charging highway. The performance modeling in this Chapter supplements system design of a single CS from another viewpoint, where the wireless charging is applied in EVs.

Range anxiety has been a big concern for EVs on the road. Moreover, it is inconvenient for EVs to spend a long time charging while driving on the highway. Wireless charging represents a potential breakthrough to alleviate the range anxiety and provides convenient service to EVs. Since
the capacity for charging EVs on the highway is limited, it is crucial to control the EVs properly in order to avoid congestion and to provide good QoS. On one hand, based on the physical motion of an EV, the velocity is a main factor for the EV’s energy consumption while driving. The high velocity causes a larger energy consumption, which results in a longer charging duration. And each time an EV charges its battery, it incurs some battery degradation cost.

On the another hand, V2I communication on the highway is necessary to provide the communication among EVs and the control center. In this Chapter, while being aware of V2I communication, we propose an optimal revenue framework for the wireless charging highway, which takes into account the physical motion of EVs and internal battery characteristics. Considering the possibly reneging behavior of EVs, the system is modeled as a $M/M/s$ loss system.

We evaluate the performance of the proposed model. Our numerical and simulation results show that the proposed scheme improves the system performance and the QoS provided to the customers.

### 3.2 Wireless Charging Highway Model

We assume a multiple-lane highway with one direction, where the right-most lane is used for the wireless charging. The wireless charging lane is divided into $N$ sections, and the length of each section is $L$. In each section, one road side unit (RSU) is deployed and acts as the control center within the range of $L$. The highway model is shown in Fig.3.1.

The power transfer rate and the density of chargers are decided by the implementation of the wireless charging system on the road. There are two potential layouts for the system [Eng15]. In layout 1, every 50m segment supplies two EVs, where the maximum power transfer rate is 100 KW. In layout 2, every 40m segment holds an EV and the maximum power transfer rate is 140 KW. Layout 1 is adopted in this Chapter and the related model is shown in Fig. 3.2.

In this Chapter, we assume that:

- All the EVs drive at the same speed.
• An independent control center is implemented in every section. The EVs sending the charging request to the control center at $Sec_j$ join the system of $Sec_j$.

• An EV charges the battery one time on the highway. Once the EV gets charged, the EV will charge the battery to be full state of charge (SoC).

• There are $S$ chargers implemented at every section.

The operation for the EVs on the highway is as follows. Let an EV $k$ ($k=1,2,...,K$) sending the request at section $Sec_j$ be $EV_j^k$. When $EV_j^k$ drives from $Sec_j$ to $Sec_{j+1}$, $S$ chargers are available at $Sec_{j+1}$ for $EV_j^k$ as it is supposed that all the EVs on the highway drive at the same speed. If $EV_j^k$ gets served at $Sec_j$, it will continue to get served at $Sec_{j+1}$. If $EV_j^k$ waits at the queue in the system of $Sec_j$, it will continue to wait at the physical location of $Sec_{j+1}$ unless there is an available charging slot for this EV. In other words, an EV joins the system locating at specific section and then the EV
keeps staying at the same virtual system regardless of the change in the physical location of the EV. The number of charging slots for a system keeps constant.

Congestion happens when the power capacity is insufficient to charge all the EVs at the same time, resulting in the reneging behavior of the EVs. There are two possibilities for EVs to renege. The first one is an EV runs out of energy before getting served. The second one is when an EV arrives at the destination before getting charged. Therefore, we model the system to be a $M/M/s$ loss system in a single section, where the arrival and service rate are independently and exponentially distributed.

### 3.3 V2I Communication Scenario on The Highway

The intelligent transportation system (ITS) and vehicular networking dramatically enhance the performance for driving and enable vehicles to communicate with vehicles (V2V) and stationary infrastructure (V2I) (e.g. access points, RSU).

In this Chapter, we consider dedicated short-range communication (DSRC) as the lower layers of V2I communication system on the highway. RSU is adopted as the infrastructure node and communicates with other RSUs via wired connection. Additionally, the vehicles and RSUs exchange the data via DSRC wireless connection.

Every RSU covers a certain range for the communication. In the uplink system, when a vehicle reaches the range, it sends a charging request to the RSU when an EV accesses an idle channel. If the EV senses that all the channels are occupied, it waits until the channel is available and then contends with other vehicles to access.

In the downlink, an RSU sends the reply back to an EV after the EV sends the charging request successfully.

Specifically, for each EV, when it successfully sends the request to $RSU_j$, this will put the EV in its queuing system. The EV will receive the CHARGE or WAIT message. The scenario is shown in Fig. 3.3, where $EV_1$ and $EV_2$ can charge immediately while $EV_3$ has to wait because of insufficient chargers. If the EV receives the WAIT, after the EV drives pass the range, it gets into $RSU_{j+1}$'s communication.
range, and sends updated information. When there is any available charger for the EV to charge, $RSU_j$ informs all other RSUs in the driving direction through wired connection. $RSU_{j+1}$ is considered as relay to forward the message to $EV_3$. The scenario is shown in Fig. 3.4. In this Chapter, we assume that the communication among EVs and RSUs is perfect, without congestion.

3.4 Optimal System Revenue Framework on The Wireless Charging Highway

In this section, by controlling the driving velocity, we proposed an optimizing system revenue framework. First, the energy consumption for an EV and average service rate of the system is derived. Secondly, based on the reneging behaviors of EVs, the loss probability of $M/M/s$ loss model is presented. Last but not least, we consider the battery degradation cost, and an admission fee of an EV in the revenue model.

3.4.1 The Estimation of Average Service Rate

When an EV drives on the highway, the resistance to motion and the velocity $v$ are the main factors of the EV’s energy consumption based on [DC15; Too].

The resistance to motion, denoted $F_{tot}$, includes the rolling friction $F_{roll}$, the acceleration resistance $F_{accel}$, the dragging resistance $F_{drag}$ and the slope resistance $F_{slope}$, which is shown...
Figure 3.4 Communication between RSUs

below:

\[ F_{\text{tot}} = F_{\text{roll}} + F_{\text{accel}} + F_{\text{drag}} + F_{\text{slope}} \] (3.1)

where:

\[ F_{\text{roll}} = f \cdot m \cdot g \] (3.2)

\[ F_{\text{accel}} = m \cdot a_{\text{accel}} \] (3.3)

\[ F_{\text{drag}} = \frac{1}{2} \cdot \rho_{\text{air}} \cdot c_{\text{drag}} \cdot s_{\text{cross}} \cdot v^2 \] (3.4)

\[ F_{\text{slope}} = s_{\text{slope}} \cdot m \cdot g \] (3.5)

Here, \( f \), \( m \), \( g \) and \( a_{\text{accel}} \) are the rolling coefficient, the mass of an EV, the gravity of the earth, and the acceleration of an EV respectively. \( \rho_{\text{air}} \) is the air density, and \( c_{\text{drag}} \) is the drag coefficient of an EV. Cross sectional area of an EV is denoted \( s_{\text{cross}} \).

The average power consumption \( P_{\text{consume}} \) is calculated according to the following relationship:
where $\eta_{drive}$ and $P_{other}$ are the driveline dynamics efficiency and the auxiliary power of an EV respectively, both of which are supposed to be constant parameters.

The charging power rate $P_{charge}$ is

$$P_{charge} = P_t \cdot \eta_t \cdot L_{device}$$  \hspace{1cm} (3.7)$$

where $P_t$, $\eta_t$ and $L_{device}$ are the power transfer rate from a coil to a secondary coil, the wireless charging efficiency and the length of on-board charging device, respectively.

The increased energy after driving one unit of distance $\Delta L$ is $\Delta E = (P_{charge} - P_{consume}) \cdot \frac{\Delta L}{v}$, and the average service rate $\mu$ of the EVs in the system is

$$\mu = \frac{P_{charge} - P_{consume}}{E_{full} \cdot (1 - \mathbb{E}(SoC))}$$  \hspace{1cm} (3.8)$$

where $E_{full}$ is the battery capacity, and $\mathbb{E}(SoC)$ is the average initial SoC when the EVs send the request to charge the battery, which range is $[0, 1]$.

### 3.4.2 Loss Probability of $M/M/s$ queue

The loss probability of the $M/M/s$ system is related to the tolerance time of the EVs. In the $M/M/s$ model, a First Come First Served (FCFS) mechanism is used. Two kinds of time duration contribute to the EV’s reneging behavior. One is the average time duration from the time when the EVs send a charging request to running out of energy completely, which is denoted $\mathbb{E}(t_{batt})$. Another one is the average time duration from the time when the EVs send a charging request to reaching the destination, which is $\mathbb{E}(t_{dest})$.

Supposedly all EVs come to the entrance of the highway with full energy. Hence, $\mathbb{E}(t_{batt})$ is

$$\mathbb{E}(t_{batt}) = \frac{E_{full} \cdot (1 - \mathbb{E}(SoC))}{P_{consume}}$$  \hspace{1cm} (3.9)$$
The average requested travel distance of the EVs is denoted $\mathbb{E}(D_t)$. The remaining distance to travel after EVs’ sending charging requests is

$$
\mathbb{E}(D_r) = \mathbb{E}(D_t) - \frac{E_{full} \cdot \mathbb{E}(SoC_i)}{E_{con}}
$$

(3.10)

where $E_{con} = P_{consume} \cdot \Delta L / v$ is the energy consumption of an EV for each distance unit $\Delta L$. Hence, $\mathbb{E}(t_{dest})$ is $\mathbb{E}(D_r) / v$.

The average tolerance time of the EVs, which is denoted $\mathbb{E}(t_{tol e})$ is the minimum value between $\mathbb{E}(t_{dest})$ and $\mathbb{E}(t_{batt})$. The formula of $\mathbb{E}(t_{tol e})$ is shown below:

$$
\mathbb{E}(t_{tol e}) = \min(\mathbb{E}(t_{dest}), \mathbb{E}(t_{batt}))
$$

(3.11)

An EV will renege when the average waiting time $\mathbb{E}(t_w)$ in the queue is larger than the average tolerance time $\mathbb{E}(t_{tol e})$, resulting in a loss of a system.

The traffic intensity is $\rho = \frac{\lambda}{\mu}$, where arrival rate $\lambda$ and $\mu$ are independent and exponential distributions. $P\{\mathbb{E}(t_w) > \mathbb{E}(t_{tol e})\}$ is the probability of the stationary waiting time larger than the average tolerance time. A stable queuing system is considered in this Chapter. Therefore, the loss probability $P_{loss}$ is given by [BT99]

$$
P_{loss} = \frac{(1 - \rho) \cdot P\{\mathbb{E}(t_w) > \mathbb{E}(t_{tol e})\}}{1 - \rho \cdot P\{\mathbb{E}(t_w) > \mathbb{E}(t_{tol e})\}}
$$

(3.12)

where the probability of the stationary waiting time larger than the average tolerance time is expressed as

$$
P\{\mathbb{E}(t_w) > \mathbb{E}(t_{tol e})\} = p_0 \left( \frac{(S \rho)^S}{S!} \right) e^{-S \mu (1 - \rho) \mathbb{E}(t_{tol e})}
$$

(3.13)

and the probability that there is no EV in the system is given by

$$
p_0 = 1 / \left( \sum_{k=0}^{S-1} \left( \frac{(S \rho)^S}{k!} \right) + \left( \frac{(S \rho)^S}{S!(1 - \rho)} \right) \right)
$$

(3.14)
### Table 3.1 System input parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>1.9/hour</td>
<td>$\eta_t$</td>
<td>0.75</td>
</tr>
<tr>
<td>$S$</td>
<td>8</td>
<td>$c_{pen}$</td>
<td>5 ($)</td>
</tr>
<tr>
<td>$v_{max}$</td>
<td>100 (km/h)</td>
<td>$m_1$</td>
<td>15 ($)</td>
</tr>
<tr>
<td>$v$</td>
<td>60 : 100 (km/h)</td>
<td>$m_2$</td>
<td>15 ($)</td>
</tr>
<tr>
<td>$P_t$</td>
<td>50 (kW)</td>
<td>$P_{max}$</td>
<td>100 (kW)</td>
</tr>
<tr>
<td>$SoCr$</td>
<td>100(%)</td>
<td>$SoCi$</td>
<td>$\mathcal{N}(30, 15)$</td>
</tr>
</tbody>
</table>

### Table 3.2 EV parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\eta_{drive}$</td>
<td>1</td>
<td>$c_{drag}$</td>
<td>0.28</td>
</tr>
<tr>
<td>$E_{full}$</td>
<td>24 (kWh)</td>
<td>$f$</td>
<td>0.012</td>
</tr>
<tr>
<td>$l_{device}$</td>
<td>1 (m)</td>
<td>$s_{cross}$</td>
<td>2.29</td>
</tr>
<tr>
<td>$a$</td>
<td>0.00495</td>
<td>$m$</td>
<td>1521 (kg)</td>
</tr>
<tr>
<td>$b$</td>
<td>0.075</td>
<td>$p_{other}$</td>
<td>0.8 (kW)</td>
</tr>
<tr>
<td>$c$</td>
<td>0.00242</td>
<td>$\rho_{air}$</td>
<td>1.225</td>
</tr>
<tr>
<td>$g$</td>
<td>9.8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 3.4.3 System Revenue Model

In this subsection, system revenue is presented with the consideration of the reward gained by an EV, the cost of battery degradation and admission fee.

#### 3.4.3.1 Reward Model

After finishing the charging service, a customer gains the reward which is related to the driving velocity and the power transfer rate. With higher velocity and higher power transfer rate, a customer is more satisfied. Hence, the reward function $R(v, P_t)$ is expressed as:
Figure 3.5 Numerical and simulation results

\[ R(v, P_t) = m_1 \frac{v}{v_{\text{max}}} + m_2 \frac{P_t}{P_{\text{max}}}, \]  

(3.15)

where \( v_{\text{max}} \) and \( P_{\text{max}} \) are the maximum velocity for EVs on the highway and the maximum power transfer rate provided to the secondary coil. And \( m_1 \) and \( m_2 \) are the constant positive parameters.

### 3.4.3.2 The battery degradation model

When charging, the customers gain reward from the service, and at the same time, they need to pay the admission fee and incur the battery degradation cost. The charging power and the charging
Figure 3.6 System revenue/hour ($/hour) ($ = 1 : 9)

duration affect the battery degradation cost. In this chapter, it is supposed that the charging power $P_{\text{charge}}$ is constant. And Li-ion batteries are analyzed in the battery model. So the expected battery degradation cost in a time unit is given by [Ma15],

$$c_{\text{batt}} = a \cdot (P_{\text{charge}})^2 + b \cdot P_{\text{charge}} + c,$$  \hspace{1cm} (3.16)

where $a$, $b$ and $c$ are the parameters of batteries described in Section 2.2.2. The total battery degradation cost during the expected charging time $\mathbb{E}(t_{\text{ch}})$ is $c_{\text{batt}} \cdot \mathbb{E}(t_{\text{ch}})$.

3.4.3.3 Admission Fee

From the point view of economics, only when the gain from charging is equal or larger than the total cost incurred, will a customer be satisfied and ready to join the system [Has15]. So the maximum admission fee the system operator can set is given by:
\[ p = R(v, P_t) - c_{batt} \cdot \mathbb{E}(t_{ch}). \] (3.17)

### 3.4.3.4 System Revenue Model

The operator gains the admission fee from the customers, but encounters a penalty when the EVs cannot obtain the charging service. Hence, for each time interval, the revenue earned by the system operator \( S_{re} \) is

\[ S_{re} = \lambda \cdot (1 - P_{loss}) \cdot p - \lambda \cdot P_{loss} \cdot c_{pen} \] (3.18)

where \( c_{pen} \) is the penalty cost for not serving an EV.

