ABSTRACT

BAYRAM, ISLAM SAFAK. A Three-Layered System Level Modeling Approach to Electric Transportation. (Under the direction of Michael Devetsikiotis.)

Transportation electrification offers solutions to an array of current societal issues, ranging from unstable oil prices to environmental concerns. The promised cost-savings prompt a growing interest to push Electric Vehicles (EVs) into the market. On the other hand, the all-electric-range of current EVs is relatively short compared to gas powered competitors, while the need for longer travel ranges requires development of a network of public fast charging facilities. Hence the envisioned change demands synchronized deployment of new vehicles and infrastructure on a massive scale. However, the required upgrades are very costly and straining the grid beyond its limits could easily lead to cascading failures and outages.

In this thesis we propose a three layered system level modeling approach to electric transportation. First layer (Design) includes the stochastic modeling of a single charging station architecture. Proposed charging station architecture ensures grid reliability at all times while sacrificing to reject small amount of EVs defined as the Quality-of-Service (QoS). First half of this layer explores the system dynamics and solves the optimal energy storage sizing problem respect to QoS targets. Second part of the Design layer examines how the charging station performance is affected both by the energy storage technology used, and the employed charging strategy.

Second Layer (Control) considers control and coordination of customer chargings in a network of fast charging stations. Acknowledging the fact that the non-uniform spatial distribution of EVs creates uneven power demand at each charging facility, the goals of the proposed control mechanism are threefold: (i) avoid straining power grid resources, (ii) increase the percentage of served customers with the same amount of grid resources and consequently maximize the revenue of charging facilities operator, and (iii) provide charging service to customers with a certain level of QoS. We further divide Control layer into two; control for (1) cooperative EV
fleets and (2) selfish drivers.

Third Layer (Communications) binds the customers to the charging infrastructure. We explore the communication requirements of EV charging requirements. In order to quantify the communications system performance, we propose a Markov-Modulated Poisson Process based model. Further, we show that as the EV population increases, the network operators will need better communications technology to handle additional demand.

We further extend our modeling approach to resource provisioning in large scale public charging stations. Acknowledging the fact that the current generation capacity could be a bottleneck during the busy hours, we present a capacity planning framework by exploiting the statistical behavior of customers. We modeled the customer demand at each charging slot with an On-Off process. Then, we introduced the concept of “effective power” that is strictly less than the peak power demand during On periods. This notion significantly reduced the required power resources when compared to the capacity planning approach based on peak demand.
A Three-Layered System Level Modeling Approach to Electric Transportation

by

Islam Safak Bayram

A dissertation submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

Computer Engineering

Raleigh, North Carolina

2014

APPROVED BY:

George Michailidis
Subhashish Bhattacharya

Joseph DeCarolis
Michael Devetsikiotis
Chair of Advisory Committee
DEDICATION

To Sináne: your motivation always inspires me.

*Intellect is priceless, education has no limit.*

*Ancient Circassian Saying*
İslam Şafak Bayram received the B.S. degree in electrical and electronics engineering from Dokuz Eylul University, Izmir, Turkey in 2007 and the M.S. degree in Telecommunications from the University of Pittsburgh in 2010. He received the Best Paper Award at the Third IEEE International Conference on Smart Grid Communications and the Student Travel Grant at a previous Smart Grid Communications Conference. Currently he is a PhD candidate in the Department of Electrical and Computer Engineering at North Carolina State University. His research interest include optimization, control and stochastic modeling of communications and power networks.
ACKNOWLEDGEMENTS

It is very hard to find to words that are capable enough to express my gratitude to everyone that have contributed to the completion of this endeavor. First, I would like to express my deepest appreciation to my advisor, Dr. Michael Devetsikiotis, for providing me the stimulating research environment and mentoring me to become an independent researcher. He has also been a great source of support and positive motivation over the course of my PhD. My gratitude also extends to my co-advisor Dr. George Michailidis for giving me the opportunity to work under his guidance. Our numerous discussions and insightful suggestions have increased the quality of my PhD tremendously.

I was also very fortunate to have Dr. Subhashish Bhattacharya and Dr. Joseph DeCarolis in my committee. Their comments have been very invaluable to me. I must also give special thanks to Dr. Aranya Chakrabortty for supporting me with his wisdom in power systems. I am indebted to my colleagues at NC State. I have always found discussions with Dr. Ioannis Papapanagiotou particularly fruitful. His assistance has been extremely helpful. Also special thanks are due to Dr. Boonyarith Saovakhriran and Sigit Pambudi.

Last, but surely not least, I am very grateful to my friends, Gökten Çınar, Mehmet İlem, Seyit Erdal Kaplan, Hasan Erkan, and Metin Atalay for their support, this journey would not have started without them.
TABLE OF CONTENTS

LIST OF TABLES ................................................................. viii

LIST OF FIGURES ............................................................... ix

Chapter 1 Introduction ....................................................... 1
  1.1 Motivation for Electric Transportation .......................... 1
    1.1.1 The Current Power Grid, EV Status, and Impacts of EV Penetration 4
    1.1.2 Challenges and Barriers ........................................ 6
  1.2 Fast Charging Station Design .................................... 7
  1.3 Network of Fast Charging Stations .............................. 8
    1.3.1 Control of EV Charging ...................................... 9
  1.4 Communication Layer ............................................. 10
  1.5 Capacity Planning in Large Scale Charging Facilities ....... 11
  1.6 Contributions of this Thesis ................................... 12

Chapter 2 Fast Charging Station Design ................................. 14
  2.1 Introduction ....................................................... 14
  2.2 Charging Station Architecture and Model ...................... 15
    2.2.1 Overview .................................................... 15
    2.2.2 Design Parameters ......................................... 16
    2.2.3 Stochastic Model for Station Dynamics .................... 17
    2.2.4 System Performance Evaluation ............................ 20
    2.2.5 Charging Station Profit Model ............................ 22
  2.3 Conclusion ....................................................... 25

Chapter 3 Strategies for Competing Energy Storage Technologies in DC Fast Charging Stations ................................. 26
  3.1 Introduction ....................................................... 26
  3.2 Charging Station Architecture and Stochastic Operating Model 27
    3.2.1 Candidate Energy Storage Technologies .................... 28
  3.3 Performance Evaluation .......................................... 31
    3.3.1 Metamodeling of System Output ............................. 33
    3.3.2 Charging Station Profit Model ............................ 36
    3.3.3 Conclusions ................................................. 37

Chapter 4 Electric Power Allocation in a Network of Fast Charging Stations ................................................. 39
  4.1 Introduction ....................................................... 39
  4.2 Charging Station Model for Multi-Class Service ............... 40
    4.2.1 Profit Model for Multi-Class Service ...................... 42
  4.3 A Network of Charging Stations ................................ 44
    4.3.1 Overview .................................................... 44
    4.3.2 Power Resource Allocation in a Charging Station Network 45
Chapter 5 Decentralized Control of Electric Vehicles in a Network of Fast Charging Stations

5.1 Introduction ........................................... 60
5.2 Electric Vehicle Admission Control (EVAC) for a Single Charging Station .... 61
  5.2.1 System Parameters .................................. 62
  5.2.2 QoS Metric & Pricing Block ......................... 63
5.3 Decentralized Control for a Network of Charging Stations ...................... 65
  5.3.1 Game Formulation .................................. 66
  5.3.2 EV Customers ....................................... 66
  5.3.3 Charging Network Operator ......................... 69
5.4 Numerical Results ...................................... 69
5.5 Conclusion ............................................. 74

Chapter 6 Enabling Communication Technologies ........................................... 77

6.1 Introduction ............................................ 78
6.2 Available Communication Standards and Technologies ............................. 79
  6.2.1 Mobile EV to Control Center Communications ............................. 80
  6.2.2 Inter-Control Center Communications ................................. 82
6.3 Communication Requirements & Performance Metrics .............................. 83
  6.3.1 System Reliability and Availability ................................ 84
  6.3.2 Quality of Service .................................... 85
  6.3.3 Cyber-Physical Security ................................ 87
  6.3.4 Scalability ........................................... 89
  6.3.5 Capacity ............................................... 89
  6.3.6 Interoperability ..................................... 90

Chapter 7 Towards a More Realistic Model: Decentralized Control Under Communication Uncertainty ........................................... 92

7.1 Introduction ............................................ 92
7.2 A More Realistic Electric Vehicle Admission Control ............................. 93
7.3 Resource Allocation in a Network of Fast Charging Stations ..................... 96
7.4 Decentralized Control .................................... 98
7.5 Numerical Results ...................................... 99
7.6 Communication System Performance ........................................... 104
  7.6.1 The Cost of Unavailability of the Communications System ............... 106
  7.6.2 Performance Modeling .................................. 109
Chapter 8 Capacity Planning at Large Scale Charging Stations: A Stochastic Modeling Approach

8.1 Introduction ................................................................. 115
8.2 Problem Formulation ..................................................... 118
  8.2.1 System Description .................................................. 118
  8.2.2 Determining Effective Power ..................................... 119
  8.2.3 Multiplexing Gains .................................................. 121
8.3 Numerical Results .......................................................... 122
  8.3.1 Toy Example-I ...................................................... 122
  8.3.2 Toy Example-II ..................................................... 124
  8.3.3 Profit Model .......................................................... 127
8.4 Conclusions ................................................................. 128

Chapter 9 Conclusions .......................................................... 130
  9.1 Summary of Findings .................................................... 130

REFERENCES ................................................................. 133
LIST OF TABLES

Table 1.1  Electric Vehicle Penetration Scenarios (Approximate in millions) by Different Organizations .................................................. 5
Table 2.1  Charging Speed(approx.) in DC Fast Charge Station [6] .................. 15
Table 2.2  Charge Method Electrical Ratings in North America [107] ............... 16
Table 3.1  Energy Storage Landscape .......................................................... 30
Table 3.2  RSM Input Parameters ................................................................. 34
Table 4.1  Traffic Intensity (T.I.) of Each Station ............................................ 51
Table 4.2  RSM Input Parameters ................................................................. 51
Table 4.3  Results for Case IIB (Mixed Population of Selfish EVs and Fleets) ...... 53
Table 4.4  Results for Case-IIA (Selfish EVs) ............................................... 54
Table 4.5  Comparison of Case-IIA (Selfish EVs) and Case-IIB (Mixed Population) 54
Table 4.6  Results for Case III (EV Fleets) ................................................... 54
Table 6.1  Summary of Candidate Wireless Communication Networks [18] ......... 86
Table 6.2  Overview of Communication Standards for Electric Vehicle Networks ... 88
Table 6.3  Communications Needs and Requirements for All Three Types of EV Charging Applications ................................................. 89
Table 7.1  Systems Parameters ....................................................................... 94
Table 7.2  Availability Performance of Wide Area Wireless Technologies [24] ...... 106
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1.1</td>
<td>Roadmap of the Thesis</td>
<td>2</td>
</tr>
<tr>
<td>Figure 1.2</td>
<td>Impacts of Electric Vehicle Penetration on Power Generation</td>
<td>3</td>
</tr>
<tr>
<td>Figure 1.3</td>
<td>The flavor of this thesis</td>
<td>7</td>
</tr>
<tr>
<td>Figure 1.4</td>
<td>Power Resource Provisioning</td>
<td>13</td>
</tr>
<tr>
<td>Figure 2.1</td>
<td>Single Charging Station Architecture</td>
<td>17</td>
</tr>
<tr>
<td>Figure 2.2</td>
<td>Continuous Time Markov Chain</td>
<td>20</td>
</tr>
<tr>
<td>Figure 2.3</td>
<td>Performance Evaluation of the Proposed Model for Different System Parameters</td>
<td>21</td>
</tr>
<tr>
<td>Figure 2.4</td>
<td>Average Gain in Blocking Probability vs. Energy Storage Size</td>
<td>22</td>
</tr>
<tr>
<td>Figure 2.5</td>
<td>Maximum Supported Arrival Rate for a Given Blocking Probability</td>
<td>23</td>
</tr>
<tr>
<td>Figure 2.6</td>
<td>Single Charging Station Net Profit</td>
<td>24</td>
</tr>
<tr>
<td>Figure 3.1</td>
<td>Continuous Time Markov Chain Charge the ESS first Strategy</td>
<td>29</td>
</tr>
<tr>
<td>Figure 3.2</td>
<td>Comparison of recharge/discharge times for batteries, flywheels, and ultracapacitors [10] [101]</td>
<td>31</td>
</tr>
<tr>
<td>Figure 3.3</td>
<td>Comparison of charging strategies: Charge from grid first vs. Charge from battery first</td>
<td>32</td>
</tr>
<tr>
<td>Figure 3.4</td>
<td>Comparison of charging strategies for varying $S$ and $\nu$</td>
<td>33</td>
</tr>
<tr>
<td>Figure 3.5</td>
<td>Comparison of charging strategies for varying $R$ and $\nu$</td>
<td>34</td>
</tr>
<tr>
<td>Figure 3.6</td>
<td>Net Profit Model for Varying $\nu$</td>
<td>37</td>
</tr>
<tr>
<td>Figure 3.7</td>
<td>Evaluation of Profit Model</td>
<td>38</td>
</tr>
<tr>
<td>Figure 4.1</td>
<td>Control Mechanism for Mobile EVs</td>
<td>40</td>
</tr>
<tr>
<td>Figure 4.2</td>
<td>Performance Evaluation of Different Energy Storage Devices</td>
<td>41</td>
</tr>
<tr>
<td>Figure 4.3</td>
<td>Multi Class Charging Station Net Profit</td>
<td>42</td>
</tr>
<tr>
<td>Figure 4.4</td>
<td>Multi Class Charging Station Performance Evaluation</td>
<td>44</td>
</tr>
<tr>
<td>Figure 4.5</td>
<td>Fast DC charging station map in Seattle, WA [64]</td>
<td>48</td>
</tr>
<tr>
<td>Figure 4.6</td>
<td>Discrete Event Simulation Flow Chart</td>
<td>50</td>
</tr>
<tr>
<td>Figure 4.7</td>
<td>Minimum grid power required to meet $\epsilon$ QoS targets</td>
<td>55</td>
</tr>
<tr>
<td>Figure 4.8</td>
<td>Evaluation of Equation 4.5</td>
<td>56</td>
</tr>
<tr>
<td>Figure 4.9</td>
<td>Comparison of three cases respect to stations 2, 3 and 4</td>
<td>57</td>
</tr>
<tr>
<td>Figure 4.10</td>
<td>Net Profit Comparison</td>
<td>57</td>
</tr>
<tr>
<td>Figure 5.1</td>
<td>System Overview</td>
<td>61</td>
</tr>
<tr>
<td>Figure 5.2</td>
<td>Illustration of Projected Customer Demand vs. Expansion of Grid’s Serving Capacity. Regional Serving Capacity: Percentage of EVs that can be charged in a specific region and time duration (e.g. University Campus noon-1pm)</td>
<td>62</td>
</tr>
<tr>
<td>Figure 5.3</td>
<td>Electric Vehicle Admission Control for Single Charging Station</td>
<td>63</td>
</tr>
<tr>
<td>Figure 5.4</td>
<td>Customer Demand for Five Stations</td>
<td>71</td>
</tr>
<tr>
<td>Figure 5.5</td>
<td>Pricing Strategy of Station Owner</td>
<td>72</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

The proper operation of the power grid and the availability of transportation sector are two fundamental parts of modern life and they have been taken granted for more than a century. The potential problems with the inevitable merge of these two sectors should be very well addressed and understood. This thesis serves as a guide to understand and address the potential issues in transforming the ground transportation system from one that is oil-dependent to one powered almost entirely by electricity. This thesis will enhance the understanding of the fundamental dynamics of the electrification of transportation and give us insights about the interactions its corresponding components, namely communications, control and the power grid operations. The roadmap of this thesis is presented in Figure 1.1.