The regulation of the speed limit is crucial as the velocity influences the energy consumption of an EV, the duration of average charging time, and the loss probability in the system. As a result, the target of the proposed scheme is to get the optimal velocity of EVs to maximize the system revenue and provide good QoS to the EVs. Since variable \( v \) has limiting value, with each increment \( \Delta v \), we can compute \( S_{re} \) until it satisfies

\[ S_{re}(v + \Delta v) \leq S_{re}(v^*) \] (3.19)

The optimal velocity \( v^* \) can be found when the system revenue reaches the maximum value.

### 3.5 Numerical and Simulation Results

In the performance analysis, the case when all the EVs drive at the maximum speed without any adjustment is served as a baseline. The performance of the proposed scheme is analyzed and compared with the baseline.

The results from the mathematical model proposed in Section IV are first numerically obtained and then validated by the simulation results.

Matlab and JAVA script are used to get the numerical and simulation results respectively, in which 100,000 EVs are simulated. The arrival rate of EVs is varied from 1 to 9. The distribution of \( SoC_i \) follows a normal distribution with mean value 30 and standard deviation 15, which is truncated
to $[5,90] \%$. The velocity is varied from 60 to 100 (km/h) with the interval of 5, and the maximum velocity is set to be 100 (km/h). The detailed system input parameters is in Table 3.1.

We choose NISSAN Leaf as the car model, in which the Li-ion battery capacity is 24 kWh. The parameters are summarized in Table 3.2 [Eng15].

In Fig.3.5a, in the proposed scheme, when the arrival rate is higher than 6, the optimal velocity decreases to improve the system performance. While the velocity keeps constant in the baseline scenario.

The difference of average charging time between two cases is obvious in Fig.3.5b. The average charging time in the proposed scheme is lower than the baseline case. When the arrival rate is 9, the average charging time in the proposed scheme is less than 0.7 hour. The tolerance time for EVs increases significantly in the proposed scheme, as shown in Fig.3.5c.

In Fig.3.5d, the numerical results are slightly different from the simulation results since the loss probability in the numerical results is approximate. The difference is within the range of 0.01. In Fig.3.6, when the arrival rate is high, the difference of system revenue among the proposed scheme and baseline is increasing.

The advantage of the proposed scheme is that the system performance improves when the traffic intensity is comparatively high, which provides a good QoS to the EVs.

### 3.6 Conclusion

In this Chapter, we presented an optimal revenue model for a wireless charging highway. First, the basic V2I communication framework was described. And then, considering the reneging behaviors of EVs, we modelled one section of the wireless charging highway as an $M/M/s$ loss system.

Our system revenue model combines different layers of the vehicle characteristics. In the low layer, the physical vehicle resistance to motion and the battery degradation cost is considered. In the higher layer, the reneging behaviors of customers and a FCFS scheduling mechanism are applied.

The proposed scheme aims to control the velocity to determine the optimal revenue and provide good QoS to the customers. Our numerical and simulation results show that the proposed scheme
improves both the system performance and the QoS to the customers under different traffic density.
4.1 Introduction

Chapter 4 further presents a hierarchical system model of a network of CSs from both traffic and service networks.

CS location decisions are a critical element in mainstream adoption of EVs. The customer confidence on EVs can be boosted with the deployment of well-planned charging infrastructure that can fuel a reasonable number of trips. The CS facility problem is complex and differs significantly from the classical literature, as the decision parameters are further linked to relatively longer charging
duration, battery parameters, and available grid resources. In this Chapter, we propose a three-layered system model of FCSs. In the first layer, we solve the flow capturing location problem to identify the locations of the CSs. In the second layer, we use a queuing model and introduce a resource allocation framework to optimally provision the limited grid resources. In the third layer, we consider the battery charging dynamics and develop a station policy to maximize the profit by setting maximum charging levels. The model is evaluated on the Arizona state highway system and North Dakota state network with a gravity data model, and on the City of Raleigh, North Carolina, using real traffic data. The results show that the proposed hierarchical model improves the system performance, as well as the quality of service (QoS), provided to the customers. The proposed model can efficiently assist city planners for CS location selection and system design.

4.2 System Model

The details of the hierarchical system model are discussed next (an overview of the algorithm and figure are depicted in Algorithm 1 and Figure 4.1). In the first layer, the objective is to maximize the captured traffic flow by efficiently locating the FCSs. Given a certain number of the FCSs, the classical FCLM is applied based on [Hod90]. After determining the location of FCSs, in the second layer, a certain number of the charging outlets is allocated to each FCS with the aim to minimize the weighted average blocking probability. The system is modeled to be a $M/G/c/c$ queuing network. In the third layer, considering the battery degradation cost and the fact that the charging time increases dramatically when SoC is close to hundred percent, a profit optimization model is proposed by reasonably limiting the SoCr. The details of the each layer are presented in the next subsections.

4.2.1 Flow Capturing Location Model (FCLM)

For the sake of clarity, we first give the FCLM background and corresponding assumptions as follows:

1. In a graph $G = (K, E)$, $K$ is a set of nodes and $E$ is a set of edges connecting any two nodes in $K$. 
2. In FCLM, it is assumed that all of the nodes in the undirected graph $G$ represent potential facility locations. In a city, usually road intersections, highway exits, or the location with heavy traffic are used as the nodes in $G$.

3. All of the nodes can be potential origin and destination nodes. Any two nodes (e.g., node $i$ and node $j$) in $K$ compose an unordered OD pair $q$. This means that order pairs $i, j$ and $j, i$ are identical.

4. The shortest path connecting two nodes is used as the unique path for the flow between this OD pair to follow. Any shortest path consists of at least one edge.

5. On the shortest path of OD pair $q$, the flow is captured if at least one facility is located at the potential locations along this path.

The goal of the FCLM is to capture as much traffic as possible given a certain number of FCSs. From the system operator standpoint, it is preferable to locate the CSs at the places that customers can drive through, so as to serve a large number of customers. For the sake of simplicity, it is assumed that the infrastructure of all CSs and the road constructions are the same, which means that customers’ preferences of selecting CSs and the probability of toll payments are neglected.
Algorithm 1: Overall algorithm of the three-layered optimization model

**Input**: Traffic data, SoC\(_i\) distribution function, battery type, \(p\), \(C_{tot}\)

**Output**: \(SoC^k, b_k, R_k\)

1. **Step 1**: Optimal FCS locations selection
   - Objective: Maximize the number of captured EVs
   - Apply FCLM in the optimization model
   - Generate the optimal FCS locations, as one of Step 2’s input data

2. **Step 2**: Capacity planning in FCSs
   - Objective: Minimizing the weighted customer blocking probability in the system
   - Model the system as \(M/G/c/c\) queue
   - Apply greedy algorithm to solve the optimization problem
   - Generate the optimal numbers of charging outlets, as one of Step 3’s input data.

3. **Step 3**: System profit maximization model
   - Objective: Maximizing the total profit in the system
   - Consider the charging model and battery degradation model in the profit model
   - Generate \(R_k, SoC^k_i, b_k\) as the output data

The flow capturing maximization problem is formulated as below:

\[
\begin{align*}
\max & \sum_{q \in Q} f_q y_q, \\
\text{s.t} & \sum_{k \in N^K_q} x_k \geq y_q \quad \forall q \in Q, \\
& \sum_{k \in K} x_k = p, \\
& x_k \in \{0, 1\} \quad \forall k \in K, \\
& y_q \in \{0, 1\} \quad \forall q \in Q.
\end{align*}
\]

Here, the objective function (4.1) aims to capture as much traffic as possible in all OD pairs.
The constraint (4.2) guarantees that the flow in OD pair \( q \) can only be captured if there is at least one FCS is selected on the shortest path of \( q \). The constraint (4.3) makes sure that the number of FCSs to be located is \( p \).

Although it is possible to obtain traffic data from national or local transportation departments for some regions, when this is not the case, the gravity spatial interaction model is an effective way to get estimates. A gravity spatial interaction model is shown below, which is based on [Hod90], originally from [SLB88]:

\[
f_q = z \frac{W_i W_j}{D_q^\beta}.
\]

In equation (4.6), \( f_q \) is the amount of traffic in a particular OD pair \( q \), where the origin node is \( i \) and destination node is \( j \), with a shortest path distance \( D_q \). \( W_i \) and \( W_j \) are the weight of nodes \( i \) and \( j \), respectively. Given the number of the FCSs, by using the method of FCLM, the locations of FCSs can be determined by maximizing the captured traffic flow.

### 4.2.2 Charging Outlet Allocation

The FCLM presented above decides on the optimal locations of CSs. However, due to varying traffic densities, stations may experience uneven customer demand. Hence, assuming that stations can capture all the flowing traffic is unrealistic for the case of EVs. Because of this, network operators need to provision more resources to the stations operating under a heavy traffic regime. Therefore, in this section, we propose a resource allocation framework to distribute the physical chargers to minimize the blocking probabilities and to provide customers a high level of QoS. In every FCS \( k \), the system is a \( M/G/c/c \) queue with an independent and exponential arrival rate \( \lambda_k \) and general distributed service rate \( \mu_k \). For a given number of number outlets \( C_{tot} \), the objective function is to minimize the weighted sum of the blocking probabilities. Two critical elements in the resource allocation framework are the arrival rate \( \lambda_k \) and the blocking probabilities \( b_k \) that are discussed below.

1. \( \lambda_k \): We assume that the probability for an EV to charge at any FCS on the path \( q \) is the same.
Moreover, for every FCS in $M_q$, the arrival rate from the path $q$ is $\frac{f_q}{\|M_q\|}$. Therefore, $\lambda_k$ of the FCS $k$ is the summation of the arrival rate on the paths that go through $k$, which is $\lambda_k = \sum_{q \in Q_k} \frac{f_q}{\|M_q\|}$. $Q_k$ is the set of the paths going through $k$.

2. $b_k$: Since each station $k$ is modeled using $M/G/c/c$ queuing, customer rejection probabilities can be calculated by using Erlang b function:

$$b_k = \frac{\left(\frac{\lambda_k}{\mu_k}\right)^{c_k}/c_k!}{\sum_{i=0}^{c_k} \left(\frac{\lambda_k}{\mu_k}\right)^i/i!}.$$

(4.7)

Now, we can define that the optimization problem can be formulated as below:

$$\min \sum_{k \in S} w_k b_k, \quad (4.8)$$

s.t

$$\lambda_k = \sum_{q \in Q_k} \frac{f_q}{\|M_q\|} \quad \forall k \in S, \quad (4.9)$$

$$\sum_{k \in S} c_k = C_{tot}, \quad (4.10)$$

$$b_k = \frac{\left(\frac{\lambda_k}{\mu_k}\right)^{c_k}/c_k!}{\sum_{i=0}^{c_k} \left(\frac{\lambda_k}{\mu_k}\right)^i/i!} \quad \forall k \in S, \quad (4.11)$$

$$c_k \in N \quad \forall k \in S. \quad (4.12)$$

The constraints (4.9) and (4.11) correspond to the formula of $\lambda_k$ and $b_k$, respectively. The constraint (4.10) shows that the number of charger outlets to be allocated is $C_{tot}$. Since the charging outlet allocation problem is a nonlinear programming problem with a complex Erlang-b formula, a greedy algorithm is used to find near-optimal solutions. The general idea of the greedy algorithm is to allocate the charging outlets one by one. During each round of distributing the charging outlets, the FCS with the highest value of the traffic intensity is allocated with this charging outlet. The detailed greedy algorithm is presented in Algorithm 2.

In the greedy algorithm, each FCS is allocated with one charging outlet initially. In each iteration
Algorithm 2: Greedy algorithm in the charging outlet model

| Input: $\{\lambda_1, \frac{1}{\mu_1}, \ldots, \lambda_p, \frac{1}{\mu_p}\}$, $C_{tot}$, $C_{cur}$, $w = \left[ \sum_{k \in S} \lambda_k, \sum_{k \in S} \lambda_k \mu_k \right]$ |
| Output: $c = \left[ c_1, c_2, \ldots, c_p \right]$, $\text{sum} = \sum_k w_k b_k$ |
| Initialization: $c_1 = c_2 = \ldots = c_p = 1$, $C_{cur} = C_{tot} - p$ |

1. while $C_{cur} \geq 1$ do
   2. $\rho = [\frac{\lambda_1}{c_1\mu_1}, \frac{\lambda_2}{c_2\mu_2}, \ldots, \frac{\lambda_p}{c_p\mu_p}]$;
   3. $m = \text{arg}\_\text{index}\_\text{max}(\rho)$;
   4. $c(m) = c(m) + 1$;
   5. $C_{cur} = C_{cur} - 1$;

6. end

7. for $k = 1$ to $p$ do
   8. $b_k = \frac{\lambda_k^{c_k}}{\sum_{n=0}^{c_k} \frac{\lambda_k^n}{\mu_k^n}}$;
9. end

10. $\text{sum} = \sum_k w_k b_k$;

of the while loop, a single outlet is allocated to the FCS with the greatest value of traffic intensity. The rationale behind this is to allocate more charging outlets to the FCS with heavy loads. In each round, the traffic intensity of every FCS is updated. The next loop describes the process of calculating $b_k$ in FCS $k$, and line 10 gives the value of the objective function.

4.2.3 Profit Optimization Model

In this subsection, we present a profit optimization model that considers battery degradation costs and the charging characteristics. We follow the idea of limiting SoCr of the EVs to a reasonable level from [Fan15], and our objective is to maximize the system profit. In the profit optimization model, both the charging characteristics and the battery degradation cost are addressed. This subsection consists of three parts: charging power model, battery degradation model and profit optimization.
4.2.3.1 Charging Power Model

In direct current (DC) FCS, constant current constant voltage (CCCV) charging mode is used for Li-ion batteries. In this charging regime, the battery is charged with a constant current until the voltage reaches a certain threshold value. Once the charging voltage reaches the threshold value, the charging voltage remains constant, while the charging current decreases significantly due to the internal resistance of the battery. In FCS applications, constant CCCV is widely employed to minimize the battery degradation and to ensure the safety of the battery. The authors in [AC12] shows experimental results using CCCV for FCS applications. It is noteworthy that the charging power approximately remains constant before a threshold of energy decreases as the stored energy gets closer to maximum capacity. A similar phenomenon can be observed in daily life when charging electronic devices with Li-ion batteries. For instance, while charging cell phone batteries (Li-ion), the charging power decreases as the battery SoC reaches and charging duration gets considerable longer. Mathematically, the charging power function [Fan15] is expressed in (2.1).

The charging time is related to the charging power, the initial energy of the battery $E_i$ and the requested energy of the battery $E_r$, which is expressed in (2.2).

As a result, the mean charging time and the mean charging power can be obtained from the charging time distribution, which are $\mathbb{E}(t_{ch})$ and $\mathbb{E}(P_{ow}) = \frac{E_r - \mathbb{E}(E_i)}{\mathbb{E}(t_{ch})}$, respectively. Here, $\mathbb{E}(E_i)$ is the mean value of the initial energy, as it is assumed that the initial SoC (SoCi) has a normal distribution. It is noteworthy that, by limiting SoCr, e.g., 85–90%, the mean charging time shortens compared to the full SoCr.

4.2.3.2 Battery Degradation Model

Electric vehicle batteries represent a large portion of the total cost. Each battery has a specific lifetime that is determined by the charging power and the charge–discharge cycles. Each time a battery is charged at a FCS, a certain amount of battery degrades, which is related to the charging
duration and the charging power [Ma15]. The expected battery degradation cost in the charging duration $\mathbb{E}(t_{ch}^k)$ at FCS $k$ is expressed in:

$$
\mathbb{E}(c_{batt})^k = (a \cdot (\mathbb{E}(P_{kw}^k))^2 + b \cdot \mathbb{E}(P_{kw}^k) + c) \cdot \mathbb{E}(t_{ch}^k),
$$

(4.13)

The work in [Ma15] provides the detailed information about the battery degradation cost and the parameter description.