1.1 Motivation for Electric Transportation

High gasoline costs, foreign oil dependency, and concerns about increasing greenhouse emissions are the main drivers of the increasing interest in pure Electric and Plug-in Hybrid Electric Vehicles (EV/PHEVs). Various studies have shown that EVs/PHEVs will be the key factor in the solution [102, 43, 27, 28, 31, 100, 30, 26]. The major advantages of electric transportation can be listed as follows [41]:
- **Already Existing Infrastructure:** According to the National Academy of Engineering, the power grid is the supreme engineering achievement of the last century. Already existing ubiquitous network of power grid eliminates the need for very costly investments and accelerates the acceptance of electric transportation.

- **Diverse Energy Sources:** Electric power is generated through diverse set of domestic sources which will increase the energy independence and decrease the energy deficit.

- **Stable Electricity Market:** Unlike the global oil market, electricity prices have been stable for the last two decades. Electricity market is much less volatile compared to global oil market. Efficient use of power resources will further increase the utilization of power.
generation and further decrease the electricity unit (kWh) prices. Moreover, with the current electricity prices, the cost of electric miles is one tenth of gas miles.

- **Sparse Generation Capacity:** The power grid is designed to meet peak demand that lasts only around 5% of the daily operation. Hence, current power grid has substantial spare capacity, especially at night to fill up light duty vehicles. In [102], it is concluded that, by considering daily average driving requirements, existing US electric power infrastructure can support up to 73% of the energy requirement of light-duty vehicle fleets if night time charging is employed. Similarly, [77] shows that the existing Vermont electric grid could support up to 100,000 PHEVs recharging during off-peak hours.

- **Political Mandates:** Most of the western world mandates to reduce the petroleum dependence and Green House Gas emissions. For instance, in the United States, Energy and Water Development Appropriations Bill for the US Department of Energy proposes policies to achieve the following reductions relative to 2005 data: (1) 50% decrease in the petroleum use by 2030 and 80% in 2050 and (2) 80% in the GHG emissions by 2050.
1.1.1 The Current Power Grid, EV Status, and Impacts of EV Penetration

The human activity, hence the power demand, follows cycles (higher demand during the day, and lower at night) [61]. The required power to meet such demand is generated through diverse energy supplies such as coal steam turbines, nuclear power plants, hydro power generation, and renewable energy (e.g. wind, solar etc.). In order to match generation to load, utilities dispatch some components of their generation portfolio. The factors in dispatching a generation includes variable O&M costs, flexibility (fast start vs slow start generators), environmental “head-room”, and the distance to load and transmission. For base load, utilities employ large (400 MW or larger) and low cost per kWh generation types (e.g. nuclear, hydro, coal etc.). This type of generation have high load factor (the percentage of hours that a power plant runs at full capacity) and low generation cost [21].

To meet intermediate load (the difference between expected customer demand and the base load generation), power plants with lower load factors (typically around 50%) such as combined cycle combustion turbine fueled by natural gas etc. are employed [68, 118]. On the other hand, utilities may need to turn on additional generation units to accommodate customer demand during peak hours. The type of power plants fall into this category are usually fast start, high cost, and environmentally unfriendly. Moreover their low load factor (5-10%), decreases utilization of electric power generation and increase the ratio of peak to average demand. As a result, the use of such sources gradually increases the average kW-h electricity price. A typical scenario is presented in Figure 1.2.

Utilities are likely to consider fast public charging stations as commercial customer (higher voltages, lower service cost than residential customers etc.). Fast charging station designs such as [29, 100] is going to increase the base load. On the other hand residential charging may be a part of all three kinds power generation depending on the time of the use.

There is an increasing body of literature on the possible EV penetration scenarios. According to [95] the Compound Annual Growth Rate (CAGR) of electric vehicle penetration will be 19.5% between years 2011-2017. Similarly Germany aims to put one million electric vehicles
<table>
<thead>
<tr>
<th>Year</th>
<th>U.S. EIA - USA</th>
<th>NRC (Probable) - USA</th>
<th>IEA - World</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>1M</td>
<td>1.5M</td>
<td>1.1M</td>
</tr>
<tr>
<td>2020</td>
<td>2.3M</td>
<td>3M</td>
<td>6.9M</td>
</tr>
<tr>
<td>2025</td>
<td>3.2M</td>
<td>7M</td>
<td>17.7M</td>
</tr>
<tr>
<td>2030</td>
<td>4M</td>
<td>14M</td>
<td>33.3M</td>
</tr>
</tbody>
</table>

U.S. EIA: United States Energy Information Administration [5][68]
NRC: National Research Council [5][68]
IEA: International Energy Agency [112]

on the road by year 2020 and six million by 2030 [92]. In the US only, one million EV/PHEV penetration is projected by the current administration [46] by year 2015 and a target is set to hit 50% of new car sales by year 2050. Similarly, [91] study shows that there will be around 50 millions grid-enabled vehicles by year 2040. Furthermore, several prediction based studies are conducted by organizations like International Energy Agency and National Research Council. In table 1.1 the projected EV roll-out is presented.

If not controlled and coordinated carefully, electric vehicles could easily lead to disruptive affects on the power grid. Such an integration requires both parties (EVs and the grid) to communicate. There is a handful of studies on the impacts of vehicle chargings on the grid [102], [43], [90], [77]. According to [90], plug-in hybrid (assuming all vehicles are PHEV20 with a battery pack of 7.2kWh) electric vehicles can increase the total load by 2.7% and the peak load by 2.5% in Colorado. On the other hand, the battery sizes of pure EVs range from 16 to 52 kWh, which means actual impacts will be more severe. Similarly [104] presents that if 5% of the EV population charge at the same time, there will be a 5 GW increase in total power demand by year 2018 in VACAR region (Virginia - North Carolina - South Carolina) [57].

Residential charging imposes an additional burden to power grid during peak hours. Although, residential customers constitute 85% of all meters, they have low per meter usage, typically around 37% with peak usage in morning and evening [11, 68]. To accommodate the additional load, grid operators need to kick-in more peak-load generators. This will further
raise the average electricity price\textsuperscript{1}. Thus, demand side management techniques like load shifting and valley filling, which will be explained in the next section, can help to decrease this cost introduced during busy hours.

1.1.2 Challenges and Barriers

Even though the global electric vehicle market is expanding rapidly, several challenges and problems need to be addressed in order to achieve widespread deployment of Electric Transportation. The major challenges can be listed as follows:

- **Charging Infrastructure:** The mainstream penetration of Electric Vehicles require the deployment of network of charging facilities. Providing access to a reliable network of charging infrastructure is extremely important for early adoption of electric transportation. In the early studies [41], it is anticipated that majority of the charging will be done overnight at customer premises. However, recent surveys show that sizable portion of the EV drivers (around 40\%) travel farther than their all-electric range, hence the demand for fast public charging is also highly desirable [86].

- **Customer Acceptance:** Easy access to network of public charging facilities will give confidence and flexibility to customers. This aspect will increase the customer acceptance for two reasons. First, drivers are able to fill up their gas tanks using ubiquitous network of gas stations. If the same level of support is not provided, it will create hesitancy to drive Electric Vehicles. Also, considering relatively long charging durations, customers demand to get service with certain level of Quality of Service (QoS). QoS can be defined as expected waiting time in a queue at a charging station or the percentage of customers that a station can serve.

- **Battery Technology:** Even though there has been tremendous upgrades in the battery technology, the current cost of on board energy storage increases the initial cost and makes

\textsuperscript{1}The increase in peak to average power generation leads to an increase in electricity price.
EVs less attractive. Also, the performance of widely used batteries limits the driving range of the vehicle.

Note that this report attacks the first two problems. In Layer-1 we propose a charging station architecture that sustains grid reliability and provides performance guarantees. In Layer-2 we propose a coordination mechanism for a network of fast charging stations. The third layer investigates the affects of performance degradations due to communication system failures.

### 1.2 Fast Charging Station Design

Studies in fast charging station designs can be categorized into two. First group considers the performance of power electronics, energy storage devices etc. Most of the proposed architectures tries to minimize the charging duration. From a pure power engineering perspective [23] proposes a fast charging station architecture with a DC bus distribution system. The station is equipped with an energy storage unit to minimize the strain on the grid, and the sizing problem was determined by Monte Carlo simulations according to average load. A similar station architecture was used in [42, 65], but two different energy storage devices were considered; a flywheel and
a supercapacitor. A mechanism that simultaneously draws power from the grid and the storage devices was introduced to decrease the EVs charging duration. However, there is a multitude of storage technologies in the market and the choice of the most appropriate one is mostly station dependent (e.g. a low energy density, large size but inexpensive storage device may not be suitable for a station located at or near city centers, due to real-estate costs) [100].

Second category includes a system level approach. These studies mostly abstract the details of the underlying technology, and focus on the performance of the charging station using the arguments from stochastic processes [113, 25, 100, 29, 27]. For instance [25] models charging facilities as a M/M/1 queue. In [113], researchers present a control mechanism for electric vehicle charging which employs broadcasting of the available power information via one-way communication. They model their charging system as a $M/M/\infty$ queuing system. They look at how to maximize the use of excess power while not overloading the grid by controlling arrival rate of the PHEVs.

Our approach is somewhere in between these two approaches. In chapter 3 we present our charging station architecture using arguments from queuing theory and economics. Considering relatively long service durations, we consider a system with no waiting line. Hence loss probability (or blocking probability) is chosen as the performance metric. We argue that charging stations should prove certain level of QoS to increase the customer acceptance. We further use the performance in the energy storage sizing problem. Moreover, we incorporate the technological properties of the energy storage device. The performance of energy storage obviously affects the performance of the charging station. Hence we propose different charging strategies and determine the optimal regions for each strategy.

1.3 Network of Fast Charging Stations

The literature on networks of charging stations is rather sparse. A model for EV charging from stations located near highway exits is studied in [22]. However, each station is equipped with a single charger and EV queueing is allowed. However, taking into account that a typical Level 3
[45] charging exceeds 20 minutes, this model has limited applicability. On the other hand, we consider a network of stations with multiple slots, offering differentiated charging rates (very fast and Level 2) and no waiting space, thus capturing more closely the realities of EV charging. [47] introduces a framework for EVs selecting charging stations using oligopolistic game theoretic ideas.

### 1.3.1 Control of EV Charging

Most studies on the control of EV charging assume stationary vehicles located at customer premises or large parking lots. In order to accommodate projected EV population, there has been an increasing interest in strategies for scheduling of electric vehicle charging (for garage charging applications). Such coordination strategies are mainly grouped into two:

1. **Centralized scheduling** employs a central authority (dispatcher) who up to a large extent controls and mandates EV charging rate, start time, etc. System level decisions, such as desired state of charge, charging intervals etc. are taken to finish all jobs by a certain deadline (e.g. by 7am in the morning). Main advantages of centralized control include higher utilization of power grid resources and real-time monitoring of operation conditions across the network. On the other hand, to enable such functionalities, an advanced communication network is needed. Studies presented in [19, 99, 81, 117, 39, 105] are examples of centralized scheduling. These studies differ by the assumptions they make; interruptible vs uninterruptible load, constant vs varying charging rate, and preemptive vs non-preemptive jobs.

2. **Distributed (Decentralized) scheduling** allows customers to choose individual charging pattern. Decisions can be based on price of the electricity or time of the day. This method eliminates the need of third party controller (dispatcher) and complex monitoring techniques. Since decisions are taken individually, game theoretic models such as mean field games potential games, and network routing games [82] are used in the literature [97, 53, 55, 54]. Even though the communication requirements is fairly less than
centralized case, information dissemination is still needed for EVs to set their charging strategies. Decentralized price based control mechanisms are discussed in a series of papers [31, 82, 54]. Note that decentralized control eliminates the need of advanced monitoring tools, whereas centralized control leads to better utilization of charging resources. Both strategies are compared deeply in [96, 82].

In this thesis, we perform a more holistic approach by taking into account that EVs are also mobile. In chapter 4 we present our control framework for mobile EVs. In a network of fast charging stations, the utilization of each charging facility depends on the spatio-temporal distributions of Electric Vehicles. To gain more insights, we evaluated the distribution of public transportation system in a big metropolitan area. Then we propose an electric power resource allocation framework by considering customer demand and QoS targets. We distinguish EV Fleets from selfish EV users. We assume that EV Fleets have agreements with customer the utility company, hence they have to follow the decisions of a central authority, whose objective is to balance the load among charging stations to meet QoS targets. On the other hand, selfish do not necessarily follow the decisions of a central authority. Hence we propose a decentralized control mechanism using game theory. In this case, network operator’s objective is to incentivize customers to cooperate and drive extra miles to neighboring stations.

1.4 Communication Layer

The realization of such control techniques requires appropriate communication architectures. The two-way communications will enable reliable interaction between the grid and the drivers. At a minimum, mobile drivers need to access charging station location and pricing information. However, spatio-temporal variations in the customer demand may create instabilities between charging stations. Communication networks will allow grid operators to interact with customers to balance the load. This can be done by offering customers incentives to drive extra miles to neighboring stations. For garage charging applications, time-differentiated tariffs can motivate
customers to charge during off-peak hours. However, implementation of such pricing scheme requires EVs to be fully equipped with the required communication modules. Smart grid applications for EVs also allow reverse power transfer (Vehicle-to-Grid (V2G)). Groups of stationary EVs can sell part of their stored energy during peak hours to alleviate the stress on the grid.

A handful of surveys have attempted to discuss general smart grid communication requirements, standards, and protocols [119, 56, 110, 116]. Such an attention is required to enable the paradigm shift in transportation sector. Nonetheless, to the best of the author’s knowledge, this is the first study that focuses on the electric vehicle network communications for smart grid applications. Hence, in Chapter 6 we focus on (1) Addressing the unique challenges introduced by the EV chargings to the power grid; (2) Identifying the communication needs to reach projected EV roll-out; (3) Surveying the communication requirements, standards, and candidate technologies that could serve EV networks smart grid applications.

1.5 Capacity Planning in Large Scale Charging Facilities

The control of EV charging in a large scale charging infrastructures has been studied in [38, 111, 73]. [38] considers a large scale EV charging facility and proposes a deadline scheduling algorithm with a pricing based admission control. [111] uses swarm optimization techniques to allocate power to customers in large scale charging station. [73] proposes an energy management system to control the demand of large number of EVs parked in a municipal parking deck. These studies assume that the charging has a fairly long duration (such as 3-5 hours). Hence their goal is to optimize power flow and maximize station profit by serving as many customers as possible. In this work, we assume that charging lasts for a relatively short period and we attack the problem of energy provisioning in a large scale charging infrastructure by exploiting the stochasticity of the customer demand.
1.6 Contributions of this Thesis

- We introduce an EV fast DC charging station architecture, introduce a stochastic model to capture its operational characteristics and evaluate its performance (defined as the percentage of served customers). The charging station is equipped with a local energy storage device that aids smoothing the stochastic customer demand.

- We develop a performance evaluation methodology to compare candidate energy storage technologies. Our main focus is on the main performance metric, namely blocking probability, is affected both by the energy storage used, and the employed charging strategy. Two different strategies were considered: charging from the storage device first and charging from the grid first. We differentiated storage devices by their power ratings and efficiencies.

- We propose a resource allocation framework that meets QoS targets at each station and minimizes the amount of power employed. This framework is evaluated under different scenarios motivated by examining actual traffic traces from the Seattle area that exhibit a non-uniform spatial distribution of vehicles trips.

- We introduce an Electric Vehicle Admission Control mechanism at each station that employs congestion pricing to shape excessive demand. We develop a game theoretic framework in which customer routing and load balancing are achieved through a pricing mechanism. Utility functions are used to capture the behavior of individual EVs and the network operator. The latter’s strategy corresponds to maximizing its profit, while the strategy of the EVs is to minimizing the associated charging cost.

- We survey candidate communication technologies and identify the corresponding requirements. Then, we couple the performance of the communications system with the proposed control mechanism by developing a Markov-modulated Poisson Process (MMPP) model. Finally, we show the relationship between the communications system performance and
the EV population.

- We extend our modeling framework to capacity planning in a large scale charging station. We consider a charging station equipped with a large number of charging slots. Customer demand at each slot is modeled as a two-state On-Off continuous time Markov process. We introduce the concept of effective power for different levels of customer satisfaction (as outlined below) for each charging slot. The effective power which is a deterministic quantity acts as a surrogate for the actual aggregate stochastic demand. By using the concept of effective power, we show that it can lead to savings regarding distribution network investments, as depicted in Figure 1.4.
Chapter 2

Fast Charging Station Design

This Chapter presents a charging station architecture which will be the basis for the next chapters.

2.1 Introduction

With advances in battery technology, EVs/PHEVs are becoming gradually more attractive than internal combustion engine vehicles. In order to gain wide acceptance and compete against gas-based vehicles, the presence of fast public charging stations is a must in the future smart grid. Even though availability of today’s electricity system in the U.S. is 99.97%, the grid is not designed to withstand the resulting increase in power demand. As a result, fast charging stations can overload the grid and unpredicted peaks in the electricity demand may impact grid reliability. Thus, the design and the development of charging stations has crucial importance.

In this chapter, we propose an EV/PHEV charging station architecture along with a quantitative stochastic model that allows us to analyze the performance of the system by using the arguments from queuing theory and economics. An important part of our proposed architecture is the addition of a storage capability to charging stations, on top of their ability to charge from the grid. Our goal is to propose a general architecture framework that can sustain grid stability while providing a required level of quality of service; and to describe a general methodology
to analyze the performance of such stations with respect to the traffic characteristics, energy storage size, pricing and cost parameters.

We provide example charging station configurations and some initial results from the performance evaluation we have performed. Our results indicate that significant gains in net cost/profit can be made with the right choice of storage size. These results also provide useful insights into the behavior of the quality of service (e.g., blocking probability) with respect to a large number of system parameters. Such insights are crucial in this early stage of designing the smart grid and charging stations of the future.

Table 2.1: Charging Speed(approx.) in DC Fast Charge Station [6]

<table>
<thead>
<tr>
<th>Charging Power</th>
<th>80% Capacity Charging Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Compact EV</td>
</tr>
<tr>
<td>50 kW</td>
<td>15 min</td>
</tr>
<tr>
<td>75 kW</td>
<td>11 min</td>
</tr>
<tr>
<td>100 kW</td>
<td>8 min</td>
</tr>
<tr>
<td>125 kW</td>
<td>6.5 min</td>
</tr>
<tr>
<td>150 kW</td>
<td>5 min</td>
</tr>
</tbody>
</table>

2.2 Charging Station Architecture and Model

2.2.1 Overview

Even though EVs/PHEVs have several benefits as described in the previous section, if not designed and controlled well, charging of a large number of EVs/PHEVs can be a nightmare for utilities. In the next few decades, as advances continue in battery technology, there will be a variety in EV battery packs, charging technology and charging rates. With only one EV, the consumer will double its residential consumption, if a family buys two or three EVs/PHEVs total power demand will grow tremendously. The current power grid is not designed to withstand this much power consumption. Consequently, unpredicted peaks in the power demand may cause
failures and outages in the power grid. SAE J1772 [107] defined a conductive charging system architecture for electric vehicles. SAE recommends three types of charging methods, namely AC level 1, AC level 2 and DC charging. Table 2.2 summarizes these requirements. Also table 2.1 presents an overview of typical charging durations for different vehicle types.

### 2.2.2 Design Parameters

The four key components of our design that try to address these issues are: (I) each station draws constant power from the grid; (II) local energy storage is employed to meet stochastic customer demand; (III) the station supports different classes of charging requests (fast service vs slow service); and (IV) the QoS metric employed is the long-term blocking probability of incoming customers. The overview of the proposed charging station is depicted in Figure 2.1. Next, we explain the system dynamics in detail.

(I) Charging stations of any significant size represent commercial size loads. Hence, it seems reasonable for station operators to draw long-term contracts with the utility where a power level is agreed in return for a lower price. This enables the utility to better anticipate its demand, and the station operator to benefit from a lower price; as argued in [115, 20], such contracts leads to lower contract, as well as average spot prices, and more efficient market equilibria.

(II) Energy storage is one of the most important components of the future smart grid [114]. Capabilities of Smart Grid are severely limited without energy storage. In our model, storage plays a crucial role to shape stochastic power demand. Since local energy storage technology is a new technology and has a high cost, the sizing of the energy storage system becomes an important task. In addition to aforementioned benefits, energy storage can help to: offset

<table>
<thead>
<tr>
<th>Charge Method</th>
<th>Nominal Supply Voltage</th>
<th>Maximum Current</th>
<th>Circuit Breaker Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC Level</td>
<td>120 vac, 1-Phase</td>
<td>12 A</td>
<td>15 A (minimum)</td>
</tr>
<tr>
<td>AC Level</td>
<td>208 to 240 vac, 1-phase</td>
<td>32 A</td>
<td>40 A</td>
</tr>
<tr>
<td>DC Charging</td>
<td>600 vdc maximum</td>
<td>400 A (maximum)</td>
<td>As Required</td>
</tr>
</tbody>
</table>
additional need for peak electricity generating capacity, integrate intermittent renewable energy storage technologies, reduce electricity transmission congestion and support demand response resources [62]

(III) We consider that the charging station provides service to multiple customer classes at different charging rates. This allows the station to accommodate customers with different charging needs and preferences, as well as EVs with different technological constraints.

(IV) As discussed in the introduction, charging times depend on the level used, but on average they are about 30 minutes. Hence, it is reasonable to assume that incoming customers would not be willing to wait and thus in our model (discussed next) a “bufferless” system was adopted. For such a system, the blocking probability becomes a natural performance metric.

2.2.3 Stochastic Model for Station Dynamics

Our stochastic model for the charging station has some similarities to an Erlang-B blocking system but also has significant differences. Details are explained in the next section. We assume that arrival and departure of EVs/PHEVs can be modeled as a Poisson Process. We are using
the term blocked customer for the customers who come to charging station but could not get service. The two types of blocking are explained below.

**Type 1**: Classical Erlang-B blocking occurs when all charging outlets are in use, so the customer does not wait and leaves the charging station. This type of blocking depends only on the number of servers (charging outlets) in the system and the traffic intensity \( A = \text{Arrival Rate} / \text{Departure Rate} \) [70].

**Type 2**: This type of blocking happens when there is not enough power or energy in the system to meet customer demand, even though there are idle charging outlets.

In this study we only consider type-2 blocking. Based on the aforementioned specifications, the proposed station architecture and the corresponding model for its behavior over time, exhibit the following operation characteristics: (i) the charging station draws a constant power from the grid; (ii) upon exceeding the available grid power, the local energy storage unit is used to meet additional demand; (iii) whenever there is idle grid power, it is used to charge the local energy storage device, if it is not in a fully charged state; (iv) depending on the amount of constantly drawn grid power and the size of the local energy storage, a certain level of QoS is provided; and (v) the station partitions its capacity with respect to demand for each customer class. Such insights can be obtained from profiling studies (e.g. customer surveys, etc). The constantly drawn grid power is discretized to \( S \) equal slots, meaning that it can accommodate up to \( S \) vehicles at the same time. In a similar way, the local energy storage can charge \( R \) vehicles in a fully charged state. Since the charging station can never serve more than \( S + R \) vehicles concurrently, the very next EV arrival is going to be “blocked”. This strategy insulates to a large extent the power grid from peak demand.

The details of the stochastic model are given next. Customers arrive to the charging facility according to a Poisson process with parameter \( \lambda \). Currently, a variety of different EV models with different battery sizes exist. Thus, the service time of customers is assumed to be a exponentially distributed with rate \( \mu \). Also, the charging duration of the energy storage device
so that it is able to accommodate one more EV is exponentially distributed with rate \( \nu \) which depends on the underlying energy storage technology.

Given the stochastic assumptions and the operational regime of the charging station, its dynamics are captured by continuous time birth-death Markov chain with finite two-dimensional state space, as shown in Figure 2.2. One dimension of the state space corresponds to the number of vehicles that can be charged by the station, while the second dimension to the charge level of the storage unit. Specifically, let \((i, j)\) denote a generic state, with \(0 \leq i \leq S + j\) and \(0 \leq j \leq R\). For example, the \((0, 0)\) state corresponds to a setting where there are no PHEVs being serviced and the storage unit is empty; similarly, all the states \((i, 0)\), \(0 \leq i \leq S\) to a setting where \(i\) vehicles are being charged, but the storage unit is also empty and so forth. The set of states \((S + j, j)\), \(0 \leq j \leq R\) represents the blocking ones, where the charging station rejects new arrivals.

The birth and death rates are described both in Figure 2.2 and in the entries of the infinitesimal generator matrix \(Q\) (see equation 2.2). Note that the death rates are proportional to the number of vehicles being served (since we have the equivalent number of competing exponential random variables) and similarly for the birth rates, since there is competition between arrivals of new vehicles and charging the storage unit. The total number of states in the Markov chain is:

\[
\kappa = (S+1)(R+1) + \sum_{i=1}^{R-1} i
\]

(2.1)

It can easily be seen that given its structure, the Markov chain is irreducible and positive recurrent, hence ergodic. Its unique stationary distribution \(\pi\) can be calculated by solving the equation \(\pi Q = 0\) subject to the constraint \(\pi e = 1\), where \(e\) denotes a vector comprising of ones, using standard numerical techniques [108].
\[ Q = \begin{pmatrix} 
-(\lambda + \nu) & \lambda & \cdots & 0 \\
\mu & -(\lambda + \nu + \mu) & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & -(S + R)\mu 
\end{pmatrix} \] (2.2)

### 2.2.4 System Performance Evaluation

Next, we evaluate different configurations of the proposed charging station for different sets of the following parameters: customer arrival rate $\lambda$ and service rate $\mu$, storage unit charging rate $\nu$, grid charging capacity $S$ and storage unit capacity $R$.

We start by looking at the blocking probabilities when the capacity of the storage unit varies from $R = 1, \cdots, 15$ with four different $S$ combinations $S=4$, 5, 6, and 7. We set $\mu=2$ and $\nu=4$ and vary the arrival rate from $1 - 10$ in increments of 0.25. The results are depicted in Figure 2.3. It can be seen that when the storage unit size increases, there is a decrease in the blocking
probability, as expected. These results can also help determine what the size of the storage unit is, if the station is interested in controlling the blocking probability. The other conclusion learned from this calculation is that the blocking probability decreases with decreased rate if $R > S$ than in the case of $R < S$. The latter finding implies that the gains from having very large storage units exhibit diminishing returns.