### 4.2.3.3 Profit Optimization Formulation

Every FCS independently regulates its value of $SoC_r$. After completing the charging service, a customer in FCS $k$ gains a reward $g_k$. Supposedly, the reward is a linear function of $SoC_r^k$, where a customer is more satisfied with the increment of $SoC_r$. Specifically, customers charging at the same FCS gain the same reward since every customer in the same FCS accepts the same value of $SoC_r$. The reward function is represented by:

$$
g_k = m \cdot SoC_r^k + n,
$$

(4.14)

where $m$ and $n$ are the constant positive parameters.

Besides the battery degradation cost, a customer has to pay an admission fee $v_k$ to FCS $k$. Therefore, the total cost for an EV at FCS $k$ is shown as below:

$$
y_{total}^k = v_k + \mathbb{E}(c_{batt}^k).
$$

(4.15)

A customer is ready to join the system only if the reward is greater or equal than the total cost. Hence, the largest $v_k$ can be obtained when $g_k = y_{total}^k$, which is $v_k = g_k - \mathbb{E}(c_{batt}^k)$.

From the system operator viewpoint, the profit is a function of the arrival rate, blocking probability and the admission fee in the FCSs. Meanwhile, it encounters a penalty for blocking the EVs.
without serving them. Hence, the system profit $R_k$ of FCS $k$ is formulated as:

$$R_k = \lambda_k(1 - b_k) \cdot v_k - \lambda_k b_k d_k - c_{in}. \quad (4.16)$$

The system profit is maximized by finding a set of optimal SoC $r_k$ for all the FCSs of EVs. On one hand, $R_k$ can be gained higher with higher SoC $r_k$. On the other hand, the higher SoC $r_k$ increases the blocking probability, which threatens the system performance. Hence, by deciding the optimal SoC $r_k$ for every FCS $k$, the maximal value of the system profit can be determined. The profit optimization problem considering all FCSs is as below:

$$\max \sum_{k \in S} R_k, \quad (4.17)$$

subject to

$$\mu_k = \frac{1}{\mathbb{E}(t_{ch})} \quad \forall k \in S, \quad (4.18)$$

$$b_k = \frac{(\frac{\lambda_k}{\mu_k})^{c_k} / c_k!}{\sum_{i=0}^{c_k} \left(\frac{\lambda_k}{\mu_k}\right)^i / i!} \quad \forall k \in S. \quad (4.19)$$

The objective function is to maximize the sum of system profit of every FCS, and the constraints (4.18) and (4.19) correspond to the formula of $\mu_k$ and $b_k$, respectively.

### 4.3 Numerical Evaluations

In this section, we present the results of the performed computational experiments used to evaluate the proposed model. Three case studies, namely the Arizona State highway network, the City of Raleigh, North Carolina and the North Dakota State network are considered based on the public data available for each network. The FCS and EV parameters for each cases are shown in Table 4.1. The values of $a$, $b$ and $c$ are adapted based on [Ma15] for Li-ion batteries. The maximum charging power for the battery is assumed to be 45 kW and the SoC $i$ is set to have a normal distribution $\mathcal{N}(30, 15)$, where the mean value of SoC $i$ is 30% with 15% for the standard deviation, and it is truncated to target a SoC within $[5, SoC_r - 10]\%$. 

56
Table 4.1 Fast charging stations (FCS) and electric vehicles (EV) input parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d$</td>
<td>1 ($)</td>
<td>$m$</td>
<td>0.1 ($)</td>
</tr>
<tr>
<td>$n$</td>
<td>9 ($)</td>
<td>$P_{\text{max}}$</td>
<td>45 (kW)</td>
</tr>
<tr>
<td>$E_{\text{full}}$</td>
<td>15 (kWh)</td>
<td>$E_c$</td>
<td>5 (kWh)</td>
</tr>
<tr>
<td>$a$</td>
<td>0.008</td>
<td>$b$</td>
<td>0.075</td>
</tr>
<tr>
<td>$c$</td>
<td>0.0015</td>
<td>$m_1$</td>
<td>67.5</td>
</tr>
<tr>
<td>$n_1$</td>
<td>4.5</td>
<td>$\text{SoC}_i$</td>
<td>(%$)</td>
</tr>
<tr>
<td>$c_{in}$</td>
<td>0.02 ($)</td>
<td>$\beta$</td>
<td>1.5</td>
</tr>
</tbody>
</table>

4.3.1 Case Study I: Arizona State Highway Network

The first case study takes the Arizona state highway system for which the hierarchical optimization framework is applied to maximize the number of vehicles that can be served with limited grid resources. As a baseline scenario, the performance of the proposed model is compared with the case when the charging outlets are allocated equally, and the case when the SoCr is not limited (SoCr = 99%) in the profit optimization model.

In Figure 4.2, the 25-node network of Arizona state highways, which is also used in [Upc09], is shown and the basemap is from [UMa]. The links among the nodes represent the major state and interstate highways. The numbers on the links are the approximate shortest path distance with the unit mile. The size of the nodes reflects the amount of the population of the 25 cities. Moreover, the amount of each traffic flow is generated using the gravity spatial interaction model as described in Section 4.3, and the external flows are excluded in this case study.

In the DC FCS, based on the parameters in Table 4.1, the service rate is calculated to be $\mu = 1.1$ (EVs/h) when the SoCr is not limited. Moreover, it is assumed that the total number of chargers $C_{\text{tot}} = 50$. Each layer in the system is evaluated as below.

4.3.1.1 FCLM

To illustrate how FCLM is applied, we assume that the number of FCS locations $p = 2$. Solving the optimization problem presented in Section 4.2.1 yield to locating the stations to Phoenix and Tucson.
to maximize the captured flow, which represents 97.29% of the whole traffic flows. Varying the number of FCS locations from 1 to 6, the captured traffic percentages are shown in the second column of Table 4.2.

### 4.3.1.2 Charging Outlet Allocation

The proposed greedy algorithm is applied to the charging outlet allocation, where the performance is compared with the case in which the method of equal resource allocation is used. Suppose $p = 2$, in equal allocation, the number of charging outlet in \{Phoenix, Tucson\} is \{25, 25\} with total weighted blocking probability 0.16. While, in the proposed method, the number of charging outlets in \{Phoenix, Tucson\} is \{33, 17\} with a total weighted blocking probability of 0.087.

The sum of the weighted blocking rate in the proposed method is 8.7%, which is lower than the case when the charging outlets are allocated equally to FCSs. We vary the number of locations for FCSs from 1 to 6, and the optimal charging outlet allocation results are shown in the third column of Table 4.2. Since the amount of the traffic flows going through Phoenix is dominant in the network,
Table 4.2 Optimal charging outlet allocations.

<table>
<thead>
<tr>
<th>FCS Location</th>
<th>Captured Traffic (%)</th>
<th>Number of Outlets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phoenix</td>
<td>89.52</td>
<td>50</td>
</tr>
<tr>
<td>Phoenix, Tucson</td>
<td>97.29</td>
<td>33, 17</td>
</tr>
<tr>
<td>Phoenix, Tucson, Prescott</td>
<td>98.58</td>
<td>30, 17, 3</td>
</tr>
<tr>
<td>Phoenix, Tucson, Prescott, Flagstaff</td>
<td>99.37</td>
<td>29, 16, 3, 2</td>
</tr>
<tr>
<td>Phoenix, Tucson, Prescott, Flagstaff, Yuma</td>
<td>99.61</td>
<td>27, 16, 2, 3, 2</td>
</tr>
<tr>
<td>Phoenix, Tucson, Prescott, Flagstaff, Yuma, Benson/Willcox city</td>
<td>99.81</td>
<td>27, 14, 2, 3, 2, 2</td>
</tr>
</tbody>
</table>

over half of the charging outlets are allocated to Phoenix.

4.3.1.3 Profit Optimization Model

Applying the optimal charging outlet allocation, the proposed method is compared to the case when SoCr is not limited, which serves as a baseline scenario. Classical FCLM was used to capture the traffic flow in the work [CZ13], which was corresponding to the case without limiting SoCr. Hence, the proposed method of optimally limiting SoCr is compared with the case without limiting SoCr.

Four FCSs are selected as an example and the number of charging outlets remains the same, $C_{tot} = 50$. The results are shown in case I of Table 4.3. With the method of limiting SoCr, the system in every FCS location improves the performance compared with the case without limiting SoCr. For example, in Phoenix, the profit increases to 220.93 ($/h) and the blocking probability decreases to zero when the SoCr is limited to 95%. The average charging power increases to 16 (kW), resulting in relatively faster charging batteries compared to the case without limiting SoCr.

4.3.2 Case Study II: Raleigh City Network

In the case study of Raleigh, the performance of the proposed model is evaluated and compared with the current installed FCSs in the real world. This case study is based on the real traffic data collected from North Carolina Department of Transportation (NCDOT) in 2015 [Tra]. The annual
average daily traffic (AADT) count of every big road is used as the input data. The network of Raleigh is shown in Figure 4.3, which includes 14 locations with the heaviest traffic and six current FCS locations. The base map of Figure 4.3 is from [Ral]. The current FCS locations are marked in yellow color. Numbers 1 to 6 represent the current FCS locations in Glenwood Ave, Corporate center Drive, North Carolina State University, Arrow Drive, Six forks Road and N new hope Road respectively. The shortest path in an OD pair \( q \) is used and 190 paths are placed.

### Table 4.3 Results of profit models for three cases.

<table>
<thead>
<tr>
<th>Case: Arizona Without Limiting SoCr</th>
<th>Limiting SoCr</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCS Location</td>
<td>Number of Outlets</td>
</tr>
<tr>
<td>Phoenix</td>
<td>29</td>
</tr>
<tr>
<td>Tucson</td>
<td>16</td>
</tr>
<tr>
<td>Prescott</td>
<td>3</td>
</tr>
<tr>
<td>Flagstaff</td>
<td>2</td>
</tr>
<tr>
<td>Total profit ($/h)</td>
<td>336</td>
</tr>
<tr>
<td>Total weighted blocking rate</td>
<td>0.14</td>
</tr>
</tbody>
</table>

| Case II: Raleigh FCS 1 | 4 | 24.6 | 0.41 | 32.96 | 0.13 | 26 | 20 | 90 |
| FCS 2 | 2 | 9.9 | 0.41 | 12.37 | 0.19 | 26 | 20 | 90 |
| FCS 3 | 2 | 10.48 | 0.48 | 14.11 | 0.18 | 20 | 24 | 85 |
| FCS 4 | 5 | 32.68 | 0.46 | 11 | 99 | 47.77 | 0.09 | 20 | 24 | 85 |
| FCS 5 | 4 | 24.68 | 0.41 | 32.84 | 0.13 | 26 | 20 | 90 |
| FCS 6 | 3 | 17.17 | 0.42 | 22.45 | 0.16 | 26 | 20 | 90 |
| Total profit ($/h) | 120 | 163 |
| Total weighted blocking rate | 0.43 | 0.13 |

| Case III: North Dakota Fargo | 9 | 63.66 | 0.49 | 102.98 | 0.06 | 20 | 24 | 85 |
| Bismarck | 4 | 24.78 | 0.42 | 56 | 11 | 99 | 33.47 | 0.14 | 20 | 24 | 85 |
| Grand Fork | 1 | 2.74 | 0.33 | 2.95 | 0.23 | 35 | 16 | 95 |
| Minot | 1 | 1.89 | 0.24 | 2.04 | 0.16 | 35 | 16 | 95 |
| Total profit ($/h) | 93 | 141 |
| Total weighted blocking rate | 0.46 | 0.08 |

#### 4.3.2.1 The Calculation of the Amount of EV Traffic Data

Using equation (4.6) for the gravity spatial interaction model, the amount of traffic along the paths can be calculated. Therefore, the first step is to get the amount of traffic in the locations as the input data. It is assumed that 30% of drivers charge their EVs at CSs. From the annual average daily traffic
(AADT) counts, the EV penetration rate (0.3%) in North Carolina [Wes], and the percentage of EV drivers charging their vehicles, the amount of traffic in the locations can be calculated. Then, the amount of traffic along the paths can be known based on the gravity spatial interaction model.

In the current FCS, the station parameters are listed in Table 4.4. This work assumes the service rate of EVs is 1.1, which is the case when the SoCr is at the full state. The numbers of charging outlets in these FCSs are 1, 2, 1, 2, 1, and 2, respectively, which taken from data in [plu].

![Figure 4.3 The network of Raleigh city [Ral].](image)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FCS1</th>
<th>FCS2</th>
<th>FCS3</th>
<th>FCS4</th>
<th>FCS5</th>
<th>FCS6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_k$</td>
<td>0.5</td>
<td>1.2</td>
<td>3.29</td>
<td>3.21</td>
<td>7.93</td>
<td>0.94</td>
</tr>
<tr>
<td>$\mu_k$</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>$c_k$</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$C_{tot}$</td>
<td>9</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

### 4.3.2.2 Comparison of Three Cases and Evaluations

There are three cases for the performance comparison, as shown below:
• Base case (BC): the case in the current station location with currently allocated chargers, which is served as a base case for the performance analysis.

• LimitSoCr (LS): the case that the proposed method of limiting SoCr is applied to the current location with currently allocated chargers.

• ReallocateChargersLimitSoCr (RCLS): the case that the number of chargers in the stations is re-allocated with limiting the SoCr is proposed.

The numerical results are shown in Figures 4.4 and 4.5 are the summary of the total weighted blocking probability and the total profit for the three cases. For the case of RCLS, the optimal number of chargers are 1, 1, 2, 1, 3 and, 1, respectively. Since the traffic intensity of FCS5 is very high in BC, resulting in the high blocking rate. From the results of our model, after relocating the charging outlets in RCLS, the blocking rate in FCS5 decreases over \( \frac{1}{4} \). In Figure 4.5, the system performance of RCLS is the best among three cases. The profit in the RCLS case doubles and the total weighted blocking rate decreases more than \( \frac{1}{3} \) compared to BC.

4.3.2.3 Re-Allocation of the FCSs in Raleigh Network

As more and more EVs are deployed on the road and more charger outlets are installed, the locations of FCSs and the amount of captured traffic flows become crucial to the transportation and city planning. Therefore, the case in which the FCSs and outlets are re-located in Raleigh is studied with the intention of analyzing potential future improvements. The case in which the newly added charging outlets are installed in the current FCSs, according to the proportion of the arrival rate, serves as a baseline scenario. In both cases, the method of limiting SoCr is applied. The baseline scenario is named LS while the proposed method is called RelocateLocationLimitSoCr (RLLS) for simplification.

In RLLS, the locations of re-located FCSs are shown in Figure 4.6 marked as green triangles. Numbers 1 to 6 represent the relocated FCS locations in Soccer park drive, Zuma way, North Carolina State University, Six forks Road, Walker street and Horton street respectively. The number of EVs
that will charge in the re-located FCSs are 5.51, 2.23, 2.71, 8.06, 5.48 and 3.88, respectively, the total of which is about 1.5 times more than in the current FCSs. We assume that the total number of charging outlets increases to 20, while the other parameters remain the same.

After implementing the two scenarios, the number of charging outlets in the current FCSs are: 1, 3, 3, 4, 6 and 3, and in the re-allocated FCSs, they are 4, 2, 2, 5, 4, and 3, respectively. The system performance comparison is shown in Figure 4.7. In order to evaluate the whole network, the total weighted blocking probability and the total profit are shown in Figure 4.7a. In Figure 4.7b, the total weighted blocking probability in LS is relatively low due to the relatively low traffic intensity. However, in the RLLS case, it can capture more traffic while still keeping the gap within 5% compared to LS. From the aspect of the system profit, the profit in RLLS increases to be 163 ($/h), which increases almost 50% compared to LS.

In order to better illustrate the performance of the proposed method, we provide a comparison with a related work published in Ref. [CZ13]. The re-allocated FCSs with an optimal number of

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**Figure 4.4** Performance comparison in three cases. (a) Traffic intensity; (b) Average charging time (minutes); (c) Average charging power (kW); (d) blocking probability; (e) SoCr (%); (f) System profit ($/h).
charging outlets is compared with the method of FCLM reported in [CZ13]. The results are shown in case II of Table 4.3. In the case with limiting SoCr, the total profit in the system is 163 ($/h), while it is 120 ($/h) in the case without limiting SoCr. By limiting SoCr, the average charging time can be shortened exponentially, which decreases the customers’ blocking probability and increases the system profit.

**4.3.3 Case Study III: North Dakota State Network**

In the third case study, the proposed model is applied to the North Dakota state network for the performance evaluation. To the best of our knowledge, there are no public FCSs in North Dakota [plu]. Therefore, the case study presented in this section will shed light on the future FCS deployments. The case without limiting SoCr is served as a baseline scenario for the performance comparison.

In Figure 4.8, we present the North Dakota State highway network and pin the locations of the top 15 cities with highest population as the potential candidates for the FCS locations [Bur].
basemap of Figure 4.8 is from [UMb]. The shortest paths between the OD pairs are used for the traffic links and a total of 105 paths are shown in the map. In equation (4.6), the gravity spatial interaction model according to the node population can be used to calculate the amount of traffic along each path. Notice that EV traffic along each path can be calculated by using the amount of traffic, EV penetration rate (0.15 per a thousand people) [ENE], and the percentage of EV drivers charging their vehicles (30% as assumed in case II).

First, FCLM is applied to locate FCSs, and the optimization problem is solved according to the procedure presented in Section 4.2.1. By varying the number of FCSs from 1 to 5, the locations and the percentage of captured traffic are shown in Table 4.5. When there is only one FCS to be located, the city of Fargo is selected to place an FCS with 72.91% of captured traffic. To capture over 99% of traffic, at least four FCS locations are needed.

Next, four FCS locations with 15 charging outlets are selected as an example to evaluate the performance of the proposed model. The arrival rates of four FCS locations (Fargo, Bismarck, Grand Fork and Minot) are 16.84, 5.64, 0.54, and 0.33 EVs/h, respectively. Solving the optimal charging outlet problem presented in Section 4.2.2 yields 9, 4, 1, and 1 for each location. Compared to the small arrival rate of Grand Fork and Minot, Fargo is able to capture a large amount of traffic. Therefore,
Figure 4.7 Performance comparison between LimitSoCr (LS) and RelocateLocationLimitSoCr (RLLS). (a) Performance in six FCSs; (b) Profit and total weighted blocking rate evaluation.

Table 4.5 Optimal FCS locations.

<table>
<thead>
<tr>
<th>FCS Location</th>
<th>Captured Traffic (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1  {Fargo}</td>
<td>72.91</td>
</tr>
<tr>
<td>2  {Fargo, Bismarck}</td>
<td>97.18</td>
</tr>
<tr>
<td>3  {Fargo, Bismarck, Grand Fork}</td>
<td>98.548</td>
</tr>
<tr>
<td>4  {Fargo, Bismarck, Grand Fork, Minot}</td>
<td>99.21</td>
</tr>
<tr>
<td>5  {Fargo, Bismarck, Grand Fork, Minot, Valley City}</td>
<td>99.56</td>
</tr>
</tbody>
</table>

more than half of the charging outlets are allocated to the FCS in Fargo.

After optimizing the charging outlet allocation, the performance of the system profit model is analyzed. The case without limiting SoCr serves as a baseline for the comparison with our proposed model. In the case when customers’ SoCr is close to hundred percent, the blocking rates of all four FCSs are high, resulting in the high total weighted blocking rate and relatively low system profit. On the contrary, the total system profit of the case with limiting SoCr is 141 ($/hour), which is 1.5 times more than the profit of the case without limiting SoCr. The performance comparison is presented in Case III of Table 4.3. It is noteworthy that the performance of Grand Fork and Minot does not improve significantly by limiting SoCr. The rationale behind this is that the arrival rates of the two FCSs are relatively low.

66
4.3.4 Numerical Results Analysis

From the numerical results of cases I, II, and III, it is observed that the percentage of captured EVs increases when the optimal placement of CSs is applied in a network. Due to the fact that the spatial distribution of EVs is uneven, the system operator is required to properly allocate the energy resource to each CS. The results in our cases show that the proposed algorithm of resource allocation is effective in decreasing the probability of blocking EVs. Furthermore, the findings from Table 4.3 and Figure 4.5 show that limiting the SoCr to a reasonable level outperforms the case of charging the battery in full. For example, applying the strategy of limiting SoCr, the total profit increases more than one third compared to the case without limiting SoCr in Figure 4.5. To that end, the results in Figure 4.7b verify that even though increasing the number of charging outlets in currently installed CSs provides a good way to improve the system performance, it becomes less effective if the value of demand is not big enough. Therefore, it shows the importance of placing CSs and allocating energy optimally.
4.4 Conclusions

In this Chapter, we have proposed a hierarchical system model of a network of FCSs from the viewpoints of both traffic and service network. The three-layered system model is composed of the placement of FCSs, the charging outlet allocation, and the system profit model with the consideration of the Li-ion battery model. The Arizona state highway network, the Raleigh city network and the North Dakota state network are applied to evaluate the system performance of the proposed model.

The numerical results indicate that the percentage of captured EVs increases with the application of optimal CS placement. The results also demonstrate the effectiveness of the proposed resource allocation and charging strategies. The number of served EVs and the total profit of the system operator increase in the proposed model. As the charging demand is increasing rapidly, the results verify the necessity to place CSs and allocate the energy resource optimally, with the consideration of the battery charging dynamics. The proposed model can be applied to a CSs planning problem, assisting city planners in making decisions efficiently.
5.1 Introduction

In previous Chapter 2, 3 and 4, we present the system design in a single CS and in a network of CSs. In Chapter 5, we analyze interplay among EVs, CSs, clouds and system operator, and present cloud-based charging management in a network of CSs.
Managing large-scale penetration of EVs requires the support of a reliable and robust communication infrastructure. Cloud-based technologies have gained popularity in smart grid for reducing computational and communication complexity. This Chapter considers the issues of peak demand in CSs with different charging levels and communication among a large-scale of EVs, CSs, and SO. More specifically, we propose a novel cloud-based hierarchical EVs’ charging management model, whereby two levels of cloud computing infrastructures are considered to meet different latency requirements of customers. We propose three algorithms for the interplay among EVs, CSs, SO and clouds. Considering the contention-based random access mechanism for EVs accessing to 4G long term evolution (LTE) network, and the QoS metrics (average waiting time, and blocking probability), the model is composed of: queuing-based clouds server planning, capacity planning in CSs, delay analysis, and profit maximization. Price-incentive method (PIM) by shifting the heavy load from peak hours to off-peak hours and capacity expansion method (CEM) are proposed to alleviate peak demand. Two methods along with the baseline are compared and analyzed. Numerical results demonstrate the effectiveness of PIM and CEM under different conditions, and the tradeoff between these two methods are discussed.

5.2 System Model

In this section, we present an overview of our system model. Then considering the QoS of the system, optimal server planning in the cloud, capacity planning in a network of CSs, delay analysis, and profit optimization are formulated.

5.2.1 System Overview

Two classes of EVs: EVs in $CS_H$ and those in $CS_P$ are considered. The rationale behind this is that customers with high mobility near $CS_H$ requires real-time communication with the cloud, while those in $CS_P$ park their EVs for a certain period of time thus has comparably longer latency requirement. SO is responsible to purchase energy from the grid to provide charging service to EVs. Also, SO distributes the energy in its own subnetworks.
We assume time is divided into $T$ time slots, where $t \in \{1, 2, \ldots, T\}$, and there are $f$ CSs near highway exits ($CS_H$) and $(K-f)$ CSs at parking lots ($CS_P$), where $k \in \{CS_1, \ldots, CS_f, \ldots, CS_K\}$. The arrival rate of EVs in $CS_k$ at time $t$ is $\lambda_{k,t}$ and follows an exponential distribution [Bay14]. $J$ charging levels are considered in these public CSs. Each CS is mapped to one of charging levels. For providing a better customized service, two types of clouds are considered: local cloud (LC) with shorter end-to-end delay ($D_{e2e}^L$) and remote cloud (RC) with relatively longer $D_{e2e}^R$, as shown in Fig. 5.1. The communication among EVs, SO and the clouds are connected through 4G LTE base stations (BS). In the information flows, EVs and SO connect to BS in the wireless communication flow while BS and the clouds are in optical fiber links. The power flows exist between EVs and CSs for the charging.

EVs in $CS_H$ and $CS_P$ publish and subscribe to LC and RC respectively. The function of RC is to obtain the information of EVs from parking lots, synchronize the data with LC, and publish the responding messages to EVs in parking lots, which is able to alleviate the load burden of LC. Note that, the deployment of LC is out of scope in this Chapter. The function of BS is to forward EVs’ information to clouds. CCC, located in LC, performs processing and controlling services. It is supposed that SO sends real-time information (e.g., real-time electricity price $U_t$ and real-time supply $S_t$) to BS. Then BS forwards the information to LC.

The detailed model framework is depicted in Fig. 5.2. EVs and SO communicate with both clouds via BS. The cloud system module collects each customer’s information (an EV $i$’s ID, spatial location $x_{i,t}$ and charging demand $d_{i,t}$) in the top left diagram, as well as $S_t$, power capacity limits of each CS $Z_k$, CS power loss rate $l_j$, charging levels $P_{c,h}$ and $U_t$ from SO in the bottom left diagram. After CCC operates the cloud server planning, CCC sends the data of optimal number of cloud servers $c^*_{L,t}$ and $c^*_{R,t}$ to LC and RC, respectively. Optimal number of charging outlets (COs) $n^*_{k,t}$ is published to SO. Next, the cloud module responds to SO with discount $g^*_{k,t}$ and profit $Y^*_{PIM,t}$, and to customers with $g^*_{k,t}$. For a better description of the model architecture and operations, Algorithms 3, 4, 5 are presented. The algorithm executed by LC is similar to RC in Algorithm 4. Therefore, LC algorithm is not shown. The details of the hierarchical model are described in the following subsections.
Figure 5.1 Two-layered cloud computing-based EV charging system.

Algorithm 3: Executed by an EV.

Input: an EV $i$'s status (ID, $x_i, s_i$)
Output: $g_{k,t}$

1 for $t = 1$ to $T$ do
2 Contend in the random access procedure for connection in 4G LTE network.
3 After connecting successfully, EV sends charging request and status to BS.
4 Receive response (e.g. charging schedule and $g_{k,t}$) from CCC via 4G LTE network.
5 Send acknowledge message to accept or reject the discount.
6 end

5.2.2 Optimal Server Planning in the Cloud

To minimize servers’ rental cost in the cloud, $c_{L,t}^+$ and $c_{R,t}^*$ with QoS thresholds are investigated. It is to ensure the average waiting time of EVs in the queue of LC $t_{w,L,t}$ and RC $t_{w,R,t}$ satisfy threshold $\epsilon_L$ and $\epsilon_R$.

Referring to [Rim17a; Cao13; Rim17b], both LC and RC centers are modeled as $M/M/c$ queuing systems in our study. The arrival rates $\lambda_{L,t}$, $\lambda_{R,t}$, and service rates $\mu_L$, $\mu_R$ are independently and exponentially distributed. Therefore, $\lambda_{L,t} = \sum_{k=1}^{f} \lambda_{k,t}$ and $\lambda_{R,t} = \sum_{k=f+1}^{K} \lambda_{k,t}$. From the merging property of Poisson processes, $\lambda_{L,t}$ and $\lambda_{R,t}$ also follow the Poisson process, which is consistent with the
Algorithm 4: Executed by RC.

<table>
<thead>
<tr>
<th>Input</th>
<th>Output: $c_{R,t}^<em>, g_{L,t}^</em>$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I D_i, x_{i,t}, t_{i,t}$</td>
<td>$S_j, U_i, Z_k, l_j, P_{o,n}$</td>
</tr>
</tbody>
</table>

for $t = 1$ to $T$ do

1. Collect EVs’ information
2. Synchronize EVs’ information with LC
3. Get $c_{R,t}^*$ from CCC
4. Get $g_{L,t}^*$ from CCC
5. Publish $g_{L,t}^*$ to EVs in parking lots

end

$M/M/c$ model.

From Eq. (5.16), $t_w^t$ has an important influence on the delay in clouds. Therefore, the target in server planning is to figure out $c_{L,t}^*$ and $c_{R,t}^*$ given the thresholds of $\epsilon_L$ and $\epsilon_R$.

The probability $C$ that customers have to wait in the queue before getting served, and $t_w$ for the $M/M/c$ is given by [Kle76]

$$C(c, \frac{\lambda}{\mu}) = \frac{1}{1 + (1 - \rho) \cdot \frac{c!}{(c \rho)^c} \cdot \sum_{r=0}^{c-1} \frac{(c \rho)^r}{r!}}$$  \hspace{1cm} (5.1)$$

$$t_w(c) = \frac{C(c, \frac{\lambda}{\mu})}{c \cdot \mu - \lambda}$$  \hspace{1cm} (5.2)$$

where $\lambda$, $\mu$ and $c$ are the arrival rate, service rate and the number of servers in a $M/M/c$ system.
Algorithm 5: Executed by CCC.

**Input**: each EV's status (ID, x, t, d, t), S, Ut, Zk, lj, Pch

**Output**: c∗L,t, c∗R,t, Y∗PIM,t, n∗k,t, g∗k,t ∀k ∈ K, ∀t ∈ T

1. for t = 1 to T do
   2. CCC collects EVs’ status, S, Ut and Zk.
   3. CCC analyzes D2e,t and D2e,t.
   4. CCC executes server planning (5.3). The target is to minimize the servers’ rental fee. With constraints εL (5.4) and εR (5.5), CCC returns c∗L,t and c∗R,t to LC and RC.
   5. CCC executes capacity planning (5.10) with constraints (5.11)-(5.15). Return n∗k,t ∀k ∈ K. Details is shown in Algorithm 6.
   6. if d < S and b<tk < ε then
      7. Return S1 to SO and g∗k,t = 0.
   8. else
      9. CCC executes profit optimization module. First, calculate λ∗k,t, ∀k ∈ K in (5.20). Second, execute PIM (5.24) with constraints (5.25)-(5.27) for load shifting. Third, calculate Ck,t in (5.7) and Ck,t in (5.22). Get g∗k,t and Y∗PIM,t.
     10. Publish g∗k,t and Y∗PIM,t to SO.
     11. Publish g∗k,t to EVs.
   12. end

The traffic intensity ρ equals to \( \frac{λ}{\mu} \).