We continue the investigation regarding storage unit size and cumulative gain (decrease) in the blocking probability. Once again fixing $S = 5$ and ranging $R$ from 1 to 13 for $\mu = 1, \nu = 1$ and averaging over a range of $\lambda$ values in $\{2, \cdots, 15\}$, we reinforce our previous finding that the largest gains are obtained for settings of $R \leq S$. This is presented in Figure 2.4. The reason is that given the regime that the charging station operates in -arrival rate exceeding service rate of PHEVs- the chances that the storage unit is ever full are slim and hence the system rarely takes advantage of its full capacity. The main message from the comparisons so far is that simply increasing the capacity of the storage unit $R$ may not be the most effective way of provisioning the station. Next, we investigate combinations of $S$ and $R$ that achieve a prespecified blocking probability and the resulting maximum allowable arrival rate, fixing again
\( \mu = 1, \nu = 1 \). It can be seen that systems with a large \( S \) are uniformly preferable. However, such charging stations configurations are not desirable in practice, since they put a lot of strain on the grid, as previously outlined. Corresponding results are depicted Figure 2.5.

### 2.2.5 Charging Station Profit Model

The previous evaluation gave us insight into the gains in terms of quality of service—captured by the blocking probability—and also how the sizing of the station in terms of the grid and the storage unit affect its capabilities in accommodating larger arrival rates. Next, we present a model that using some simple financial principles relates pricing parameters to the stochastic model’s parameters. This model can provide guidance for choosing the best operating range for the charging station, as well as possible control strategies.

The principles of the profit model are as follows: The model is based on the following principles: the charging station’s operator obtains revenue from each charged EV. On the other hand, a penalty is paid for each blocked EV because:
Figure 2.5: Maximum Supported Arrival Rate for a Given Blocking Probability

1. It leads to dissatisfied customers and degrades the reputation of the station;

2. It enables to control the QoS to foster EV adoption [112];

3. It allows station operators to size its capacity to maximize its profit. It is assumed that a higher penalty is paid to customers charged more for service.

Let $R_g$ and $R_l$ be the revenue obtained per customer when charged from the grid and the storage unit, respectively. Further, let $C_b$ denote the cost per blocked PHEV. Finally, we assume that the storage unit has a fixed installation cost $C_0$ and an acquisition cost proportional to its size (i.e. $C_a R$). To calculate the profit we need to specify the charging states in our stochastic model from the grid and from the storage unit, respectively. Let $\rho^{(g)} = \{(i, j) : 0 \leq i \leq S, 0 \leq j \leq R\}$ denote the grid charging states and $\rho^{(l)} = \{(i,j) : S+j \leq i \leq S+R, 1 \leq j \leq R\}$ the storage unit charging ones. Also, we denote by $\rho^{(bl)}$ the blocking states respectively. Finally, $\pi(s)$ denotes the stationary probability for generic state $s \equiv (i,j)$ and $i(s)$ the number of PHEVs receiving service in states $s$. 

23
We evaluate the profit model for the following set of parameters. We assume that $R_{g} = R_{l} = 1.25$, $C_{b} = 1.5$, $C_{a} = 0.25$, $C_{0} = 0.02$. Also, we assume $\mu = 2$ and $\nu = 4$. We present the results of the profit model for $S = 4$ and $S = 5$ cases in Figure 4.3. For low arrival rate, the cost related to acquisition and installation outweighs the revenue gained from chargings, thus negative profit occurs. On the other hand, for high arrivals, the cost of blocking customers becomes dominant and the total net profit decreases.

In practice, the customer charging rate $\mu$ and the energy storage charging rate $\nu$ are fixed by technological constraints. Also, the storage unit is assumed to have already been acquired, thus its size, $R$ can not be changed. Then, this model shows that to obtain maximum profit, more grid power $S$ should be allocated to busier stations. If grid power is limited, decreasing arrival rate (by routing them to other stations) becomes the alternative. Having introduced the dynamics of the single charging station model, we proceed to explain the operation of the
charging station network.

2.3 Conclusion

In this chapter, we proposed an EV/PHEV charging station architecture and a quantitative stochastic model that allows the performance analysis of the system by using queuing theory and economics. An important part of our proposed architecture is the addition of a storage capability to charging stations, on top of their ability to charge from the grid. Our goal was to propose a general architecture framework that can sustain grid stability while providing a required level of quality of service; and to describe a general methodology to analyze the performance of such stations with respect to the traffic characteristics, energy storage size, pricing and cost parameters.

We provided example charging station configurations and initial results from the performance evaluation we have performed. Our results provide useful insights into the behavior of the quality of service (e.g. blocking probability) with respect to a large number of system parameters.
Chapter 3

Strategies for Competing Energy Storage Technologies in DC Fast Charging Stations

3.1 Introduction

The universal acceptance of electric vehicles depends on the widespread presence of charging stations. These stations have to be designed intelligently so as not to overwhelm the fragile power grid with the additional load. In this chapter we extend our previous work in Chapter 2 and examine how the charging station performance, namely the blocking probability, is affected both by the energy storage technology used, and the employed charging strategy. We consider two strategies: charging from the energy storage first, and charging from the power grid first. We compare their performance for different sets of system parameters and identify the optimum operating rule. Finally, we describe an economic model, which allows us to determine the trade-offs involved when choosing between an energy storage with higher capacity or one with a higher power rating.

Towards this goal, a generic charging station architecture equipped with a local energy
storage device was presented in Chapter 2 together with an operating stochastic model. The latter combined results from queueing theory and financial considerations for the station’s operator, thus allowing one to evaluate the performance of the station with respect to different performance metrics, including blocking probabilities for customers receiving service and profit realized by the operator. The upshot of the availability of the extra energy source results in better service for the vehicles.

However, the proposed charging mechanism gave priority to supply vehicles with power from the grid and using the local storage device as a back-up. In this Chapter, we are building on our previous work in Chapter 2 and evaluate the performance of the system for different charging strategies, namely, charge from the grid first and charge from local storage first. The obtained results indicate that, depending on the charging mechanism employed, choosing the optimal charging strategy results in improved system performance. Further, we explore different types of technologies for the storage device, as well as the trade-off between larger size devices versus faster ones.

3.2 Charging Station Architecture and Stochastic Operating Model

The architecture of the charging station system is shown in Figure 2.1, where the station draws constant power from the grid, but is also equipped with a local energy storage device. It is assumed that up to S vehicles can be simultaneously serviced from the grid resources, while an additional R vehicles can be accommodated by the storage device when fully charged. The presence of the storage device allows the station to smooth out the stochasticity of the demand for power, and thus enhance the quality of service provided to its customers.

In Chapter 2, we assume that customer demand is first met by the grid power, and when the total number of customers present exceeds S, their demand is met by the local energy storage. The idea is that when fewer than S customers are present at the station, the excess capacity
available from the grid is used to charge the local storage device, thus effectively smoothing out
the demand for power over time. One of the aims of this study is to investigate an alternative
charging strategy, where customer demand is first met by the local storage device, and when
that source is exhausted, grid supplies kick in to meet customers demand. Further, if a vehicle
requests service when all available power (grid and local storage unit) resources are in use, that
customer is “blocked” and leaves the system.

Next, we discuss a stochastic model that describes the new charging strategy. Vehicles arrive
to the charging station according to a Poisson process of rate $\lambda$. Further, the service times of
vehicles are exponentially distributed with rate $\mu$. When grid resources are idle, they are used to
charge the local storage device. It is assumed that the charging time is exponentially distributed
with rate $\nu$. The dynamics of the charging station can be described by a continuous time birth-
death Markov chain with a finite two-dimensional state space, as shown in Figure 3.1. The
states of the Markov chain correspond to quantized numbers of vehicles that can be serviced,
with the "horizontal" dimension corresponding to the number of vehicles that can be charged
by the station, while the "vertical" one to the charge level of the storage unit.

Specifically, let $(i, j)$ denote a generic state, with $0 \leq i \leq S + j$ and $0 \leq j \leq R$. For example,
the $(1, R)$ state corresponds to a setting where there is 1 EV/PHEV being serviced and the
storage unit is full charged. The set of states $(S + j, j), \ 0 \leq j \leq R$ represents the blocking ones,
where the charging station rejects new arrivals. Also, we assume that there is no competition
between the storage unit and the grid, hence the “death” rates depicted in the diagram, and
similarly between vehicle arrivals and recharging the storage unit.

3.2.1 Candidate Energy Storage Technologies

In the previous chapter, we abstract the technical details of the energy storage. On the other
hand, the specifications of the energy storage technologies may affect the system performance.
Also choosing the optimal storage technology is also very important to lower the cost. Several
specifications and costs are presented in table 3.1.
For illustration, assuming $R=S$

Figure 3.1: Continuous Time Markov Chain Charge the ESS first Strategy

Next, we explore candidate energy storage technologies with respect to their efficiencies ($\eta$) and power ratings ($SPR$) for our fast charging station model. In [42, 65], researchers presented different charging station architectures and considered three different energy storage technologies; namely, batteries, flywheels and ultra-capacitors. In Figure 3.2, we present a comparison of these three technologies with respect to their power ratings and efficiencies. The charge and discharge rate of an energy storage is upper-limited by its power rating parameter. Thus, energy stored during each unit of time can be calculated by the product of power rating and the efficiency (ratio of stored energy and total amount of energy spent to charge battery) of the storage device. This means depending on the values of these two parameters, different amounts of energy can be stored.

A simple example follows to clarify the latter point. Assume that our fast charging station can charge an EV (battery with $\eta = 0.9$) in 30 minutes using the maximum power rating, $SPR = 1 (\mu = 2)$. Also, we employ a storage device with the same efficiency, but with a higher...
Table 3.1: Energy Storage Landscape

<table>
<thead>
<tr>
<th>Technology</th>
<th>Power Subsystem Cost $/kW</th>
<th>Energy Subsystem Cost $/kWh</th>
<th>Storage Subsystem Cost $/kWh</th>
<th>Round-trip Efficiency(%)</th>
<th>Cycles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Lead-acid Battery</td>
<td>400</td>
<td>330</td>
<td>80</td>
<td>2000</td>
<td></td>
</tr>
<tr>
<td>Sodium/sulfur Batteries</td>
<td>350</td>
<td>350</td>
<td>75</td>
<td>3000</td>
<td></td>
</tr>
<tr>
<td>Lead-acid Batteries with Carbon-enhanced Electrodes</td>
<td>400</td>
<td>330</td>
<td>75</td>
<td>20000</td>
<td></td>
</tr>
<tr>
<td>Zinc/bromine Batteries</td>
<td>400</td>
<td>400</td>
<td>70</td>
<td>3000</td>
<td></td>
</tr>
<tr>
<td>Lithium-ion Batteries</td>
<td>400</td>
<td>600</td>
<td>85</td>
<td>4000</td>
<td></td>
</tr>
<tr>
<td>Flywheels</td>
<td>600</td>
<td>1600</td>
<td>95</td>
<td>25000</td>
<td></td>
</tr>
<tr>
<td>Supercapacitors</td>
<td>500</td>
<td>10000</td>
<td>95</td>
<td>25000</td>
<td></td>
</tr>
</tbody>
</table>

power rating $S_{PR} = 3$ than the corresponding EV battery; i.e. in the same amount of time (30 minutes), we can store up power to satisfy the demand of 3 vehicles in the device ($\nu = 6$). Note that the charging rate $\nu = f(\hat{S}, \eta)$, where $\hat{S} \leq S_{PR}$ is the available power. For example, assume that the power rating of an energy storage is, $S_{PR} = 3$ and its efficiency is $\eta_{ES} = 0.95$. Also assume that we are drawing $S = 4$ from the grid and the storage unit’s size is $R = 5$. We further assume that with one unit of power ($S = 1$), we can charge up to two EV/PHEV demand in the energy storage ($\nu = 2$). Then, by considering the available power, $\nu$ rate for states (0, 0) to (0, 1) and (1, 0) to (1, 1) would be $\nu = 6$. On the other hand, since we are using $S = 2$ to charge customers at state (2, 0), the charge rate would be $\nu = 4$ from state (2, 0) to (2, 1). We examine the effects of $\nu$ on the choice of charging strategy; it can be seen that depending on the type of the employed energy storage, the charging facility operator will choose a charging strategy that gives better performance in terms of blocking probability of customers by the system.
3.3 Performance Evaluation

As in Chapter 2, it can be seen that the two dimensional birth-death process presented in Figure 3.1 is irreducible and positive recurrent, whose stationary distribution $\pi$ can be calculated by solving the equation $\pi Q = 0$ subject to the constraint $\pi e = 1$, where $e$ denotes a vector comprising of ones, and $Q$ is the infinitesimal generator matrix (general case shown in Equation 3.1), using standard numerical techniques [108].

\[
Q = \begin{pmatrix}
-2\lambda & \lambda & \cdots & 0 \\
\mu & -(\lambda + \mu) & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & -(S + R)\mu
\end{pmatrix}
\]  \hspace{1cm} (3.1)

As mentioned in the introductory section, the goal is to compare two charging strategies: charge from the grid first and charge from the storage device first, by calculating the total blocking probabilities (rightmost states):

\[
\sum_{i=1}^{S} \pi \left( \frac{i(i + 2S + 1)}{2} \right), i = 1 \ldots S
\]  \hspace{1cm} (3.2)
for different $S$, $R$, and $\lambda$, and $\nu$ parameters. In Figure 3.3, we fixed $S = R = 5$ and $\mu = 2$ and vary $\lambda$ and $\nu$. It can be seen that for slow energy storage technologies (i.e., $\nu = 2$ or 3, charging from grid first strategy [29] gives a battery blocking performance. However, as energy storage gets faster, the charge from energy storage first strategy outperforms the alternative strategy. Similarly, in Figure 3.4, we examine the system’s performance for different $(S, \nu)$ combinations. As expected, a storage device with a higher $\nu$ parameter exhibits better performance with respect to the probability of rejecting (blocking) incoming customers; thus, it can charge more vehicles in the same amount of time. Note that these comparisons only focus on blocking probabilities and do not take into consideration the cost of these competing storage technologies.

In order to present the system performance for different combinations of $R$ and $\nu$, we fixed $S = 8$, $\mu = 2$, $\eta_{ES} = 95\%$, $\eta_{EV/PHEV} = 80\%$ and vary $\lambda$ from 0 to 15. We present these results in Figure 3.5.
3.3.1 Metamodeling of System Output

Next, we are interested in estimating the nonlinear relationship between the blocking probability as a function of various system parameters (S, R, $\mu$, $\nu$). To this end, we use a second order polynomial model [84] for the blocking probability function $B=f(S, R, \mu, \nu)$, under the charge from the storage device first strategy. For input, we used the parameters presented in Table 3.2. Note that the $\mu$ parameter is a technological constraint, thus it is fixed at $\mu = 2$ (one charger can charge two EVs/PHEVs in one unit of time) at all times. The disadvantage of this approach is that the blocking probabilities are bounded between 0 and 1, whereas, the resultant polynomials can take any real value. Thus, in order to remove the range restrictions, and map regression polynomials to (0,1) interval, we apply logit ($y = \log(x/(1 - x))$) and inverse-logit ($x = 1/(1 + e^{-y})$) transformations to input data and resultant polynomials, respectively. In equation 3.3.1, we present the regression model after the logit transformation.

Figure 3.4: Comparison of charging strategies for varying $S$ and $\nu$
Figure 3.5: Comparison of charging strategies for varying $R$ and $\nu$

Table 3.2: RSM Input Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Interval</th>
<th>Increments</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S$</td>
<td>[1,15]</td>
<td>1</td>
<td>Integer</td>
</tr>
<tr>
<td>$R$</td>
<td>[1,15]</td>
<td>1</td>
<td>Integer</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>[0.25,30]</td>
<td>0.25</td>
<td>Float</td>
</tr>
<tr>
<td>$\nu$</td>
<td>[2,10]</td>
<td>1</td>
<td>Integer</td>
</tr>
</tbody>
</table>

\[
B(S, R, \lambda, \nu) = -4.1417 - 1.1462S - 0.5364R - 0.5206\nu \\
+ 1.4170\lambda + 0.0014SR - 0.0102S\nu + 0.0514S\lambda - 0.0215R\nu \\
+ 0.0147R\lambda + 0.0247\nu\lambda - 0.0211S^2 + 0.0198R^2 + 0.0109\nu^2 \\
- 0.0490\lambda^2
\] (3.3)
The \( R \)-squared statistic for our regression model is 93.6\%. It is also possible to work with a higher order regression model, but the second order RSM model appears already good enough to show us the effects of each parameter on the system performance. Based on the given model, we continue to quantify the sensitivity of response on all of the four system parameters \( S \), \( R \), \( \nu \), and \( \lambda \). For this purpose, we present the Jacobian matrix in equation 3.4. We can see that parameter \( S \) has the biggest impact on reducing customer blocking. However, picking a big \( S \) would stress the grid and may cause outages. Row four shows how the blocking probability increases by one unit increase in the arrival rate. The second and the third rows show the effect of local energy storage size \( R \) and the charge rate \( \nu \). We will compare these two later in this section.

We compare these two parameters for the given set of settings in Figure 3.5. Graphs at the second column show how a faster energy storage can improve the system performance. As mentioned before, the choice of energy storage type is very application dependent and there is no single correct answer. For example, assume that we will employ a local energy storage unit in a charging station in a big metropolitan downtown area where real-estate is very expensive. In this case, it would be cost effective to can see that parameter \( S \) has the biggest impact on reducing customer blocking. However, picking a big \( S \) would stress the grid and may cause outages. Row four shows how the choose a smaller device, with a bigger \( \nu \) parameter. Just to demonstrate the latter point with an example, assume that one EV battery pack is 16kWh and we want to employ a local energy storage size of \( R = 4 \) (16kWh \( \times \) 4=64kWh of energy would be required for storage). In order to illustrate how much physical space this would require, we use the Maxwell BMOD0083P048 module (each can possess 26.6W h) [12]. One would need
2406 of these modules to store 26.6kWh of charge. Consider that the physical volume of one unit is $0.01m^3$, the total volume would then be about $24m^3$.

The example above shows how physical space can be problematic in real world applications. One potential solution could be to place these modules underground. Of course, if the charging station is to be placed at a big shopping mall, or near a highway exit, where physical space is relatively cheaper, the station owner can employ a slower storage, but of bigger size.

### 3.3.2 Charging Station Profit Model

In the previous section, we compared two different charging strategies and showed how different storage technologies affect this choice. Then, we make an argument for increasing the size of the storage device, as opposed to employing a more efficient one (bigger $\nu$), under the *charge from the local unit first* strategy. Next, we proceed to present a model, that relates pricing parameters to the stochastic system's parameters which can guide charging station operators to select various parameters (e.g. $S$, $R$, etc).

The underlying principle guiding this model is presented in section 8.7. For the *charge from the local unit first* case we have the following states. Let $\rho^{(g)} = \{(i, j) : 0 \leq i \leq S, 0 \leq j \leq R\}$ denote the grid charging states and $\rho^{(l)} = \{(i, j) : S + j \leq i \leq S + R, 1 \leq j \leq R\}$ the storage unit charging ones. Also, we denote by $\rho^{(bl)}$ the blocking states respectively. Finally, $\pi(s)$ denotes the stationary probability for generic state $s \equiv (i, j)$ and $i(s)$ the number of EVs/PHEVs receiving service in states $s$. Note that the net profit function is presented in equation 4.3.

We evaluate the profit function for number of settings. In Figure 3.6, we fixed $S = 5$, $R = 4$, $\mu = 2$, varied $\nu = 2 \ldots 8$ and $\lambda = 0.25 \ldots 18$. Also, we assumed that $R_g = R_l = 1.4$, $C_b = 1.5$, $C_1 = 0.5$, $C_2 = 0.2$, and $C_0 = 0.001$.

It can be seen that, for small arrival rates, we are not charging enough customers to have positive profit, thus, energy storage is overdetermined. On the other hand, for large arrivals, net profit decreases due to cost of blocking customer. This model motivates charging station owner to pick appropriate size and storage model to maximize its profit.
As a second evaluation, we compare two cases: \( R = 4, \nu = 6 \) and \( R = 6, \nu = 4 \). We used the same settings except for \( C_1=C_2=0.25 \) for a fair comparison. From Figure 3.7 shows that faster storage gives higher profit. Aforementioned comments about output of net profit model for small and large arrival rates still holds.

### 3.3.3 Conclusions

In this Chapter, we extended our previous work where we proposed an EV/PHEV DC fast charging station architecture with a stochastic model to analyze its performance by using arguments from queuing theory together with some simple financial considerations that provide guidance on how to select key parameters of the model. Our main focus was on how the main performance metric, namely blocking probability, is affected both by the energy storage used, and the employed charging strategy. Two different strategies were considered: charging from the storage device first and charging from the grid first. We differentiated storage devices by their power ratings and efficiencies. Different sets of system parameters were used to evaluate various operational regimes. Finally, with our financial model, we showed the trade-off between choosing a storage device with higher capacity or one with a higher power rating.
Figure 3.7: Evaluation of Profit Model
Chapter 4

Electric Power Allocation in a Network of Fast Charging Stations

In the previous chapters, we propose charging station architecture and evaluate the performance of it respect to percentage of customer it can serve. In the next two chapters, we proceed to explain our control mechanism for a network of charging stations. The overview of our approach in Figure 4.1.

4.1 Introduction

In order to increase the penetration of electric vehicles, a network of fast charging stations that can provide drivers with a certain level of quality of service (QoS) is needed. However, given the strain that such a network can exert on the power grid, and the mobility of loads represented by electric vehicles, operating it efficiently is a challenging and complex problem. In this Chapter, we examine a network of charging stations equipped with an energy storage device and propose a scheme that allocates power to them from the grid, as well as routes customers. We examine three scenarios, gradually increasing their complexity. In the first one, all stations have identical charging capabilities and energy storage devices, draw constant power from the
grid and no routing decisions of customers are considered. It represents the current state of affairs and serves as a baseline for evaluating the performance of the proposed scheme. In the second scenario, power to the stations is allocated in an optimal manner from the grid and in addition a certain percentage of customers can be routed to nearby stations. In the final scenario, optimal allocation of both power from the grid and customers to stations is considered. The three scenarios are evaluated using real traffic traces corresponding to weekday rush hour from a large metropolitan area in the US. The results indicate that the proposed scheme offers substantial improvements of performance compared to the current mode of operation; namely, more customers can be served with the same amount of power, thus enabling the station operators to increase their profitability. Further, the scheme provides guarantees to customers in terms of the probability of being blocked (and hence not served) by the closest charging station to their location. Overall, the paper addresses key issues related to the efficient operation, both from the perspective of the power grid and the drivers satisfaction, of a network of charging stations.

4.2 Charging Station Model for Multi-Class Service

We continue to employ the charging station model proposed in the previous chapter. However, we extend this model to the case where different classes of customers are present; namely, $c \in \{1, \cdots, C\}$. Also, denote by $\bar{\rho}$ the percentage of customers that demand class-$c$ type of
service. Then, the station operator partitions the power drawn from the grid into $C$ components by solving the following optimization problem.

$$\arg \min_{S^{(c)}} \sum_{c \in C} B^{(c)}(\bar{\rho}, S^{(c)}, R^{(c)})$$

s.t. \quad \sum_{c \in C} S^{(c)} = S$$ \quad (4.1)

\(\bar{R}^{(e)}\), \(\bar{\rho}\), and \(\lambda\) are given

To illustrate how the characteristics of the energy storage device improve performance of the station we use the following example. We fix the size of two devices, but we vary their efficiency and power rating parameters. There is a fast energy storage with 95% efficiency and \(S_{PR}=2\), and a slow one with efficiency of 85% and \(S_{PR}=1\). Storage size is set to \(R=5\) and the EV arrival rate varies between \((\lambda = 1 - 7)\). To ease the demonstration, a single customer class is assumed requesting a charging rate of \(\mu=2\). As shown in Figure 4.2, the fast energy storage device outperforms the slow one in terms of blocking probabilities. Next, we evaluate the system performance (percentage of vehicles it can charge), under the following sets of parameters. There are two customer classes; in class-1 EVs request fast charging, while in class-2 request slower charging. A typical charging duration takes 30 minutes, thus the charging rate \(\mu^{(1)}\) is set to 2 and \(\mu^{(2)}=1\).
We assume that the station operator picks the energy storage according to the following specifications (note that superscript denotes the customer class): storage size $R^{(1)}=R^{(2)}=5$, efficiency $\eta^{(1)}=0.95$ and $\eta^{(2)}=0.85$ and power ratings $S_{PR}^{(1)}=2$ and $S_{PR}^{(2)}=1$. Based on an EV profiling study, it is estimated that the total arrival rates varies between $\lambda = 1 - 7$. We look at three different compositions of the EV population: $(\rho^1, \rho^2) = \{(75\%, 25\%), (50\%, 50\%), (25\%, 75\%)\}$. Then, the station operator solves optimization problem 4.1 to calculate the optimal $\vec{S}^{(c)}$ given by $[6, 4]$, $[4, 6]$, and $[2, 8]$ for the given $(\rho^1, \rho^2)$ pairs, respectively. The resulting blocking probabilities are shown in Figure 4.4. It can be seen that the system can serve more customers, in the presence of a larger percentage of fast charging customers. This is expected, since the overall “service rate” is faster in that case.

### 4.2.1 Profit Model for Multi-Class Service

The principles of the profit model for $C$ different customer classes are as follows: the charging station earns differential revenue for each served EV according to its class (e.g. more revenue from fast charging customers etc.). On the other hand, a penalty is paid for each blocked EV because (1) it leads to dissatisfied customers and degrades the reputation of the station; (2) it enables to control the QoS to foster EV adoption [112]; (3) it allows station operators to size its capacity to maximize its profit. It is assumed that a higher penalty is paid to cus-
tomers charged more for service. Let $R_g^{(c)}$ and $R_l^{(c)}$ be the revenue gained per EV class-$c$, when served from the grid and the energy storage, respectively. Further, let $C_b^{(c)}$ denote the blocking cost of a single EV in class-$c$. Finally, let $C_0$ represent the fixed installation cost and $C_a^{(c)}R$ the acquisition cost, assumed to be proportional to size, for customer class-$c$ of the storage unit. In order to calculate the net profit, for each customer class, we classify the charging states in the Markov chain model to: the “grid charging states” and the “storage unit charging states”. Let $\rho^{(g)} = \{(i, j) : 0 \leq i \leq S, 0 \leq j \leq R\}$ denote “the grid charging states” and $\rho^{(l)} = \{(i, j) : S + j \leq i \leq S + R, 1 \leq j \leq R\}$ “the storage unit charging states”. Similarly, $\rho^{(bl)}$ represents the “blocking states”, while $i(s)$ denotes the number of EVs at state $s$. Then, the proposed profit function can be written as

$$P = \sum_{c \in C} \sum_{s \in \rho^{(g)}} R_g^{(c)} i^{(c)}(s) \pi^{(c)}(s) + \sum_{c \in C} \sum_{s \in \rho^{(l)}} R_l^{(c)} i^{(c)}(s) \pi^{(c)}(s) - (C_0 + \sum_{c \in C} R^{(c)} C_a^{(c)}) - \sum_{c \in C} \sum_{s \in \rho^{(bl)}} C_b^{(c)} i^{(c)}(s) \pi^{(c)}(s)$$

We evaluate the profit model for the following set of parameters in the presence of two customer classes (fast/slow): $R_g^{(1)}=R_l^{(1)}=3, R_g^{(2)}=R_l^{(2)}=1.5, C_b^{(1)}=3.5, C_b^{(2)}=2, C_a^{(1)}=0.25, C_a^{(2)}=0.15$ and $C_0=0.02$. The results are shown in Figure 4.3. For low arrival rates, the cost related to acquisition and installation outweighs the revenue gained from charging EVs, and hence a negative profit is earned. On the other hand, for high arrivals rates, the cost of blocking customers becomes dominant and the total net profit decreases. Moreover, since fast charging lowers the blocking probability, the system means more profit when the proportion of class-1 customers is higher.
4.3 A Network of Charging Stations

4.3.1 Overview

Fast public charging stations are key to build confidence in the early stages of EV adoption. At present, the number of fast charging stations in the US is quite low, and deployment plans in the short term are limited to selected highways only [49, 106]. In order to compete against gas stations, deploying urban charging facilities becomes necessary [66]. In this section, the operation of a network of fast charging stations in an urban environment is studied, where each individual station is modeled according to the architecture introduced in section 2.