The total server rental cost is composed of the cost from LC and RC. The optimization problem at time t is formulated as follows:

\[
\begin{align*}
\min \quad & p_L \cdot c_{L,t} + p_R \cdot c_{R,t} \\
\text{s.t.} \quad & t_w^{L,t}(c_{L,t}) \leq \epsilon_L \\
& t_w^{R,t}(c_{R,t}) \leq \epsilon_R \\
& t_w^{L,t}, t_w^{R,t}, c_{L,t}, c_{R,t} \geq 0
\end{align*}
\]  

(5.3)

(5.4)

(5.5)

(5.6)

where \( p_L \) and \( p_R \) are rental fee of a server in LC and RC in one time period. Due to the real-time function of LC, suppose \( p_L > p_R \) and \( \mu_L > \mu_R \). The objective function (5.3) is to minimize the total cost of cloud services from both LC and RC. The constraints (5.4) and (5.5) guarantee the QoS to customers. Constraint (5.6) shows \( c_{L,t} \) and \( c_{R,t} \) are non-negative. It is assumed \( c_{L,t} \) and \( c_{R,t} \) are integers. Further, from Eqs. (5.1) and (5.2), \( t_w \) is decreasing with \( c \). When \( c_{L,t}^* = \lceil argmin_{c_{L,t}} (t_w^{L,t} = \epsilon_L) \rceil \) and \( c_{R,t}^* = \lceil argmin_{c_{R,t}} (t_w^{R,t} = \epsilon_R) \rceil \), the optimal cost is found.
5.2.3 Capacity Planning in the Network of CSs

Due to CSs’ different geographical locations, CSs may encounter uneven charging demands. Therefore, it is necessary to provide more COs to stations with heavy loads. On the other hand, a limited power supply may not satisfy all customers’ charging demands in a timely manner during peak hours. Customers who are not getting served in a timely manner are blocked out of the system. For gaining high reputation and providing a high QoS, it is critical to guarantee a low blocking probability. Because of this, the total weighted blocking probability is used for the performance evaluation.

In every CS, the system is modeled $M/M/c/c$. The service rate $\mu_k$ is a function of the charging level $j$ and charging efficiency in CS $k$. Power losses occur in a CS. Referred to [EM07; AI17], the power losses rate $l^j$ through a CO in class $j$ is

$$l^j = \frac{p^j_{ch} - p^j_{out}}{p^j_{ch}} \quad (5.7)$$

where $p^j_{ch}$ and $p^j_{out}$ are the power going in and going out of a CO in class $j$. Therefore, the charging efficiency of a CS with charging level $j$ is $\eta_j = 1 - l^j$. The expected value of $p^j_{ch}$ and $l^j$ are described in Section 5.3.

The blocking probability of $CS_k$ is computed as follows [All14]:

$$b_{k,t} = \frac{\left( \frac{\lambda_{k,t}}{\mu_k} \right)^{n_{k,t}} / n_{k,t}!}{\sum_{i=0}^{n_{k,t}} \left( \frac{\lambda_{k,t}}{\mu_k} \right)^i / i!} \quad (5.8)$$

where $\mu_k$ is given by

$$\mu_k = \frac{1}{(SoC_r - SoC_i) \cdot E / p^j_{ch} \cdot \eta^j} \quad (5.9)$$

In Eq. (5.8), $n_{k,t}$ and $\mu_k$ denote the number of COs and the service rate in $CS_k$. In Eq. (5.9), $E$, $SoC_r$ and $SoC_i$ are an EV’s battery capacity, expected value of requested state of charge (SoC) and expected value of initial SoC, respectively.
Due to internal resistance of EV battery, the charging time is increasing exponentially when SoC is close to full, resulting in the general distribution of $\mu_k$. The detailed battery characteristics can be found in [Fan15; Kon15]. For the sake of simplicity, the battery characteristics are not considered in this Chapter. We assume $\mu_k$ follows exponential distribution. Since the system is modeled as a $M/M/c/c$, the expected value of SoC is considered instead of individual SoC of every EV.

Customers in $CS_p$ is more willing to delay the charging if a discount is offered, while those in $CS_H$ would delay charging because of bigger discount, since they are more time sensitive. Thus, the time sensitivity parameters $\alpha_H$ and $\alpha_P$ are considered in the capacity planning, where $\alpha_H > \alpha_P$.

Hence, in $CS_k$, when $k \leq j$, $\alpha_k = \alpha_H$; else, $\alpha_k = \alpha_P$.

The maximal power capacity of $CS_k$ denoted $Z_k$ is considered as the power constraint. The variables in the optimization problem are $n_k$, $\forall k \in K$.

The problem formulation at time $t$ is given by

$$\min \sum_{k=1}^{K} a_k \cdot (w_{k,t} \cdot b_{k,t}) \quad (5.10)$$

subject to

$$b_{k,t} = \frac{\left(\frac{\lambda_{u,k,t}}{\mu_{k,t}}\right)^{n_{k,t}}}{n_{k,t}!} \cdot \sum_{i=0}^{n_{k,t}} \left(\frac{\lambda_{u,k,t}}{\mu_{k,t}}\right)^i / i! \quad \forall k \in K \quad (5.11)$$

$$\lambda_{u,k,t} = \lambda_{k,t} + \lambda_{k,t-1} \cdot \theta(g_{k,t-1}) \quad \forall k \in K \quad (5.12)$$

$$P_{ch}^j \cdot n_{k,t} \leq Z_k \quad \forall k \in K \quad (5.13)$$

$$\sum_{k=1}^{K} n_{k,t} P_{ch}^j \leq S_t \quad (5.14)$$

$$n_{k,t} > 0 \quad \forall k \in K \quad (5.15)$$

where the weighted value $w_{k,t} = \frac{\lambda_{k,t}}{\sum_{k=1}^{K} \lambda_{k,t}}$. Constraint (5.12) describes the updated arrival rate $\lambda_{u,k,t}$, after providing discount $g_{k,t}$, is composed of both newly arrival rate $\lambda_{k,t}$ and delayed EVs from previous time periods. $\theta(g_{k,t})$ is an EV’s probability of delayed charging, which is described in Section 5.2.5. Constraint (5.13) guarantees the amount of electricity (kW) distributed to a CS is no
Algorithm 6: CO allocation algorithm

Input : $\lambda_{u1}, t_{\mu1}, \ldots, \lambda_{uK}, t_{\muK}, \alpha_k, S_t, P_j^{ch}, Z_k, n_k, t \forall k \in K, \forall j \in J$

Output : $n = [n_{1,t}, n_{2,t}, \ldots, n_{K,t}], result_t = \sum_{k=1}^{K} w_k b_{k,t}$

Initialization: $n_{1,t} = \ldots = n_{K,t} = 1, temp = S - K \sum_{k=1}^{K} \sum_{i=1}^{n_k} \frac{\lambda_{uK}}{n_{K,t} \mu_{K,i}}, \rho_{k,t} = \frac{\lambda_{uK}}{n_{K,t} \mu_{K,i}}$

1. $V_t = [\lambda_{u1,n_{1,t}}, \lambda_{u2,n_{2,t}}, \ldots, \lambda_{uK,n_{K,t}}]$
2. while $temp \geq 0$ and $V_t \neq [0]$ do
3. \hspace{1em} $L = \arg \max \text{index}(V_t)$;
4. \hspace{1em} if $n(L) + 1 \leq \frac{Z_k}{n_{K,t}}$ and $temp \geq P_j^{ch}$ then
5. \hspace{2em} $n(L) = n(L) + 1$;
6. \hspace{2em} $temp = temp - P_j^{ch}$;
7. \hspace{1em} else
8. \hspace{2em} $\lambda_{k,t} = 0$;
9. \hspace{2em} Update $V_t$ and $\rho_{k,t}$;
10. end
11. for $k = 1$ to $K$ do
12. \hspace{2em} $b_{k,t} = \frac{\lambda_{uK,n_{k,t}}}{\sum_{i=0}^{n_k} \frac{\lambda_{uK}}{n_{K,t} \mu_{K,i}}}$
13. \hspace{1em} $\rho_{k,t} = \frac{\lambda_{uK}}{n_{K,t} \mu_{K,i}}$
14. end
15. $result_t = \sum_{k=1}^{K} w_k b_{k,t}$;

more than the maximal charging power rate of a CS. The discount mechanism will be presented in the Subsection 5.2.5.

Based on our previous work [Kon17], here we develop a greedy algorithm to find the near-optimal solutions. However, note that different from [Kon17], we have incorporated $Z_k, J$ charging levels, $\alpha_k$ in the algorithm when selecting CS. The details are presented in Algorithm 6.

Algorithm 6 presents the procedures of allocating COs. First, a CS with heavy load is selected in the further step of allocating one CO. The time sensitivity $\alpha_k$ is incorporated with the server intensity $\lambda_{u1,t} / n_{1,t} \mu_{1,t}$ in this operation (See Line 1). Second, after selecting a CS, its charging level $j$ and maximum power in this CS $Z_k$ are considered. At each iteration, if the remaining power supply can support an EV with its charging level and the power is not exceeding $Z_k$, then one CO is allocate to this CS, as shown in Line 4. Towards this end, we calculate the weighted blocking probabilities based on the CO allocation.
5.2.4 Delay Analysis

5.2.4.1 End-to-end delay

At time $t$, the expected end-to-end delay $D_{e2e}^t$ is the summation of EVs’ expected contention delay to connect 4G LTE $D_{con,t}$, expected packet transmission delay, expected propagation delay, expected queuing time in the cloud, and expected cloud servers’ processing time. Hence, $D_{e2e}^t$ is computed as follows:

$$D_{e2e}^t = D_{con,t} + D_{trans,req}^e + 2D_{prop}^e + D_{trans,req}^c + 2D_{prop}^c + \frac{1}{\mu} + t_w^t + D_{trans,res}^e + D_{trans,res}^c$$

(5.16)

where $D_{con,t}$, from Eq. (5.17), is a function of the arrival rate of EVs and the number of available preambles in 4G LTE system. Hence, the impact of traffic loads to $D_{con,t}$ and how it influence the system profit, will be analyzed in Section 5.3.

$D_{trans,req}^e = \frac{P_{req}}{R_{BS}}$ is the transmission delay from EVs to BS, where $P_{req}$ and $R_{BS}$ are packet size and the transmission rate of 4G LTE network. $D_{trans,req}^c = \frac{P_{req}}{R_c}$ is the transmission delay from BS to cloud server, where $R_c$ is the transmission rate in the link between BS and cloud server. $D_{prop}^e$ and $D_{prop}^c$ are the expected propagation delay between EVs and BS, and between BS and the cloud servers, respectively. In particular, $D_{prop}^c = D_{prop}^R$ when it is between BS and LC, while $D_{prop}^c = D_{prop}^R$ when it is between BS and RC.

Similarly, $D_{trans,res}^e = \frac{P_{res}}{R_{BS}}$ and $D_{trans,res}^c = \frac{P_{res}}{R_c}$. The responding packet size denotes $P_{res} \cdot t_w^t$ is from Eq. (5.2), where it is the average waiting time before getting served in $M/M/c$ system. It is noteworthy that cloud server processing time $\frac{1}{\mu}$ and $t_w^t$ of LC and RC are different, which depends on their service rate and number of servers.
5.2.4.2 Contention delay

When EVs do not have grant for uplink data transmission and no Physical Uplink Control Channel (PUCCH) has been configured for scheduling request (SR), random access procedure is initiated [3GP]. The mechanism of random access based on preamble transmitted is employed [Tya15]. Since EVs are already connected to 4G LTE, the response packet is transmitted to EVs by 4G LTE downlink directly. Hence only the contention delay from uplink network is considered.

The probability of sending a preamble without collision successfully at time $t$ denotes $p_{s,t}$. A slot duration, the maximum number of transmission attempts, and the number of preamble denote $\Delta T_s$, $W$ and $O$, respectively.

The total newly arrival rate $\lambda_{s,t} = \sum_{k=1}^{K} \lambda_{k,t}$. The expected number of EVs, including the newly and previously collided, transmitting a preamble at time $t$, denotes $N_{s,t}$. The expected number of EVs per preamble denote $x_{s,t}=\frac{N_{s,t}}{O}$. Here, $p_{s,t}$ is a function of $\lambda_{s,t}$ and $O$.

For the sake of simplicity, the backoff time is assumed zero when an EV encounters collision. The average delay from request generation to successful preamble transmission $D_{con,t}$ is computed as follows [Tya15]

$$D_{con,t}(\lambda_{s,t}, O) = \Delta T_s \cdot \left( \frac{1}{p_{s,t}} - 1 \right) \cdot \frac{1 + (W - 1)(1 - p_{s,t})^W}{1 - (1 - p_{s,t})^W} - \Delta T_s \cdot \left( \frac{1}{p_{s,t}} - 1 \right) \cdot \frac{W(1 - p_{s,t})^{W-1}}{1 - (1 - p_{s,t})^W} + \frac{\Delta T_s}{2}$$

where

$$p_{s,t} = e^{-x_{s,t}}$$

$$\frac{x_{s,t}}{\lambda_{s,t}} = \frac{1 - (1 - e^{-x_{s,t}})^W}{e^{-x_{s,t}}}$$

It is proved that when $W \leq 8$, the balance Eq. (5.19) has a single unique solution given $\lambda_{s,t}$ and $W$ [Tya15]. Therefore, unique value of $p_{s,t}$ can be obtained by Eq. (5.18) and (5.19).
5.2.5 Profit Optimization

The goal of SO is to maximize the system profit and guarantee a large percentage of EVs being served. In capacity planning, the total weighted blocking probability is minimized. However, this can not guarantee fairness among CSs. For better QoS and to be fair, our aim is to ensure every $b_{k,t}$ in (5.8) is no bigger than $\varepsilon$. The optimal arrival rate is given by

$$\lambda^*_{k,t} \leq \arg\max_{\lambda} (b_{k,t} \leq \varepsilon)$$

(5.20)

SO hopes to serve the largest number of EVs given a certain $\varepsilon$ threshold, thus $\lambda^*_{k,t}$ is the maximal value and can be achieved when $b_{k,t} = \varepsilon$.

When the supply satisfies EVs’ demand with the blocking rate threshold, CCC notifies SO with sufficient supply. On the other hand, in peak hours, $\lambda_{k,t}$ may be larger than $\lambda^*_{k,t}$. Thus, PIM, by offering discount to EVs, is proposed to shift the load from peak hours to off-peak hours. Meanwhile, another scheme: CEM, by purchasing sufficient amount of energy, is proposed and compared with PIM in Section 5.3. In CEM, a penalty for burdening the grid due to purchasing energy in peak hours is considered.

5.2.5.1 Price-Incentive Method (PIM)

PIM is a method to incentive EVs to shift their charging demand from peak hours to off-peak hours by offering discount. When the supply is insufficient to guarantee QoS level of $\varepsilon$, the system provides a discount to encourage customers to shift the demand by one time period. We apply load shifting concepts, as presented in [Bay14; KA05]. However, we have modified the models from one CS to a network of CSs, and included the penalty costs for not serving customers, rental fee from cloud services, and our price-sensitivity function for delayed charging in profit model.

Assume the price sensitivity function is known to the system. Applying the concept of linear price sensitivity function in [Ban12], we have modified to a linear price-delay probability function. Suppose the admission fee of an EV at CS $k$ of class $j$ for one-time charge is $A_j$ and the discount
offered by $CS_k$ of is $g_{k,t}$. The discount ranges of EVs in $CS_H$ and $CS_P$ of class $j$ are $[0, g_{max}^{H,j}]$ and $[0, g_{max}^{P,j}]$, respectively, mapping to $\theta(g_{k,t}) \in [0,1]$. The higher the discount offered, the more customers are willing to delay charging to next time period. For the same class $j$ of CSs, $g_{max}^{P,j} < g_{max}^{H,j} \leq A_j$ because customers in $CS_H$ are more time sensitive.

![Figure 5.3 Price sensitivity function](image)

In Fig. 5.3, x-axis is the discount offered by SO and y-axis is the probability of accepting the discount offer. The blue line represents the function of $CS_P$ while the red one represents $CS_H$ for the same charging level $j$.

From the perspective of a $CS_k$ at time $t$, we consider the admission fee of new coming EVs without delaying charging and delayed EVs from previous time period to current time, the penalty of not serving a EV $p_{pen}$, the cost of power losses, the penalty of a EV’s $D_{2e}^{k,t}$ and the maintenance cost of a CS $p_m$. The number of delayed EVs from $t-1$ to $t$ is $\dot{\lambda}_{k,t-1} = \lambda_{k,t-1} \cdot \theta(g_{k,t-1})$. The average charging demand of an EV denotes $d$, where $d = (SoC_f - SoC_i)E$. 

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At time period \( t \), the cost of energy loss in a CS \( k \) \( C_{loss}^{k,t}(\lambda_{k,t}^d) \) with charging level \( j \) is computed as below

\[
C_{loss}^{k,t}(\lambda_{k,t}^d) = U_t \cdot l^j \cdot p_{ch}^j \cdot \lambda_{k,t}^d \cdot (1 - b_{k,t}(\lambda_{k,t}^d)) \tag{5.21}
\]

where \( \lambda_{k,t}^d \) is the number of EVs in the system at time \( t \), including the newly arrivals rejecting to delay and the arrivals accepting to delay from time \( t-1 \). Hence, \( \lambda_{k,t}^d = \lambda_{k,t} \cdot (1 - \theta(g_{k,t})) + \lambda_{k,t-1} \).

Eq. (5.21) describes the cost of the amount of energy loss in a unit of time in CS\( k \), which is related to the electricity price, the power loss rate, the duration of charging time, and the number of served EVs.

\( D_{e2e}^{k,t} \) is differentiated by the connection of either LC or RC, which is given by

\[
C_{delay}^{k,t}(\lambda_{k,t}) = \begin{cases} 
\zeta_H \cdot \lambda_{k,t} \cdot e^{(D_{e2e}^{k,t} - D_H)} & k \leq f \\
\zeta_p \cdot \lambda_{k,t} \cdot e^{(D_{e2e}^{k,t} - D_P)} & otherwise 
\end{cases}
\tag{5.22}
\]

where \( \zeta_H \) and \( \zeta_P \) are the penalty factor, and \( D_H \) and \( D_P \) are the delay threshold for CS\( H \) and CS\( P \), respectively. Referring to [Kal10], exponential function is used to quantify the impact of an EV’s \( D_{e2e} \).

Therefore, at time \( t \), the profit after offering discount \( R_{k,j,t}^{PIM} \) at CS\( k \) in class \( j \) is given by

\[
R_{k,j,t}^{PIM} = (1 - b_{k,t}) \cdot \lambda_{k,t} \cdot (1 - \theta(g_{k,t})) \cdot (A_j - U_t \cdot d) + (1 - b_{k,t}) \cdot \lambda_{k,t-1} \cdot (A_j - g_{k,t-1} - U_t \cdot d) - b_{k,t} \cdot \lambda_{k,t} \cdot p_{pen} - C_{loss}^{k,t}(\lambda_{k,t}^d) - C_{delay}^{k,t}(\lambda_{k,t}) - p_m
\tag{5.23}
\]

Considering the rental cost Eq. (5.3), the total profit in a network of CSs by offering discount,
$Y_{PIM,t}$ is formulated.

$$\max \sum_{k \in K} R_{k,j,t}^{PIM} - p_L \cdot c_L - p_R \cdot c_R$$

(5.24)

s.t \quad \lambda_{k,t} \cdot (1 - \theta(g_{k,t})) + \lambda_{k,t-1} \cdot \theta(g_{k,t-1}) \leq \lambda^*_k, \forall k \in K

(5.25)

g_{k,t}, g_{k,t-1} \geq 0, \forall k \in K

(5.26)

$0 \leq \theta(g_{k,t}) \leq 1, \forall k \in K$

(5.27)

The objective function (5.24) depicts the total profit in a network of CSs. The constraint (5.25) guarantees the sum of customers who reject delaying charging and customers who accept delaying charging from one previous time period is no bigger than the optimal arrival rate.

### 5.2.5.2 Capacity Expansion Method (CEM)

CEM is a method for SO to purchase extra electricity to satisfy the peak demand, with the penalty of expanding the system capacity. The algorithms of CEM executed by CCC, an EV and RC are similar to those in PIM. Thus, CEM algorithms are not shown. QoS performance ($b_{k,t} \leq \epsilon$) is considered. Hence, in $CS_k$, $n_{k,t}$ should satisfy $n_{k,t} \geq \arg\min(b_{k,t} \leq \epsilon)$. From Eq. (5.8), $b_{k,t}$ is decreasing with $n_{k,t}$, so $n^*_{k,t} = \lceil \arg\min(b_{k,t} = \epsilon) \rceil$.

Therefore, the extra COs needs to be deployed at $CS_k$ is

$$\Delta n_{k,t} = \begin{cases} n^*_{k,t} - n_{k,t} & \text{if } n_{k,t} < n^*_{k,t} \\ 0 & \text{otherwise} \end{cases}$$

(5.28)

Applying the penalty concept in [Jin13], when the demand is larger than the pre-decided supply, SO has to pay $\bar{U}_t = U_t \cdot (1 + \sigma)$ for extra power, whereby $\sigma$ is real-time price penalty factor.

The arrival rate at $t$ is $\lambda_{k,t}$ since no discount is offered. Hence, the profit of purchasing electricity in a network $Y_{CEM,t}$ is as follows:
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_L, p_R$</td>
<td>0.15, 0.1 ($/h$)</td>
<td>$J$</td>
<td>2</td>
</tr>
<tr>
<td>$p_{ch}, p_{ch}'$</td>
<td>50, 19.2 (kW)</td>
<td>$\epsilon$</td>
<td>0.1</td>
</tr>
<tr>
<td>$A_1, A_2$</td>
<td>10, 8 ($) [Bli08]</td>
<td>$p_m$</td>
<td>0.05 ($/h$)</td>
</tr>
<tr>
<td>$\epsilon_L, \epsilon_R$</td>
<td>0.5, 3 (sec)</td>
<td>$S$</td>
<td>5 (MW)</td>
</tr>
<tr>
<td>$D_H, D_P$</td>
<td>2, 10 (sec)</td>
<td>$\sigma$</td>
<td>0.7 [Jin13]</td>
</tr>
<tr>
<td>$\zeta_H, \zeta_P$</td>
<td>0.2, 0.1 ($)</td>
<td>$p_{pen}$</td>
<td>2 ($)</td>
</tr>
<tr>
<td>$s_{max}, s_{max}'$</td>
<td>4, 3 ($)</td>
<td>$W$</td>
<td>8 [Tya15]</td>
</tr>
<tr>
<td>$s_{max}'$</td>
<td>2, 1.5 ($)</td>
<td>$\Delta T_s$</td>
<td>10 (ms)</td>
</tr>
<tr>
<td>$D_{prop}'$, $D_{prop}$</td>
<td>0.01, 50 (ms) [Rim17a]</td>
<td>$R_{BS}$</td>
<td>2 Mbps</td>
</tr>
<tr>
<td>$SoC_i$</td>
<td>$N(30, 15)$ (%) [Luo13]</td>
<td>$SoC_r$</td>
<td>85 (%)</td>
</tr>
<tr>
<td>$\eta_1, \eta_2$</td>
<td>88.7, 99 (%) [STA08]</td>
<td>$a_H, a_P$</td>
<td>1, 7</td>
</tr>
<tr>
<td>$R_c$</td>
<td>10 Gbps [Rim17a]</td>
<td>$\mu_L, \mu_R$</td>
<td>2400,600</td>
</tr>
<tr>
<td>$P_{req}, P_{res}$</td>
<td>256 (Bytes) [MF14]</td>
<td>$O$</td>
<td>54 [Tya15]</td>
</tr>
<tr>
<td>$D_{prop}'$</td>
<td>0.00033 (ms) [Rim17a]</td>
<td>$Z_{1-5}$</td>
<td>4000 (kW)</td>
</tr>
</tbody>
</table>

\[ Y_{CEM,t} = \sum_{k=1}^{K} \left( \lambda_{k,t} \cdot (1 - b_{k,t}(\lambda_{k,t}, n^*_{k,t})) \cdot (A_j - U_t \cdot d) \right. \\
- \lambda_{k,t} \cdot (1 - b_{k,t}(\lambda_{k,t}, n^*_{k,t})) \cdot \frac{\Delta n_{k,t}}{n^*_{k,t}} \cdot U_t \cdot \sigma \cdot d \\
- b_{k,t}(\lambda_{k,t}, n^*_{k,t}) \cdot \lambda_{k,t} \cdot p_{pen} - C_{loss}^{k,t}(\lambda_{k,t}) \\
- C_{delay}^{k,t}(\lambda_{k,t}) - p_m - p_L \cdot c_L - p_R \cdot c_R. \]

The first component is the profit gained from served EVs. The second component is the penalty for extra energy. The formula, $\lambda_{k,t} \cdot (1 - b_{k,t}(\lambda_{k,t}, n^*_{k,t}))$, is the number of customers using the extra power to charge their EVs. The third component includes the penalty of blocking EVs and the cost of energy loss. The fourth component is composed of the penalty of communication delay, the maintenance cost and the rental fees from cloud servers. CEM is a method to ensure the high QoS provided to customers. However, because of purchasing more electricity, CEM burdens the grid in peak hours. The comparison of PIM and CEM is discussed from the perspective of profit maximization in the Section 5.3.
In this section, we evaluate the performance of the proposed system. The case without using load shifting and capacity expansion is used as the baseline. The comparison among PIM, CEM and baseline are described.

We consider $T = 24$ hours in the evaluation. The performance metrics include the end-to-end...
delay, cloud servers allocation, hourly charging demand, COs allocation, discount, weighted blocking rate, and total profit. Two CS_H and three CS_P are considered and denoted CS_1-CS_5, respectively. Specifically, suppose CS_2 and CS_3 adopt level 2 three phase chargers, while other CSs adopt direct-current (DC) fast chargers. 2017 Nissan leaf with 30 kWh Li-ion battery is used. Suppose the scheduled supply in a network of CSs is 5 MW, and the arrival rates of CSs are [500, 400, 400, 500, 300]. The arriving time distribution of CS_H and CS_P are referred to [Cai14] and [Guo16]. In 4G LTE networks, it is assumed the average wireless transmission rate \( R_{BS} \), both downlink and uplink, is 2Mbps. Detailed parameters are listed in Table 5.1.

Fig. 5.4 presents the obtained results. During offpeak hours [1, 7] and [12, 24], the statistics are the same in all cases (Baseline, PIM and CEM) because the supply is sufficient to satisfy EVs’ charging demand and ensure high QoS. However, the results in three cases are not the same in hours [8, 11] when the system cannot satisfy all EVs’ charging demand.

The number of EVs requesting to charge battery in a network of CSs is shown in Fig. 5.4a. The charging demand of every hour in baseline and CEM is the same, because no load shifting is applied. On the contrary, in PIM, load is shifted from peak hours [8,9] to offpeak hours, so as to satisfy the QoS requirement in Eq. (5.20).

Fig. 5.4b depicts the number of LC and RC servers in 24 hours, which correspond to their service rate, the average waiting time thresholds and the number of EVs in Eqs. (5.1)-(5.6). More cloud servers are allocated to RC than LC during peak hours [8,9], this is because of the comparably larger number of EVs in parking lots in peak hours and smaller RC service rate. In Fig. 5.4c, a large number of EVs request to charge during peak hours [8,9], hence \( D_{con} \) in Eq. (5.17) is relatively high. It is noticeable that \( D_{e2e}^R \) (see Eq. (5.16)) at time 14 is higher than those at peak hours [8, 9], because the dominant parameter \( t_{w}^R \) at time 14 is larger than those at [8, 9]. Moreover, \( c_R \) at time 14 is smaller than that at [8,9] (see Fig. 5.4b), resulting in the larger \( t_{w}^R \).

Due to the capacity expansion characteristic in CEM, the number of COs both in DC fast CSs and Level 2 three phase CSs are the largest among three cases during peak hours [8,9], as shown in Fig. 5.4d. In Fig. 5.4e, it shows the total weighted blocking rate in three cases. During peak hour [8,
9], baseline's charging load is heavy (over 350 EVs requesting demand), resulting in high blocking probability (about 26%). On the contrary, PIM alleviates the heavy load during peak hours by load shifting. The total weighted blocking rate is within 0.1 (threshold in Eq. (5.20)) in PIM and CEM. Fig. 5.4f depicts the detailed blocking rates of CSs in different locations (highway exits and parking lots).

In Fig. 5.4g, the cost of total charging power loss in CEM is the highest due to more EVs can be served during hours [8,9]. In hours [9,10], the cost in PIM is relatively higher because the load from peak hours was shifted to hours [9,10].

The discounts provided in PIM are depicted in Fig. 5.4h. To satisfy the arrival rate constraint (5.25) and maximize the profit (5.24), the optimal discounts of CS_1 and CS_2 at hours [8,9] are [$1.6, $2.13]. As discussed in Section 5.2.5, customers in CS_H are time sensitive and only delay charging if offering a big discount. Hence, the discount in CS_H is greater than the one of CS_P in the result.

Compared to the total profits of Baseline in a day, PIM and CEM increase the total profit by 6.9% and 3.9%. Fig. 5.4i shows the hourly profit, which mainly depends on the number of arrival rates, the average blocking rate, and real-time electricity price. The profits during hours [8,9] in CEM are larger than other two cases because more EVs can be served. At hour 9, due to relatively larger demand in baseline and discount in PIM, baseline's profit is slightly bigger than the PIM. However, the total profit for 24 hours of PIM improves 6.9% compared to the baseline. PIM guarantees a low blocking probability while gaining higher profit. That is crucial since it satisfies EVs’ charging demand and gain high reputation to SO.

On one hand, the obtained results show that by purchasing more energy, CEM can ensure high system performance and gain higher profit compared to the baseline. However, CEM burdens the load of the grid, which is not good for the long-term development. On another hand, PIM is able to alleviate the heavy load and maintain high system performance (low blocking probability and high system profit).
5.4 Conclusion

In this Chapter, we proposed a hierarchical charging model for EVs. Considering the diverse service requirements of customers, we focused on a two-layered cloud (i.e., local and remote clouds) computing infrastructure. To solve the issues of heavy load demand and uneven charging demand in CSs, we proposed to combined cloud server planning, with capacity planning in CSs and profit maximization, in the model design. To satisfy different EVs’ service requirement, end-to-end delay and different charging levels are considered and analyzed. Given the QoS metrics, the proposed model guarantees a low percentage of customers not getting served. The obtained results demonstrate the efficiency of our models. The system profits in both PIM and CEM increase and more customers can be served compared to the case with uncontrolled customers. The model ensures EVs’ blocking probability and the queuing time in the clouds are bounded by a small threshold.
6.1 Introduction

This Chapter investigates cloud-based charging management of EVs in IoV to reduce computational and communication complexity while yielding better profit, thus maintaining a different QoS.

Decentralized and complex grid edge faces many challenges for planning, operation, and management of legacy power system. Therefore, providing a reliable and robust communication infrastructure is vitally important. The multidisciplinary perspectives of the fourth industrial revolution, that is, a cyber-physical system in conjunction with the Internet of Things (IoT) and coexistence of
edge (fog) computing and cloud computing bring new ways of dealing such challenges and help to maximize benefits of power grids.

The future Internet of Vehicles (IoV) ecosystem will provide new roles for the power grid. The vision of IoV is to connect people, a fleet of EVs, utilities, power grid (centralized generation, distributed renewable energy generation, distributed storage), peer-to-peer (P2P) transactions, heterogeneous communication networks (e.g., IEEE 802.11p, IEEE 802.11n/ac, 3G/4G LTE/5G), and computing infrastructures in the loop for the sustainable and green society. Fig. 6.1 illustrates the vision of IoV. As the world enters the era of the IoV, where Vehicle-to-Grid (V2G) networks, Vehicle-to-Roadside (V2R) communications, Vehicle-to-Vehicle (V2V) communications, Vehicle-to-Pedestrian (V2P), and Vehicle-to-Infrastructure (V2I) communications are the building blocks of IoV ecosystems, a cloud computing (both centralized and distributed) based connected platform is essential not only for mitigating management complexity but also for computing and storing of big data and supplying resources to P2P direct energy trading between consumers and producers as well as for the economies of scale.