In the real world, urban traffic movements are far from being uniform. In fact, people drive between specific points of interest, such as their home, school, workplace, etc. Driving patterns vary according to the time of the day (weekday rush hours, weekends etc.) and hence traffic density represents a dominant factor in the utilization of each node in a charging station network. As the power grid limitations prevent stations from providing more capacity, grid operators have to consider the fact of spatial and temporal demand to optimally allocate their power resources.
4.3.2 Power Resource Allocation in a Charging Station Network

Case-I: No Allocation

In the first case, all charging stations in the network are assumed to be identical. Let \( l = 1, 2, ..., N \) be the index set of charging stations. Further assume that each station serves \( c \in C \) types of customer classes, so that \( S_1^{(c)} = S_2^{(c)} = \ldots = S_N^{(c)} \) and \( \lambda_1^{(c)} = \lambda_2^{(c)} = \ldots = \lambda_N^{(c)} \). The only parameter that differs in these stations is the arrival rate \( \lambda_i \) and composition of the customer class populations \( \bar{\rho} \), which comes from the traffic density (note that we consider rational customers who always drive to the nearest station).

Case-II: Optimal grid power-S allocation within a large geographical urban areas

Similarly to the case above, there are \( N \) charging stations deployed in a large urban environment. However, customers also have access to charging station location information provided by a central authority\(^1\). This case is divided into two subcases. The first subcase assumes that all drivers are selfish and similarly to Case I, they choose the nearest charging station. The second subcase assumes a hybrid population of selfish drivers and EV fleets. Note that unlike selfish users, EV fleets adhere to the decisions of the power utility to fulfill the requirements of customer agreements. Hence, the arrival rate of each station can be shaped within a \([\lambda_{\text{min}}, \lambda_{\text{max}}]\) range.

Let \( S_{\text{max}} \) be the maximum level of generation capacity that the grid can supply to the network in a metropolitan area. Also each station serves \( c \in C \) types of customer classes. Using the discretization assumption at each charging node, two resource allocation problems are formulated as a mixed integer non-linear programming problem in Equations 4.3 and 4.4. For both subcases, the proposed scheme allocates more power resources to the busier stations, while taking into account \( \text{QoS} \) targets. If the total power required to satisfy the \( \text{QoS} \) requirements is greater than \( S_{\text{max}} \), then the charging station network provides best-effort service with the maximum allowable grid power, \( S_{\text{max}} \).

\(^1\) Via smart apps or on board communication systems [8]
\[
\min_S \sum_{i \in l} \sum_{c \in C} B_i(\tilde{\rho}_i \lambda_i, S_i^{(c)}, R_i^{(c)}) \\
\text{s.t.} \quad \sum_{i \in l} \sum_{c \in C} S_i^{(c)} = S \\
0 \leq B_i(\tilde{\rho}_i \lambda_i, S_i^{(c)}, R_i^{(c)}) \leq \epsilon \\
S_i^{(c)} \in \mathbb{Z}^+ \\
R_i^{(c)}, \lambda_i, \text{ and } \tilde{\rho}_i, \text{ are given} \\
\forall i \in l, \forall c \in C
\]

\[
\min_{S, \lambda} \sum_{i \in l} \sum_{c \in C} B_i(\tilde{\rho}_i \lambda_i, S_i^{(c)}, R_i^{(c)}) \\
\text{s.t.} \quad \sum_{i \in l} \sum_{c \in C} S_i^{(c)} = S \\
0 \leq B_i(\tilde{\rho}_i \lambda_i, S_i^{(c)}, R_i^{(c)}) \leq \epsilon \\
\lambda_{\min}^{(c)} \leq \lambda_i^{(c)} \leq \lambda_{\max}^{(c)} \\
S_i^{(c)} \in \mathbb{Z}^+ \\
R_i^{(c)}, \tilde{\rho}_i, \lambda_{\min}^{(c)} \text{ and } \lambda_{\max}^{(c)} \text{ are given} \\
\forall i \in l, \forall c \in C
\]

**Case-III: Optimal S and λ allocation in small geographical areas**

Let \( l^* \subset l \) and \( 0 < n \leq N \). In this case, a charging station network deployed over a relatively well confined small geographical area with \( n \) stations is considered. This case is different from the previous scenario in the following aspect: the total population consists of EV fleets and through agreements, customers can be assigned to any neighboring station. Since the considered distances between stations are reasonably short \((2 - 3 \text{ miles}^2)\), routing customers to other stations would have negligible cost to drivers. Thus, customers can be assigned to neighboring area stations to minimize the total blocking probability. In all cases, the local energy storage

\(^2\text{It would require } 0.5 - 1 \text{ kWh of stored energy and would cost } 10-20 \text{ cents with the current rates.}\)
is assumed to have already been acquired by the charging station (e.g. $R = 5$), thus its size is fixed. Finally, each station serves $c \in C$ classes of customers, and routed customers get the same type of service. Then, the optimization problem becomes:

$$\min_{S, \lambda} \sum_{i \in l} \sum_{c \in C} B_i(\bar{\rho}_i \lambda_i, S_i^{(c)}, R_i^{(c)})$$

s.t. $$\sum_{i \in l} \sum_{c \in C} S_i^{(c)} = S$$

$$\sum_{i \in l^*} \lambda_i = \lambda$$

$$0 \leq B_i(\bar{\rho}_i \lambda_i, S_i^{(c)}, R_i^{(c)}) \leq \epsilon$$ (4.5)

$$\lambda_i^{(c)} \geq 0, \forall i \in l^*$$

$$S_i^{(c)} \in \mathbb{Z}^+$$

$$R_i$$ and $\bar{\rho}_i$ are given

$$\forall i \in l^*, \forall c \in C$$

In addition to the system constraints presented for each allocation problem, there may be additional constraints, depending on the existing power network, such as distribution network limitations, etc. However, since the interaction of the charging stations with the grid is limited to the constant power drawn from it, these case-by-case varying constraints may only affect the maximum power allocation for individual stations. Thus, these constraints can easily be incorporated within the existing formulation to address these allocation problems.

4.4 Evaluation & Results

4.4.1 Overview

Collecting vehicular traffic traces, especially in urban areas, is a challenging and costly task. Hence, vehicles movements are not well calibrated. However, in [64] bus movements from the
Seattle area were obtained. Due to the city’s physical layout and extensive bus network\(^3\), it is claimed that these movements resemble actual traffic patterns quite closely. In the next subsection (4.4.2), we use this publicly available data to investigate the spatial distribution of vehicles, during weekday rush hour (7am-9am and 5pm-7pm). The remainder of this subsection is organized as follows. In subsection 4.4.3, we explain our methodology in locating fast charging stations on the city map. In subsection 4.4.4, we use the Response Surface Methodology to approximate charging station blocking probabilities into a second order regression metamodel.

\(^3\)1200 buses in a 5000 square kilometers area
Finally, in subsection 4.4.5, we solve the optimization problems presented in section 4.3.2 using our metamodel.

4.4.2 Input Analysis

According to [64], the location of each bus was recorded frequently. We start by normalizing the \(x\) and \(y\) coordinates of the input data. Subsequently, the ARENA Input Analyzer [1] is used to fit a spatial distribution to the data. The results indicated that with mean squared error of 0.6\%, the spatial distribution of vehicles is a piecewise beta distribution for weekday rush hours. The results are presented in equations 4.6 and 4.7.

\[
f(X) = \begin{cases} 
44 \times BETA(4.42, 0.763) & 0 \leq X \leq 44 \\
44 + 137 \times BETA(0.752, 4.7) & 44 \leq X \leq 180 
\end{cases} \tag{4.6}
\]

\[
f(Y) = \begin{cases} 
150 \times BETA(2.42, 0.799) & 0 \leq Y \leq 150 \\
150 + 121 \times BETA(1.07, 5.44) & 150 \leq Y \leq 270 
\end{cases} \tag{4.7}
\]

In addition, we analyze the correlation of \(x\) and \(y\) coordinates, and calculate the correlation coefficient as 0.06.

4.4.3 Charging Station Placement

In [64], researchers placed eight base station towers in such a way that base stations can communicate with all mobile nodes. Since the charging station layout problem is outside the scope of this paper, a similar approach is used and the same number of charging stations is deployed in the same locations given by the following coordinates: \(\{x_i, y_i\} = \{60, 45\}, \{60, 90\}, \{60, 135\}, \{60, 180\}, \{60, 225\}, \{100, 90\}, \{100, 160\}, \{100, 225\}\). Figure 4.5 presents the map with the locations of the charging stations. In order to calculate the traffic intensity at each station, a discrete event simulation model is used. We present its flowchart in Figure 4.6. The station parameters are given by \(S = 5, R = 5, \mu = 2, \nu = 4\) (assuming only fast charging...
customers) for all stations. The simulation is terminated when one million vehicles get serviced. It is run for a total of 30 times and 95% confidence intervals of the parameters of interest are obtained. The traffic intensity for each station is shown in Table 4.1. It can be seen from Table 4.1 that charging stations three and four are used to meet most of the charging demand, whereas other stations have relatively little demand. For instance, letting the overall arrival rate be $\lambda = 50$, then the blocking probabilities for the eight identical stations would be $\vec{B}_i = [0.019, 0.053, 0.58, 0.58, 0.0158, 0.0153, 0.043, 0.014]$. It can be concluded from this expository calculation that, without any power allocation, there could be severe fluctuations in terms of QoS among the charging facilities\(^4\).

\(^4\)Some stations(e.g. station-3) will exhibit a very high blocking probability, whereas overprovisioned stations (e.g. station-8) will exhibit a very low blocking probability.
Table 4.1: Traffic Intensity (T.I.) of Each Station

<table>
<thead>
<tr>
<th>Sta. ID</th>
<th>mean(T.I.)</th>
<th>95% CI</th>
<th>Sta. ID</th>
<th>mean(T.I.)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.56%</td>
<td>0.030%</td>
<td>2</td>
<td>9.68%</td>
<td>0.022%</td>
</tr>
<tr>
<td>3</td>
<td>36.99%</td>
<td>0.060%</td>
<td>4</td>
<td>36.68%</td>
<td>0.035%</td>
</tr>
<tr>
<td>5</td>
<td>1.85%</td>
<td>0.037%</td>
<td>6</td>
<td>1.65%</td>
<td>0.018%</td>
</tr>
<tr>
<td>7</td>
<td>8.6%</td>
<td>0.055%</td>
<td>8</td>
<td>0.98%</td>
<td>0.016%</td>
</tr>
</tbody>
</table>

4.4.4 Output Analysis

Metamodeling of Blocking Probabilities

In Chapter 2, numerical methods are used to calculate EV blocking probabilities. However, new calculations are needed for each set of new input parameters $S$, $R$, $\nu$, and $\lambda$ to determine the blocking probability $B$. Using the Response Surface Methodology (RSM) we are able to calculate an approximate second order polynomial model for the functional relationship between $B$ and the input parameters ($B = f(S, R, \nu, \lambda)$ [84]. As input parameters we used those presented in Table 4.2, keeping $\mu$ is fixed to 2. The handicap of this approach is that the blocking probabilities have to be in the $[0, 1]$ interval, whereas the RSM model can predict values outside it. For that reason, we fit the RSM model to the logit transformation ($y = \log(x/(1 - x))$) of $B$ and then use the inverse-logit ($x = 1/(1+e^{-y})$) transformation to obtain the final results. The regression model where the response variable corresponds to logit($B$) is given in Equation 4.8.

Table 4.2: RSM Input Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Interval</th>
<th>Increments</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S$</td>
<td>[1,15]</td>
<td>1</td>
<td>Integer</td>
</tr>
<tr>
<td>$R$</td>
<td>[1,15]</td>
<td>1</td>
<td>Integer</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>[0.25,30]</td>
<td>0.25</td>
<td>Float</td>
</tr>
<tr>
<td>$\nu$</td>
<td>[2,10]</td>
<td>1</td>
<td>Integer</td>
</tr>
</tbody>
</table>
\[ B(S, R, \lambda, \nu) = -3.990 - 2.666S - 1.6152R - 0.1492\nu \\
+3.840\lambda - 0.0645SR - 0.002S\nu + 0.209S\lambda - 0.0078R\nu \\
+0.094R\lambda + 0.003\nu\lambda - 0.0175S^2 + 0.055R^2 + 0.0089\nu^2 \\
-0.271\lambda^2 \quad (4.8) \]

Then, the blocking probability becomes,

\[
Blocking \ Prob. = \begin{cases} 
B(\cdot) & \text{if } \lambda > 0 \\
0 & \text{if } \lambda = 0 
\end{cases} \quad (4.9)
\]

For the above regression model, the R-Square statistic is 88.06\% and the mean square root error is 0.52\%. Some key quantities like the Jacobian (equation 4.10) and the Hessian matrix

\[
\begin{bmatrix} 
\frac{\partial B}{\partial S} \\
\frac{\partial B}{\partial R} \\
\frac{\partial B}{\partial \nu} \\
\frac{\partial B}{\partial \lambda} 
\end{bmatrix} = \begin{bmatrix} 
-0.035S - 0.0645R - 0.002\nu + 0.21\lambda - 2.66 \\
0.0014S + 0.11R - 0.008\nu + 0.094\lambda - 1.62 \\
-0.002S - 0.078R + 0.178\nu + 0.025\lambda - 0.15 \\
0.209S + 0.094R + 0.003\nu - 0.54\lambda + 3.84 
\end{bmatrix} \quad (4.10) 
\]

\[
H = \begin{bmatrix} 
-0.035 & -0.0645 & -0.002 & 0.21 \\
0.0014 & 0.11 & -0.008 & 0.094 \\
-0.002 & -0.078 & 0.178 & 0.025 \\
0.209 & 0.094 & 0.003 & -0.54 
\end{bmatrix} \quad (4.11) 
\]

(equation 4.11) are given to aid assessing the sensitivity of \( B \) with respect to inputs \( S, R, \nu \) and
Table 4.3: Results for Case IIB (Mixed Population of Selfish EVs and Fleets)

<table>
<thead>
<tr>
<th>Σi∈l λi</th>
<th>Station1</th>
<th>Station2</th>
<th>Station3</th>
<th>Station4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S1 λ1 B1</td>
<td>S2 λ2 B2</td>
<td>S3 λ3 B3</td>
<td>S4 λ4 B4</td>
</tr>
<tr>
<td>ε=0.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>1 0.77 0.0037</td>
<td>2 2.656 0.015</td>
<td>5 7.3 0.0347</td>
<td>5 6.084 0.032</td>
</tr>
<tr>
<td>25</td>
<td>1 0.9625 0.0153</td>
<td>3 2.832 0.0125</td>
<td>6 8.98 0.047</td>
<td>6 8.90 0.041</td>
</tr>
<tr>
<td>30</td>
<td>1 1.155 0.032</td>
<td>3 3.3984 0.031</td>
<td>7 10.767 0.05</td>
<td>7 10.4760 0.046</td>
</tr>
<tr>
<td>ε=0.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>1 0.77 0.057</td>
<td>1 2.2656 0.0317</td>
<td>4 7.178 0.10</td>
<td>4 6.98 0.0932</td>
</tr>
<tr>
<td>25</td>
<td>1 0.9625 0.0153</td>
<td>1 2.832 0.03491</td>
<td>5 8.9725 0.10</td>
<td>5 8.73 0.0936</td>
</tr>
<tr>
<td>30</td>
<td>1 1.155 0.032</td>
<td>2 3.3984 0.031</td>
<td>6 10.76 0.10</td>
<td>6 10.476 0.0934</td>
</tr>
</tbody>
</table>

λ variables is presented. It can be seen that grid power \( S \) has the highest impact for decreasing the blocking probability. Note that during periods of high arrival rates, there is going to be little spare capacity left and hence the local storage device would be frequently in an empty state, as indicated by these results.