Table 6.1 Comparison between emerging cellular V2X (C-V2X) communications and conventional dedicated short-range communications (DSRC).

<table>
<thead>
<tr>
<th></th>
<th>C-V2X</th>
<th>DSRC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Channel coding</strong></td>
<td>Turbo codes</td>
<td>Convolution codes</td>
</tr>
<tr>
<td><strong>Synchronization</strong></td>
<td>Synchronous</td>
<td>Asynchronous</td>
</tr>
<tr>
<td><strong>Transmission scheme</strong></td>
<td>Single-carrier frequency division multiplexing (SC-FDM), which allows more transmit power than OFDM</td>
<td>Orthogonal frequency division multiplexing (OFDM)</td>
</tr>
<tr>
<td><strong>Resource multiplexing across vehicles</strong></td>
<td>Frequency-division multiplexing (FDM) and time-division multiplexing (TDM)</td>
<td>TDM</td>
</tr>
<tr>
<td><strong>Resource selection</strong></td>
<td>Semi-persistent scheduling or dynamic scheduling</td>
<td>Carrier sense multiple access with collision avoidance (CSMA-CA)</td>
</tr>
<tr>
<td><strong>Spectrum used</strong></td>
<td>30 MHz (dedicated), 20 MHz (primary), 20 MHz (may be shared)</td>
<td>North America: 5850−5925 MHz, Europe: 5795−5815, 5855/5875−5905/5925 MHz, Japan: 755.5−764.5, 5770−5850</td>
</tr>
<tr>
<td><strong>Standard</strong></td>
<td>3GPP-Release 14</td>
<td>IEEE 802.11p</td>
</tr>
<tr>
<td><strong>Retransmission</strong></td>
<td>Hybrid Automatic Repeat Request (HARQ)</td>
<td>No HARQ</td>
</tr>
<tr>
<td><strong>Transmission range</strong></td>
<td>upto 225m</td>
<td>Over 450m via direct mode and more than that via cellular</td>
</tr>
<tr>
<td><strong>Use case</strong></td>
<td>Wide range of use cases (e.g., road safety services, traffic flow optimization, emergency stop, curve speed warning, vehicle platooning, sensor and state map sharing, dynamic ride sharing, collective perception of the environment)</td>
<td>Limited use cases (e.g., vehicular safety applications, V2V communications, toll collection)</td>
</tr>
<tr>
<td><strong>Roadmap</strong></td>
<td>Leverages and enhances existing LTE networks and rich roadmap towards 5G-based V2X</td>
<td>Not much new activities in the IEEE 802.11 standards for next-generation DSRC technology. Perhaps cellular D2D may obsolete IEEE 802.11p but hybrid and complementary solution is possible.</td>
</tr>
</tbody>
</table>
In this Chapter, from the charging management perspective, the proposed cloud-based EV charging system includes cloud server planning, capacity planning for CSs and price-incentive mechanism. From an architectural viewpoint, we introduce a network architecture of two-tier cloud computing-based EV charging system. We present three important trends and enabling technologies, which are beyond the traditional power and communications disciplines and will require collaborative and sustained efforts from these areas. First, we discuss blockchain-based energy trading. The blockchain is the distributed and transparent public ledger that records all transaction data, allowing all non-trusting peers to interact with each other without a third-party intermediary. Blockchain technology consists of cryptography, mathematics, algorithms, and economic models, combining P2P networks using a distributed consensus algorithm. Among many blockchain technology platforms, Bitcoin, created by the mysterious Satoshi Nakamoto in 2009 [Nak08], is one of the most popular decentralized cryptocurrencies.

Second, we explore how behavioral economics can be applied to IoV. Behavioral economics that
incorporates insights from psychology, judgment, and decision-making, and economics to make better predictions about economic behavior [TS08], has been recently applied in the context of the energy sector, is a relatively new area. Looking beyond the short-term, with no doubt, bringing the principles of behavioral economics into energy and transportation sectors in conjunction with edge computing and artificial intelligence is the thriving field of research, but there are theoretical and empirical gaps between them to become more sophisticated and effective, in which the experimental and theoretical studies should be performed in large-scale scenarios to study the impact of both short-run and long-run behavioral changes.

Third, given the emergence of artificial intelligence (AI) in other sectors such as wireless communications, artificial and computational intelligence should be the core part of IoV as well. We briefly outline its application to IoV.
Electric vehicles (EVs) contend to connect in 4G LTE network

EVs in highway exits and parking lots send charging requests to edge cloud and remote cloud, respectively

System operator (SO) sends the information (e.g., power supply and electricity price) to the cloud control center (CCC) located at edge cloud

CCC collects the information such as power supply, power demand and electricity price

CCC executes Capacity Planning Algorithm for charging stations (CSs):
• The objective is to guarantee high QoS to EVs. We aim to minimize the expected number of EVs being rejected to charge (expected blocking rate), given a limited supply
• Our greedy algorithm finds the near-optimal numbers of charging outlets in every CS

CCC executes the price-incentive algorithm:
• Ensures the QoS (low blocking rate) and calculates the optimal number of EVs to charge in a time slot
• Encourages extra EVs to shift the charging demand from peak hours to off-peak hours
• Finds the optimal discounts to maximize the system profit, where the cost of CSs’ power loss, penalty of not serving EVs, end-to-end delay of EV, and the cloud servers’ rental fee are considered

SO receives capacity planning and price information from the CCC and reaches an agreement on the capacity and discount price

Edge cloud and remote cloud send the discounts information to EVs

According to the preference, an EV decides whether to accept the discount offer or not

An EV delays charging for one time unit and gets a discount for the delay

An EV joins the system in first come first serve (FCFS) basis. Delayed EVs have higher priority compared to the EVs rejecting the discount

Admission control:
CCC evaluates whether accepting an EV to charge according to the current available charging outlets

Yes

An EV receives charging service

Since there is no available charging outlet for the EV, the EV is blocked

No

CCC informs system operator that no discount algorithm will be executed

Figure 6.3 Overall functionality of our approach for cloud-based EV charging management that describes the function and interactions among entities.

6.2 Two Tier Cloud-based EV Charging Management

6.2.1 Network Architecture

The existing grid networking architecture is mainly focused on grid protection or power distribution, and thus cannot account for the large-scale communication demands of EVs in the IoV era. Therefore, we aim to integrate cloud computing infrastructure and power grid infrastructure as a multi-purpose asset. Specifically, our proposed architecture, as illustrated in Fig. 6.2, consists of multiple layers: a)
cloud computing, b) edge (fog) computing [Sat09; Rim17a], and c) V2G and V2I communications. V2I communication on highways and parking lots is necessary for EVs to communicate with CSs and system operators (e.g., Pacific Gas and Electric Company). Note that from a safety perspective, a low-latency and higher reliability V2I solution, in the long run, is significantly more important than V2V communication [Che14]. Edge computing exploits one-hop communication, and the store-and-forward principle offers EVs low-latency, high-bandwidth, high availability, low-cost communication, improved network reliability, fast response, and backhaul traffic reduction. Edge (fog) computing infrastructures are decentralized and serve as a caching of the remote centralized cloud, periodically synchronizing with it, and deliver a wide range of innovative edge services and applications [Rim17a].

The future IoV may rely on the emerging cellular V2X (C-V2X) communications, which consists of V2V, V2I, and vehicle-to-pedestrian (V2P) direct communications, and vehicle-to-network (V2N) wide-area communications to serve next-generation smart EVs. C-V2X is expected to bring significant value to advanced driver assistance services, such as traffic signal timing/priority, collision avoidance safety systems, real-time traffic/routing service, cloud services, and safety alerts to pedestrians, and bicyclists. Some features and differences in C-V2X communications over the DSRC are summarized in Table 6.1.

6.2.2 Operations

We have developed a hierarchical charging management system, where two classes of EVs communicate with two different clouds depending on their QoS requirements. Actors and their functionalities in our system are described as follows.

*Electric Vehicles and Charging Stations:* We consider two classes of EVs, namely EVs in CSs in highway scenario and EV in parking lot scenario. Further, each EV is equipped with a Li-ion battery that enables them to store energy. Their different QoS requirements are considered. EVs in highways or parking lot communicate to edge cloud or remote cloud to send their information (e.g., spatial location, charging demand) and receive messages from the cloud (e.g., price, discount,
charging capacity of nearby CSs, charging schedule). Multi-class CSs (DC fast charge and Level 2) are considered. CSs are located at a certain location (normally with high EVs penetration), and equipped with a number of plug-in charging slots to charge multiple EVs. The CSs are randomly deployed under a city-scale scenario and their locations, capacity, availability are available to all EVs through both clouds. It is important to note that the class of CSs affect the performance of our proposed solutions, as discussed in Section 6.3.

System Operator: System operator (SO) is responsible for purchasing energy from utilities to provide charging service to EVs. Also SO, as the operator (e.g., Pacific Gas & Electric, Southern California Edison or third party), distributes energy to its sub-networks and allocate energy to CSs. It is responsible for keeping a secure system operation as well as keep tracking the power schedule. Furthermore, SO interacts with cloud control center (CCC) via LTE network to provide power supply information and pricing signal of electricity as well as the SO receives capacity planning and price information from the CCC and reaches an agreement on the capacity and discount price (see Fig. 6.3). The SO aims at maximizing the profit in two ways. It either encourages EVs to shift their load from the peak hours by offering an incentive or the SO may purchase additional electricity from the utility, when the charging demand is higher than the supply.

Computing and Control: Remote cloud (e.g., Amazon EC2) that has large-scale computing infrastructures, provides computing, storage, caching, networking facilities to EVs. On the other hand, edge cloud that offers cloud computing like services (computing, storage, caching, networking) and is deployed at the edge of networks, provides mobile broadband experiences to EVs [Rim17a]. The CCC is a functional component that runs in the cloud, has three functionalities. The CCC is responsible for executing server planning, capacity planning and price-incentive algorithms at the edge cloud. The goal of cloud server planning is to reduce the rental fee of a server, given the QoS requirements. The main aim of capacity planning is to minimize the blocking probability, given a limited power supply. CCC encourages EVs to shift their charging schedule to an off-peak hour by offering some discount.

Finally, CCC performs the admission control, where CCC checks all requests and determines
whether to admit the EV or not for charging in the current timeslot. The criteria are based on the availability of charging outlets and capacity at that particular time. The unadmitted requests will be blocked. The overall operations of the system are illustrated in the functional diagram in detail in Fig. 6.3.

### 6.3 Performance Evaluation of Cloud-based EV Charging

In this section, we discuss results and findings of cloud-based EV charging obtained from an analytical evaluation of the considered scenarios.

The evaluation of the proposed mechanism is based on M/M/c queuing model in Chapter 5. The performance is evaluated in cases with a large scale of EVs. The values of considered parameters include 20 MHz bandwidth, EV arrival rate with Poisson distribution, average transmission rate of EV is 5Mbps, 2017 Nissan leaf with 30 kWh Li-ion battery is considered. Time is divided into 24 hours. The supply in a network of CSs is 100 MW. Suppose there are 10 CSs in highways and 10 CSs in parking lots, and the arrival rates in 24 hours (in thousand) are [4.3, 2, 3.2, 3, 2.5, 1, 4, 3.5, 2.8, 2.5, 3.2, 2.5, 2.2, 6, 3.5, 2.5, 2.7, 1.6, 3.4, 2] respectively, with hourly arrival time distribution in [Cai14] and [Kur15]. In parallel, we assume half of CSs in highways adopt DC fast charging (50 kW) and half use level 2 three phase charging (19.2 kW), and same settings of CSs in parking lots. Amazon EC2 California is considered remote cloud.

We compare and analyze two proposed methods (price-incentive method (PIM) and capacity expansion method (CEM)) with baseline of uncontrolled EVs. More specifically, PIM is to shift the high demand from on-peak to off-peak hours by offering discount to EVs; CEM is for SO to purchase sufficient electricity from the grid to satisfy EVs’ need. The performance metrics include the number of edge and remote cloud servers, charging demand, charging outlet allocation, weighted blocking probability, discount and hourly profit. Weighted blocking probability is defined the average percentage of EVs without getting served in a network. Profit in a network of CSs, mainly depends on the number of EVs getting served, an EV’s admission fee, rental fee of cloud servers, cost of charging power loss in CSs and real-time electricity price, penalty of not serving an EV and end-to-end delay.
Fig. 6.4 depicts the performance comparison. The number of edge and remote cloud servers are shown in Fig. 6.4a. In peak hours [8,9] and 16, more remote cloud servers are used to satisfy the average waiting time threshold. Compared to the remote cloud, less servers are allocated to edge cloud because of its faster processing ability and comparably more even hourly arrival time distribution.

In off-peak hours [1, 7], [11, 15] and [18, 24], the statistics of three cases in Fig. 6.4b- 6.4f are the same due to the supply sufficiency. Fig. 6.4b depicts the hourly charging demand. Specifically, when the supply is insufficient to ensure the blocking probability is within the threshold, the load in peak hours [8,9] and 16 is shifted to off-peak hours in PIM. In CEM, SO is willing to purchase more electricity to alleviate the peak load in hours [8,9] and 16. Therefore, in Fig. 6.4c, CEM’s number of charging outlets both in DC fast CSs and slow CSs during these peak hours are larger than other two cases.

Fig. 6.4d shows the total weighted blocking rate in a network of CSs. Consistent with the results in Fig. 6.4b, the weighted blocking rate in baseline in peak hour [8,9] and 16 are higher than 0.21, while it is within the threshold value (0.1) both in PIM and CEM. In Fig. 6.4e, it depicts the discount in PIM. In peak hours [8, 9], the discount of CSs in highways is higher than those in parking lots because EVs in highways (time sensitive) are willing to delay charging if the discount is bigger compared to those in parking lots. Note that in another peak hour 16, the discount in highways is small. This is because the charging demand in parking lots is smaller and more charging outlets are allocated to those in highways in hour 16, compared to the case in hours [8, 9].

Fig. 6.4f presents the hourly profits. The profits of CEM in hours [8,9] are larger than other two cases due to larger number of served EVs and reasonable real-time electricity price with penalty. However, in hour 16, profit in CEM is slightly smaller than PIM because higher real-time electricity price with penalty in CEM, which dominates its performance. During peak hours, the profits in both PIM and CEM are higher than CEM. Total profits for 24 hours in PIM and CEM are increased by 10.2% and 4.3%.

From the obtained results, it presents that PIM and CEM outperforms baseline, from the aspects
of system profits and QoS metrics. CEM requires simpler communication procedures compared to PIM, however, it weakens the stability of grid. On the other hand, PIM can attenuate the negative impact to the grid while maintain high system performance and ensure QoS provided to customers.

6.4 Emerging Trends and Open Issues

In this section, three major emerging trends and open issues are presented in more detail in the following.

**Decentralized Energy Trading Based on Blockchain in IoV:** An open energy market has several unique features, which render price competition differently from an oligopoly market. For instance, each prosumer may have an abundance or deficit power at any point in time, which leads to uncertainty about the actual number of competing agents [Rim16]. Moreover, these agents are often localized. There is an emerging concept of a local energy market (neighborhood, village, town), where prosumers balance the supply and demand using bilateral contracts that enable neighbor-to-neighbor transactions [Nak08; CD16]. Functionally, blockchain is the distributed and transparent public ledger that records all transaction data, allowing all non-trusting peers to interact with each other without a third-party intermediary. The basis of blockchain technology is the decentralized consensus mechanisms (i.e., all blockchain nodes agree on the same state of a system), which has been studied and applied in the area of distributed computing. Blockchain technology is increasingly becoming popular as an economic overlay in the connected world, e.g., IoT [CD16]. Other industries, including the energy ecosystem, also have recently begun to experience the advantages of blockchain-based technology. Applying these technologies would allow metering and billing for electricity consumption, and in many cases, for the decentralization of energy transactions and supply systems. P2P energy trading based on blockchain is showing promise and is prompting industry, such as Siemens have teamed up with LO3 Energy to test energy blockchain on Brooklyn's microgrid and over the past two years Brooklyn MicroGrid is changing the business model of energy trading.