4.4.5 Comparison of three cases

Next, we compare the performance of the following three scenarios: (i) all eight stations are identical (case-I); (ii) power resource allocation for selfish EV population (case-IIA) and mixed (selfish and EV fleets) population (case-IIB); and (iii) power resource allocation for EV fleets only (case-III). Standard interior point methods are used to solve the optimization problems introduced in section 4.3.2. Problems formulated in case-II and case-III are non-linear integer programs and they are solved by relaxing the integer constraint and ceiling to the nearest integer. For case-IIA, suppose that the station operator wants to provide \( \epsilon \)-level QoS at all
Table 4.4: Results for Case-IIA (Selfish EVs)

<table>
<thead>
<tr>
<th>( \sum_{i \in l} \lambda_i )</th>
<th>Station 1</th>
<th>Station 2</th>
<th>Station 3</th>
<th>Station 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \varepsilon = 0.05 )</td>
<td>( S_1 )</td>
<td>( B_1 )</td>
<td>( S_2 )</td>
<td>( B_2 )</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>0.0023</td>
<td>2</td>
<td>0.0094</td>
</tr>
<tr>
<td>25</td>
<td>1</td>
<td>0.0067</td>
<td>2</td>
<td>0.0269</td>
</tr>
<tr>
<td>30</td>
<td>1</td>
<td>0.0148</td>
<td>3</td>
<td>0.0082</td>
</tr>
<tr>
<td>( \varepsilon = 0.10 )</td>
<td>( S_1 )</td>
<td>( B_1 )</td>
<td>( S_2 )</td>
<td>( B_2 )</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>0.023</td>
<td>2</td>
<td>0.0094</td>
</tr>
<tr>
<td>25</td>
<td>1</td>
<td>0.0067</td>
<td>2</td>
<td>0.0269</td>
</tr>
<tr>
<td>30</td>
<td>1</td>
<td>0.0148</td>
<td>2</td>
<td>0.0568</td>
</tr>
</tbody>
</table>

Table 4.5: Comparison of Case-IIA (Selfish EVs) and Case-IIB (Mixed Population)

<table>
<thead>
<tr>
<th>( \sum_{i \in l} \lambda_i )</th>
<th>Case IIA</th>
<th>Case IIB</th>
<th>Savings</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \varepsilon = 0.05 )</td>
<td>( S_i )</td>
<td>( \lambda_i )</td>
<td>( S_i )</td>
</tr>
<tr>
<td>20</td>
<td>18</td>
<td>16.67</td>
<td>10%</td>
</tr>
<tr>
<td>25</td>
<td>22</td>
<td>20.83</td>
<td>4.55%</td>
</tr>
<tr>
<td>30</td>
<td>24</td>
<td>24.9</td>
<td>4%</td>
</tr>
<tr>
<td>( \varepsilon = 0.10 )</td>
<td>( S_i )</td>
<td>( \lambda_i )</td>
<td>( S_i )</td>
</tr>
<tr>
<td>20</td>
<td>18</td>
<td>16.67</td>
<td>18.75%</td>
</tr>
<tr>
<td>25</td>
<td>22</td>
<td>20.83</td>
<td>15%</td>
</tr>
<tr>
<td>30</td>
<td>24</td>
<td>24.9</td>
<td>9%</td>
</tr>
</tbody>
</table>

Table 4.6: Results for Case III (EV Fleets)

<table>
<thead>
<tr>
<th>( \sum_{i \in l^r} S_i )</th>
<th>( \sum_{i \in l^r} \lambda_i )</th>
<th>Station 2</th>
<th>Station 3</th>
<th>Station 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_2 )</td>
<td>( \lambda_2 )</td>
<td>( B_2 )</td>
<td>( S_3 )</td>
<td>( \lambda_3 )</td>
</tr>
<tr>
<td>18</td>
<td>16.67</td>
<td>6</td>
<td>5.56</td>
<td>0.004</td>
</tr>
<tr>
<td>24</td>
<td>20.83</td>
<td>8</td>
<td>6.94</td>
<td>0.0327</td>
</tr>
<tr>
<td>30</td>
<td>24.9</td>
<td>10</td>
<td>8.3</td>
<td>0.005</td>
</tr>
</tbody>
</table>
stations. One of the main goals of this scheme is to use the minimum amount of power grid resources (for illustration assume all customers demand fast charging). Hence, the minimum required grid power $S_{\text{min}}$ to meet the QoS targets is calculated. As long as $S_{\text{min}} \leq S_{\text{max}}$ where $S_{\text{max}}$ is the total allocated generation capacity, this target is going to be reached. A generic calculation is presented in Figure 4.7.

Next, let us compare cases-I and -IIA. Suppose that the charging station operator wants to ensure that each station can meet 90% of the customer demand at all times ($\epsilon=0.10$). For the eight stations, the arrival rate is assumed to be $\lambda = 27$. Since the majority of the population resides near Stations 2, 3 and 4, we assume that these two stations serve two types of customers; class-1 (fast charging $\mu=2$) and class-2 (slow charging $\mu=1$). The same set of parameters from previous evaluations are used for the efficiency and the power rating of the local energy storage units. Since these regions are close to downtown we further assume that $\vec{\rho}=(75\%, 25\%)$. The remainder of the stations serve customer class-1. Solving equation 7.7 results in $\vec{S}=[1, 2, 9, 9, 1, 1, 2, 1]$. With the allocated grid power, blocking probabilities for

Figure 4.7: Minimum grid power required to meet $\epsilon$ QoS targets
each station are $\bar{B}=[0.0094, 0.028, 0.099, 0.087, 0.0004, 0.0023, 0.016, 0.0001]$. In order to compare the performance of the whole network, we calculate the weighted sum of stations’ blocking probabilities:

$$\sum_{i \in l} w_i B_i, \text{ where } w_i = \frac{\lambda_i}{\sum_{i \in l} \lambda_i} \quad (4.12)$$

Then, the weighted sum of blocking becomes $\sum_{i \in l} w_i B_i=0.0440$. To compare these results with case I, assume that each station has $S_i = 3$ (except $S_3 = S_4 = 4$) and $R = 5$. Arrival rates are the same as case II. For this case, the weighted sum of blocking becomes $\sum_{i \in l} w_i B_i=0.4365$. This sample calculation shows that with power resource allocation, more vehicles can receive service with the same amount of grid power.

For the allocation problem in cases II-B and III, a two-way communication infrastructure is used to offer customers incentives to charge from other stations. In the first case, a central authority can route a certain percentage of customers in the $[\lambda_{\text{min}}, \lambda_{\text{max}}]$ range. In the latter one, any customer can be assigned to any station in the same neighboring area. Thus, for the first case suppose that the arrival rate of each station is in the $\lambda \pm 10\%$ range. For instance, if station-3 the arrival rate is $\lambda_3 = 10$ arrival rate will be assigned in $[9,11]$ interval. Next, two allocation problems 4.3 and 4.4 are solved for six different combinations: $\epsilon = 0.05, 0.10$ and
$\sum_{i \in \Omega} \lambda_i = 20, 25, \text{ and } 30.$

We proceed to compare three cases for all stations in detail. Table 4.4 presents the results for a population of selfish EV users. The utility can only allocate optimal power (problem 7.7). On the other hand, for a mixed population of EVs (selfish and Fleets) allocation problem 4.4 is solved. We present detailed results for each charging facility in Table 4.3. Note that since the central authority can partially affect the customer choices, blocking probability targets can be achieved with less grid power. For instance, customer routing can lead to 10% power savings to provide $\epsilon=0.05$ QoS. Detailed results are given in Table 4.5. Case-III assumes a
population of pure EV fleets. Note that the network map (Figure 4.5) is divided into smaller geographic areas, and inside each region the cost of driving between charging stations has a negligible cost. We assume that charging stations 2, 3, and 4 constitute a charging network. Similar to the previous case, a central authority through the use of two-way communications, can assign customers to any station in this subarea. To evaluate this case, assume that stations 2, 3, and 4 are in a small well-confined neighborhood and driving between these stations has a negligible cost. Then, in optimization problem 4.5, minimum customer blocking probabilities are obtained at $S_i=S/N$ and $\lambda_i^{(1)}=\lambda^{(1)}/N$ where $N$ is the number of charging stations (also $R_1^{(1)} = R_2^{(1)} \ldots R_N^{(1)}$ and $R_1^{(2)} = R_2^{(2)} \ldots R_N^{(2)}$). We present the results for $\epsilon = 0.05$ and varying arrival rate parameters in Table 4.6. Moreover, we run a sample calculation for two stations, with the following parameters: $\sum_{i \in \ell} \lambda_i = 10$, $\sum_{i \in \ell} S_i = 10$ and $R_1 = R_2 = 5$. The results are shown in Figure 4.8.

Next, we compare the baseline scenario (no allocation of any kind) and three allocation schemes for stations 2, 3, and 4 since they serve both fast and slow customer classes. For a fair comparison, we fixed the total grid resources, and employ the same type of energy storage devices. Results are depicted in Figure 4.9 for three different arrival rates. In order to quantify the effects of power allocation and customer routing on the charging network, the profit model of section 4.2.1 is applied to all stations. Previously presented results for all three cases are used for $\epsilon = 0.05$ and arrival rates $\lambda = 20$, 25, and 30. The same set of parameters from section 4.2.1 is employed. In Figure 4.10, average net profit per charging station is depicted, which shows that the proposed framework improves both the system (in terms of QoS) and its financial performance significantly.

### 4.5 Conclusion

In this chapter, we proposed a general resource allocation framework for metropolitan area fast charging station networks. Individual stations are modeled as a loss system and analyzed in

---

5 Note that customer profile $\bar{\rho}$ is approximately the same since stations are physically close to each other.
terms of grid reliability. We show that the spatial and temporal customer demand is the main
driver behind the lack of uniformity in the load at each station. To gain more insight, we used
the real world traces of customers in Seattle, WA. Our framework, with an efficient usage of
grid resources, enables more customers to get service. Moreover, stations meet their QoS targets
with minimum amount of grid resources.
Chapter 5

Decentralized Control of Electric Vehicles in a Network of Fast Charging Stations

5.1 Introduction

To facilitate the adoption of electric vehicles (EVs) and their plug-in hybrid (PHEVs) counterparts and to avoid straining the capacity of the power grid there is a strong need for developing a network of fast charging facilities and coordinate their service. Incorporation of EVs in the vehicle fleet would decrease greenhouse gas emissions and overall dependency on fossil fuels.

A key issue in charging EVs is that the corresponding time is fairly large, which can lead to very long delays. Hence, for the network of charging stations to provide good quality of service to customers, we first propose an admission control mechanism based on pricing for a single charging station. Subsequently, we develop a decentralized routing scheme of EV drivers, employing a game theoretic model. The latter entices drivers through price incentives to require charging from less busy stations, thus leading to a more efficient utilization of power across the network, while it enhances profit for the charging facilities operator. Of note, the proposed
scheme does not require advanced monitoring tools for power usage and pricing calculations. The drivers receive and send back the necessary information through the communication infrastructure and the routing is initiated only when the network has exceeded a critical threshold. The numerical results illustrate the discussed benefits of the proposed scheme. Overview of the System is depicted in Figure 5.1.

5.2 Electric Vehicle Admission Control (EVAC) for a Single Charging Station

In order to spur universal EV adoption the widespread presence of fast charging stations is required. However the projected EV demand is going to outpace the required improvements in the grids serving capabilities (illustrated in Figure 5.2). Hence, the key issue addressed in this section is to develop intelligent operation regimes to cope with stochastic customer demand and increase the percentage of served EVs. As the customer preferences (e.g. where to get service, price willing to pay etc.) determine the overall system performance, many aspects of the charging network are governed by the economic incentives [30]. To that end, we develop a pricing based decentralized control mechanism to improve the grid’s service performance.
We discuss an Electric Vehicle Admission Control mechanism that can be employed at a single charging station level to provide QoS guarantees. The EVAC will: (1) balance the customer load among different charging facilities, (2) attain given QoS targets and (3) increase total revenue for station operators by more efficient use of energy resources. Such an admission control mechanism can be implemented through a pricing mechanism. For instance, during high EV demand for charging, the station operator can offer relative lower prices in a neighboring charging station to balance the customer demand.