The blockchain is part of a larger computing infrastructure that should also include storage,
communications, file services, and other functions. Blockchain in general and particularly in the energy sector has multidimensional challenges, thus moving assets to the blockchain is still in the early stage rather than a viable mainstream currency. Technical issues include scalability, network bandwidth, network size, cybersecurity, handling of privacy-sensitive data (e.g., consumption, locations, transactions), interoperability among blockchain systems, and storage requirements. Further, investigating the communications between the blockchain ledger and control systems at different granularity (i.e., local, system, and system of systems levels) [MG17], is also challenging. It is essential to develop an open source testbed for the blockchain based transactive energy to fully understand its potential benefits and pitfalls in a real-world scenario. From a business point of view, blockchain lacks best practices, business model, and significant legal settlement. Currently, Bitcoin is dominating the market. However, for healthy competition multi-currency systems should be developed. A fundamental hurdle of blockchain is the huge amount of energy consumption per transaction. It should be noted that approximately 300KWh of electricity is needed for each Bitcoin transaction. As an example, Fig. 6.5 illustrates relative energy consumption of Bitcoin of some countries.

It should be noted that blockchains are not suitable for handling massive computations and running consensus algorithms in EVs because EVs have very computational power and storage capabilities. To address high computation and high bandwidth issues, mobile-edge computing empowered fiber-wireless (FiWi) broadband networks, that offer distributed cloud computing capabilities (computing, storage, network, caching) at the edge of networks, and combine reliability and high capacity of the optical backhaul (e.g., 10 Gbit/s Ethernet Passive Optical Network (EPON) or any next-generation EPON) with the flexibility and cost-savings of wireless front-end networks (e.g., WiFi, 4G LTE, 5G) [Rim17a], may be one of the potential candidates. To address standardization issues, the ISO has recently established a new technical committee (ISO/TC 307) for blockchain and distributed ledger technologies. Further, very recently, the Blockchain Interoperability Alliance announced its aim to promote interconnectivity between blockchain networks and develop common industry standards protocol and architecture.
**Applying Behavioral Science and Behavioral Economics in IoV:** The widespread and successful adoption of EVs and energy efficiency in IoV not only depends on the efficient control and communications systems, and charging infrastructures but also significantly depends on the human dimensions of energy systems, that is, behavioral science and human psychology. *Nudge*\textsuperscript{1} theory – a bridge between the economic and psychological (e.g., adaptation, loss-aversion, reflection, mental accounting) analyses of individual decision-making, explains about encouraging people to make better choices for themselves and society [TS08] can be applied in IoV to nudge prosumers and overcome cognitive barriers (e.g., unawareness of relevant information sources, status quo bias, extremeness aversion, endowment effect, choice overload, heuristics). It is worth mentioning that nudge-based mechanisms that include simplification and framing of information, changes to the physical environment, changes to the default option, and use of descriptive social norms, have been widely applied in the context of pension funds or financial services but not yet been widely employed as a means of changing customer behavior in energy sector [Leh16]. Since human behavior within and between individuals varies depending on context, social norms, and values, public appeals, incentives, rewards, and time, how prosumers make decisions and act on them in a particular context, should be taken into account while designing dynamic pricing algorithms, routing of EVs, willingness to delay for charging models, energy efficiency models, time-varying discount models, dynamic ride-sharing options, and energy trading models for a local energy market. This can be done by analyzing big data of actual behavior, designing systematic predictive models, and estimating predictive accuracy with the help of AI and deep learning.

**Artificial and Computational Intelligence and its Applications to IoV:** Due to the massive integration of EVs, there will be the issue of power stability and resilience in power grids. Thus, to improve the resilience of the grid, AI, and machine learning techniques can be used to analyze the big amounts of data and predict the operations and build the models for knowledge how power distribution, transmission, and generation systems work and how efficiently allocate energy resources.

\textsuperscript{1}“A nudge is any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives” [TS08]. Richard H. Thaler, the father of “nudge theory”, has been awarded the Nobel prize in behavioural economics.
Additionally, machine learning can be used to study the behavior of players in energy markets, energy pricing patterns, and recover faster from major storms, cyber attacks, solar flares and other disruptions [Rig15]. Furthermore, computational intelligence techniques, such as evolutionary algorithms [Rim16] have shown great potential due to their capability to deal with multiobjective optimization problems in smart grids with a relatively low demand for computational resources. A similar approach can be applied in IoV to address multiobjective optimization issues in energy trading, mobility and routing, and demand-response under uncertainty conditions of distributed renewable energy resources. It should be noted that EV routing problems in the network of CSs is a logistics issue and mostly takes the distance between CSs and the energy-constrained shortest path problem. Machine learning-based distributed routing algorithm helps resolve this issue, in which different types of constraints, such as uneven demand at the CSs, availability of CSs, cost of routes, and capacity constraints should be considered. The algorithm should ensure that EV chargers receive a proportionally fair (axiomatically justified fairness) share of the available capacity of the network of CSs.

6.5 Conclusions

In this Chapter, we introduced an unified vision of the IoV. Cloud-based EV charging management is presented by incorporating the diverse service requirements of customers, and two-tier cloud (coexistence of edge and cloud computing) computing infrastructure. The introduced architecture has several benefits. For example, due to the proximity of edge computing infrastructures to EVs, real-time IoV services can be supported. Further, the coexistence of edge and cloud computing helps reduce computational and communications complexity in a low-cost and scalable manner. The obtained results demonstrate the efficiency of our models. Compared to the performance with uncontrolled customers, the system profit in our models increases by 10.2%, and guaranteed QoS (low blocking probability and short queuing time in the clouds) is provided to customers.

Being a multidisciplinary and integrative research area, IoV must address both technological and social dimensions from architecture to innovations in users behaviors or social change to realize its
full potentials and support overall societal well-being. Specifically, the integrated communications, modern control, and computing technologies for IoV is of vital importance and yet one of the most complicated systems. We elaborated some of them in this Chapter. More specifically, blockchain-based energy trading, behavioral economics for the energy sector, and power system complexity are thoroughly discussed in the context of the IoV that may open up new directions of future R&D work for researchers. Finally, putting all together, one of the most innovative and exciting avenues in IoV would be to develop a decentralized local energy trading platform based on the blockchain, which is synergistically empowered by AI, the nudge theory, and edge computing. That may enable smart and connected communities to create new levels of economic opportunities and growth, where the pace of innovation continues to stimulate. However, there is still a long way to reach this goal.
Figure 6.4 Performance comparison: (a) Cloud servers in edge cloud and remote cloud, (b) Charging demand comparison, (c) Charging outlet allocation, (d) Weighted blocking rate comparison, (e) Average offered discount in CSs (PIM), (f) Total profit comparison.
Figure 6.5 Relative energy consumption (in %) of Bitcoin (Energy consumption of each countries are based on the International Energy Agency and bit coin energy index is adopted from https://digiconomist.net).
In this dissertation, we propose smart charging management models in charging stations (CSs) and the frameworks of the communication among electric vehicles (EVs), system operator (SO), CSs and the clouds. The main contributions of this dissertation are listed as below.

In Chapter 2, the contributions of the revenue optimization frameworks for multi-class EV charging station are listed as:

- We model the charging facility as a $M/G/s/k$ queue and choose the blocking probability and waiting time as the Quality of Service (QoS) metrics. We analyze the queuing model and support the numerical results with simulation studies. Furthermore, we present a detailed battery cost model for Li-ion batteries, which are widely used for automotive applications.

- We propose two different optimization frameworks. In the first one, single-class customers are considered and an optimal revenue model is proposed. In the model, customers gain
reward by reaching higher State of Charge (SoC) levels, while the cost of battery degradation, customer discomfort due to waiting and blocking events, and admission fee constitute the cost part.

- We extended our work to a multi-class setting, where customers are differentiated by their preferences; sizes of their battery packs, amounts of requested demands, and the available charger technologies. In addition to the aforementioned revenue model, we propose two charging strategies: shared chargers and dedicated chargers for different classes. We show that under different traffic regimes, the operating revenue can be increased by optimally choosing the charging strategy.

In Chapter 3, we consider the wireless charging model in a single CS, and the contributions are listed as:

- Considering the behavioral characteristic that EVs would renege when EVs run out of electricity or reach the destination before getting served, we model the wireless charging system on the highway as $M/M/s$ loss queuing system.

- We consider the power consumption based on the resistance to motion, the degradation model for Li-ion batteries, an admission fee model and the velocity behavior in the proposed model.

- We introduce the scenario of V2I communication on the wireless charging highway to enable the data exchange between EVs and the infrastructure.

We further propose a hierarchical optimization model for a network of CSs in Chapter 4. Extended from the classic FCLM, the limited power supply, charging duration and the characteristics of battery model are considered in our model, which are crucial design parameters.

- We solve the flow capturing location problem to identify the locations of the CSs. We use a queuing model and introduce a resource allocation framework to optimally provision the limited grid resources.
• we consider the battery charging dynamics and develop a station policy to maximize the
revenue by setting a maximum charging level

• The framework is further evaluated on the Arizona state highway network with a gravity data
model, and on the City of Raleigh, North Carolina, using real traffic data traces. The results
demonstrate that the proposed hierarchical model improves the system performance as well
as the QoS provided to the customers.

In Chapter 5, we present cloud-base charging management of smart EVs in a network of CSs
from the viewpoints of power and communication networks. Toward this end, the contributions of
this paper are summarized in the following:

• First, we present cloud-based charging management models in a network of CSs. To satisfy
EVs’ different latency requirements, two levels of cloud computing infrastructures (i.e., remote
cloud (RC) and local cloud (LC)) are considered. We develop a novel algorithm to interplay
among EVs, SO, CSs, and both clouds. Further, queuing-based cloud server planning model is
proposed to minimize the cloud rental fee while ensuring the high QoS metric (the expected
waiting time).

• Second, two classes of EVs are considered: EVs in CS in highway exits (C_S^H) and in parking lots
(C_S^P). In a network of CSs, multiple charging levels are examined: CSs with level II three phase
charging, and with DC fast charging. Further, we propose charging outlet (CO) allocation given
by limited energy, and present a greedy algorithm to reduce its complexity. The multi-charging
settings, EVs’ charging preference (time sensitivity based on CS locations) and maximal power
constraint in CSs are incorporated in the CS capacity planning. The blocking probability is
used as QoS metric for analysis.

• Third, EVs’ contention delay from contention-based random access mechanism in 4G long
term evolution (LTE) network is analyzed. The cost of EVs’ end-to-end delay and CSs’ power
loss are considered in the profit maximization model
Fourth, we develop a profit optimization frameworks, whereby two strategies are introduced, namely, price-incentive method (PIM) and capacity expansion method (CEM). The goal of these strategies is to control and coordinate EVs, thereby ensuring more EVs can satisfy their charging needs and different communication latency requirements.

In Chapter 6, we present a two-tire cloud-based electric vehicle charging framework during peak hours and communications among large-scale electric vehicles in a network of CSs and SO in Internet of Vehicles (IoV). Further, we presents three major trends: blockchain, behavioral economics, and artificial intelligence (AI) for the connected EVs in IoV.

- The blockchain is the latest General Purpose Technology, still in its infancy and has not been adopted widely in transactive energy and digitization of electron exchanges. Given the paramount importance of democratizing energy trading to enable micro-transactions to create local energy market, we discuss the opportunities and potential challenges of decentralized energy trading based on blockchain technology in IoV.

- Going forward, we also explore the potential of behavioral economics theory, a Nobel-Prize-winning theory, as a decision-making framework that can help understand how uncertainty can impact overall energy trading in IoV.

- Given the emergence of artificial intelligence (AI), its applications in IoV are described.
REFERENCES


APPENDIX
Let $\rho = \frac{\lambda}{\theta \mu}$ be traffic intensity and the system is assumed to be stable and in steady state. Then the probability of having $j$ customers in the system is [Kim96; Kim94],

$$P_j = \begin{cases} 
\frac{(s \rho)^j}{j!} - P_0 & j = 0, \ldots, s - 1, \\
\frac{(s \rho)^{s-1} \gamma^{j-s}}{s! - \rho^s} - P_0 & j = s, \ldots, K - 1, \\
\frac{(s \rho)^{s-1}}{s!} - \gamma^{K-s} - P_0 & j = K, 
\end{cases}$$

where
\[ R_0 = \left[ \sum_{j=0}^{S-1} \frac{(S\rho)^j}{j!} + \frac{(S\rho)^S}{S!} \frac{1-\rho}{1-\rho} \right]^{-1}. \]  

(A.2)

Here,

\[ \zeta = \frac{\rho R_G}{1-\rho} + \rho R_G, \]

(A.3)

and

\[ R_G = \frac{E_W(M/G/S)}{E_W(M/M/S)}. \]

(A.4)

where \( E_W(M/M/S) \) and \( E_W(M/D/S) \) are the mean waiting time in a \( M/M/S \) and a \( M/D/S \) systems, respectively. \( E_W(M/G/S) \) can be approximated in terms of \( E_W(M/M/S) \) and \( E_W(M/D/S) \) as below

\[ E_W(M/G/S) \approx \frac{1 + c_s^2}{2c_s^2 + \frac{1-c_s^2}{E_W(M/M/S) + E_W(M/D/S)}}, \]

(A.5)

where \( c_s^2 \) is the squared coefficient of variance of charging time distribution of PEVs. In terms of quantity of \( R_G \), approximation of (A.4) can be rewritten as

\[ R_G = \frac{1 + c_s^2}{2} \left( \frac{1 + c_s^2}{1 - c_s^2} \right) \frac{R_D}{(2R_D - 1)c_s^2 + 1}. \]

(A.6)

where \( R_D \) is the quantity of (A.4) in \( M/D/S \) system. \( R_D = \frac{E_W(M/D/S)}{E_W(M/M/S)} \). Based on [Kim94], simplified approximation of \( R_D \) is shown as follows,

\[ R_D = \frac{1}{2} \left[ 1 + F(\theta) g(\rho) \left( 1 - e^{-\frac{\theta}{E_W(M/D/S)}} \right) \right], \]

(A.7)

where

\[ \theta = \frac{S-1}{S+1}, S \geq 1, \]

(A.8)

\[ F(\theta) = \frac{\theta}{8(1+\theta)} \left( \sqrt{\frac{9+\theta}{1-\theta}} - 2 \right), \]

(A.9)
and
\[ g(\rho) = \frac{1 - \rho}{\rho}. \] \hspace{1cm} (A.10)

An approximation for the mean waiting time in the queue is presented next. According to Little’s Law \( E(L_q) = \lambda \cdot E(t_w) \), the value of mean waiting time \( E(t_w) \) can be derived if the average number of PEV in the queue \( E(L_q) \) is known. The method in [Kim96] is adopted to approximate \( E(L_q) = \sum_{j=S}^{S+R} (j-S)P_j \) as below:

\[
E(L_q) = \frac{(S\rho)^S}{S!} \frac{\zeta}{(1-\rho)(1-\zeta)} \{1 - \zeta^r - r(1-\zeta)\rho\zeta^{r-1}\} P_0. \] \hspace{1cm} (A.11)

Hence,

\[
E(t_w) = \frac{1}{\lambda} \frac{(S\rho)^S}{S!} \frac{\zeta}{(1-\rho)(1-\zeta)} \{1 - \zeta^r - r(1-\zeta)\rho\zeta^{r-1}\} P_0. \] \hspace{1cm} (A.12)