5.2.1 System Parameters

Next, we explain the dynamics of the single charging station admission control presented in Figure 5.3. We assume that each vehicle chooses to go to the nearest station to get service. The arrival rate for each EV is represented by $\lambda_{EV}(t)$. Each new EV enters the pricing block, and $\lambda_{AC}(t)$ is the proportion of the arrival rate that accepts the offered price. Similarly, $\lambda_{R}(t)$ is the arrival rate for routed vehicles from neighboring stations and $\lambda_{AD}(t)$ is the arrival rate of admitted EVs. We define two types of EV blocking probability: (i) $B_{EV}$: blocking of EVs who

Figure 5.2: Illustration of Projected Customer Demand vs. Expansion of Grid’s Serving Capacity. Regional Serving Capacity: Percentage of EVs that can be charged in a specific region and time duration (e.g. University Campus noon-1pm)
come to the nearest station (ii) $B_{RB}$: blocking of a routed EV.

### 5.2.2 QoS Metric & Pricing Block

As explained in [100], we define the blocking probability as the key QoS metric. The performance metric is denoted by $(P_{BT})$ as the weighted sum of the two blocking types:

$$ P_{BT} = \gamma_1 B_{EV} + \gamma_2 B_{RB} $$

(5.1)

where,

$$ \gamma_1 + \gamma_2 = 1 $$

(5.2)

Since blocking an EV that is routed from a neighboring station leads more dissatisfaction, it is assumed that $\gamma_2 > \gamma_1$.

Pricing policies in loss systems can be classified into three categories [58]. The first category includes static policies that use flat prices at all times. Even though they are easy to implement, such pricing schemes fail to alleviate congestions. On the other hand, dynamic policies monitor the load of the system continuously and adjust the prices accordingly to prevent congestions. However, implementation of such pricing mechanisms for charging station operations is rather impractical, since it requires expensive real time monitoring and measurement tools.

The pricing block, $P(t)$ in EVAC uses myopic policy that falls in between the first two categories. Pricing $P(t)$ works as follows. Unless the arrival rate $\lambda_{EV}(t)$ exceeds a threshold $\lambda^*_{EV}$,
the station offers normal prices $p_{\text{normal}}$ that are acceptable by each EV. During a congestion period, $\lambda_{EV}(t) > \lambda_{EV}^*$, the station operator increases prices to congestion price $p_c > p_{\text{normal}}$, so that EVs will prefer to go to neighboring stations.

The station pays a penalty $p_b$ for each blocked EV (see [100]), because (1) it leads to dissatisfied customers and degrades the reputation of the station, (2) it enables to control the QoS to foster EV adoption [91] and (3) it allows station operators to size their capacity so as to maximize profit. It is assumed that the paid penalty is more than the price charged for service.

Next we define the optimal arrival rate $\lambda_{EV}^*$ as follows: it is the maximum arrival threshold that satisfies blocking probability targets $\delta$ and can be calculated by:

$$\lambda_{EV}^* = \arg \max_{\lambda_{EV}}(P_{BT}(\lambda_{EV}) \leq \delta) \quad (5.3)$$

where the QoS target $\delta$ is specified in the Service Level Agreement (SLA). Also note that the pricing block $P(t)$ determines the percentage of EVs that will accept the offered price at time $t$, thus $\lambda_{EV}(t)P(t) = \lambda_{AC}$ and this yields,

$$P(t) = \frac{\lambda_{AC}}{\lambda_{EV}} \leq \frac{\lambda_{EV}}{\lambda_{EV}} \quad (5.4)$$

This shows that the percentage of customers who accept the offered price will be inversely proportional to the load of the station. Thus, to capture the response of EVs to price changes, demand functions are used. From microeconomics, it is known that the inverse of the demand function explicitly gives the price function,

$$p(t) = D^{-1}\left(\frac{\lambda_{EV}}{\lambda_{EV}^*}\right) \quad (5.5)$$

where

$$\frac{\lambda_{EV}}{\lambda_{EV}^*} \quad (5.6)$$
is the load on the system. In this paper, we use the demand function proposed in [50]. Then, $p(t)$ the price at time $t$ becomes:

$$ p(t) = \begin{cases} 
  p_{\text{normal}} & \text{if } \lambda_{EV}(t) \leq \lambda^*_{EV} \\
  p_c = p_{\text{normal}} \left( 1 + \theta \sqrt{-\log(\frac{\lambda^*_{EV}}{\lambda_{EV}(t)})} \right) & \text{if } \lambda_{EV}(t) > \lambda^*_{EV}
\end{cases} $$

(5.7)

where $p_c$ is congestion pricing and $\theta$ is a positive constant set by the station operator.

### 5.3 Decentralized Control for a Network of Charging Stations

The rationale for introducing decentralized control strategies is to examine how to accommodate a large number of EVs under QoS guarantees without requiring significant upgrades on the power grid’s capacity. To that end, we employ a game theoretic framework and propose a decentralized control mechanism to balance the EV load at different charging stations. The customer’s objective is to receive service that has a QoS guarantee and to minimize total cost, which is proportional to the price paid for charging and the distance to the charging station. The operator of the charging stations objective is to maximize profit and provide QoS guarantees to the EV drivers. Recall that the QoS metric used is the long-term probability is ”blocked” when it arrives at a station. The end goal is to incentivize selfish EVs to cooperate and route customer demand to neighboring stations with lower utilization, if necessary.

To make this framework operational, it is assumed that each charging station can communicate with a central unit that can forward price signals to EVs and influence their choices, while EVs communicate their positions. The EVs respond to these price signals following a best response strategy outlined below. It is assumed that the necessary communications infrastructure is in place (e.g. 3G/4G or a wireless mesh network) to support the proposed mechanism.
5.3.1 Game Formulation

EVs have access to location information and pricing offers by the central communication unit, whose role as outlined above is to communicate with each charging station and forward their price signals; e.g. offer relatively lower prices to attract customers to drive to a more distant station to balance the arrival rate at each station. Thus, the operator of the charging stations network acts as a leader who can commit to a strategy before followers (EVs) pick their strategies. In this respect, a Stackelberg game will help us to model this system. Let us define the game in its strategic form:

\[
\Gamma = \{\mathcal{N} \cup \mathcal{K}, \{\tilde{p}_k\}, \{X_{k \in \mathcal{K}}\}, \{U_{n \in \mathcal{N}}\}, \{U_{k \in \mathcal{K}}\}\}
\]

(5.8)

where \(\mathcal{N}\)={1,\ldots,N} is the set of charging stations and \(\mathcal{K}\)={1,\ldots,K} the set of EVs that require charging at a given time. The strategies of each set of players are as follows. \(\{\tilde{p}_k\}\) denotes a \(1 \times N\) price vector offered by the network operator. The EVs strategy, \(X_k\), is to choose a charging station from \(\mathcal{N}\). \(U_n\) and \(U_k\) are the functions that represent the payoffs (utility) for the players. Next, we describe the components of the game in detail.

5.3.2 EV Customers

Based on the assumption of rationality, and in the absence of any incentives, each EV will just choose to go to its nearest charging station. Through the use of two-way communications, the network operator aims to route EVs to less busy stations (if necessary) by offering relatively lower prices, but still avoid penalties for poor QoS (blocked EVs). The EVs can either Accept to go to a less busy charging station or Reject and go to the nearest one. The EV strategy is
given below.

\[ EV_{Strategy} = \begin{cases} 
  \text{Accept,} & \text{if } c_{k\text{near}} - c_{k\text{desired}} \geq c_{k\text{inactv}}, \quad P_{\text{desired}} \leq \delta \\
  \text{Reject,} & \text{otherwise} 
\end{cases} \quad (5.9) \]

Suppose that EV-$k$, $k \in K$ needs charging from station-$n$, $n \in N$. The cost of selecting the nearest station is equal to $c_{k\text{near}} = p_n + c(d_{nk}^2)$, where $p_n$ is the price paid to the station, and $c(d_{nk}^2)$ is the cost related to driving to station-$n$ for EV-$k$. Note that $p_n$ equals $p_{\text{normal}}$ when there is no congestion at the nearest station-$n$, and to the congestion price $p_c$ otherwise. Similarly, when the network operator wants to route a vehicle to a station other than the nearest one, it costs $c_{k\text{desired}}$. In order to project customer behavior into our formulation, we assume that EV-$k$ will only choose to go to the desired station if it gains at least $c_{k\text{inactv}}$ (considering current electricity prices there should be a reasonable level of savings e.g. 10% savings).

The utility function of a single EV is a function of QoS metric $\bar{P}_{BT}$, the offered price for each station $\bar{p}_k$, and the distance to each station $d_k$. Note that each component of the utility corresponds to a $1 \times N$ row vector, where the position of each element is associated with the corresponding station parameter (blocking probability, price, and distance). Also the pricing scheme proposed in section is employed at each station. Then, the utility function for EV-$k$ becomes:

\[ U_k(\bar{P}_{BT}, d_k, \bar{p}_k) = h(\bar{P}_{BT})e_n \left\{ \bar{p}_k + c_k(d_k) + f_k(d_k) \right\} \quad (5.10) \]

where,

\[ h(\bar{P}_{BT}) = e^{\xi(\bar{P}_{BT} - \delta)} \quad (5.11) \]

The $h(\cdot)$ function denotes the disutility of experiencing high blocking probability [75], $\xi$ is a constant and $\delta$ is the QoS target. These components capture the dissatisfaction introduced by
a high blocking probability. Note that

$$\xi = \begin{cases} 
0 & \lambda \leq \lambda^* \\
\xi \in \mathbb{R}^+ & \text{otherwise}
\end{cases}$$

(5.12)

The EV chooses one station $n \in \mathcal{N}$ and $\vec{e}_n$ represents a column vector comprising of all zeros except for the $n^{th}$ position which is 1. Similarly, $\vec{p}_k$ is the price vector offered by the network operator. The next term in the utility function reflects the cost of driving to a charging station which is a function of distance to each station from the current location of EV-$k$. Finally, $f_k(\vec{d}_k)$ is related with the dissatisfaction of EV-$k$ when it selects to go to a more distant station. Even though the total cost is lowered, some level of dissatisfaction occurs due to spending extra time to drive the extra miles (e.g. time cost etc.).

Thus, the optimization problem of the EVs is a mapping $\mathbb{R} \rightarrow \{\text{reject, accept}\}$ that gives rise to a vector $\vec{e}_n$, where (Accept) sets the $n^{th}$ position to 1 while all other remain 0 (Reject). Note that the objective is to minimize driver’s cost. This can be expressed as follows:

$$\arg \min_{n} h(\vec{P}_{BT})\vec{e}_n \left\{ \vec{p}_k + c_k(\vec{d}_k) + f_k(\vec{d}_k) \right\}$$

s.t. $n \in \mathcal{N}$

(5.13)

where EV-$k$ picks station-$n$ and pays $p_n$ unit of money. The second parameter represents the cost of driving: $c_k(\vec{e}_n \vec{d}_k) = p_d d_{kn}^2$ (price of driving one unit of distance times distance to station-$n$). The last component reflects the dissatisfaction of drivers to go extra miles. A linear dissatisfaction model is used $f_k(\vec{e}_n \vec{d}) = p_{dis} (d_{kn} - d_{nearest})$ where $p_{dis}$ is the cost of driving one unit of distance, and $(d_{kn}-d_{nearest})$ is the total amount of extra miles traveled. This component approximates the behavior of drivers in real life, since it is unlikely that one would drive a significant extra distance for limited savings. Moreover, the above optimization problem is subject to the EV having stored adequate energy to drive to station-$n$, which we assume that this is the case (about $0.5 - 1 kWh$ of stored energy).
5.3.3 Charging Network Operator

In the Stackelberg game, the network operator acts as the leader who is willing to coordinate non-cooperative EV charging so that, he can maximize his profit while minimizing customer blocking. The strategy of the leader is to set the pricing parameter vector $\theta$ at each station. Then the offered $1 \times N$ price vector becomes a function of vector-$\theta$, $\tilde{p}_k = h(\theta)$. Also we assume that regulations and policies do not allow the operator to take advantage of the EV’s location information to demand a high price of those whose battery levels are low. The utility function of the operator becomes:

$$\arg \max_{\theta} \quad \tilde{p}_k(\theta)\tilde{q} - p_B\tilde{q}_B$$

subject to:

$$\tilde{p}_k, \tilde{q}, \tilde{q}_B \in \mathbb{R}^N, \ p_B \in \mathbb{R}^+$$

(5.14)

where, $\tilde{q}$ is calculated from equation 5.13 and equals to $\tilde{e}_n$. Similarly,

$$\tilde{q}_B = \begin{cases} 
0, & \text{If gets service} \\
\tilde{e}_n, & \text{If blocked} 
\end{cases}$$

(5.15)

and the price vector $\tilde{p}_k$ is the same as in Equation 5.13. Finally, $p_B$ is a scalar and represents priced paid when blocking occurs.

5.4 Numerical Results

In this section, we illustrate the proposed EV routing scheme. The simulation scenario is set as follows: there are five charging stations in a $30 \times 30$ unit square area. The coordinates of the locations of the five stations are: $(5, 25)$, $(10, 10)$, $(25, 25)$, $(15, 15)$, and $(25, 5)$. To capture the spatial variability of EVs we used the following mixture distribution, whose parameters are
Algorithm 1 Decentralized control with pricing

Require: $\theta \geq 0$, $|\mathcal{N}|, |\mathcal{K}| \in \mathbb{Z}^+$

for customer-$k$ ← 1 to $K$ do

    network owner offers $\vec{p}_k(\theta) \in \mathbb{R}^N$ to Eq.(5.13)
    calculate utility $\vec{U}_k \in \mathbb{R}^N$
    pick station $n=$indexOf(min($\vec{U}_k$))
    enter station, set $\vec{e}(n)=1$
    if gets service then
        set $q=\vec{e}(n)$, $q_B=0$
    else
        set $q=0$, $q_B=\vec{e}(n)$
    end if
    calculate Eq.(5.14)
end for

calibrated based on results from Chapter 4.

$$f(X) = \begin{cases} 15 \times Be(4.42, 0.763) & , 0 \leq X \leq 15 \\ \end{cases} \quad (5.16)$$

$$f(Y) = \begin{cases} 15 \times Be(2.42, 0.799) & , 0 \leq Y \leq 15 \\ \end{cases} \quad (5.17)$$

where $Be$ denotes the Beta distribution function. The spatial distribution is illustrated in Figure 5.10, which shows that half of the EV population resides in the lower left of the area under consideration, while the remaining half in the rest of the area. Given this spatial distribution of EVs and in the absence of a control mechanism, customer demand for each station would be 1%, 50%, 42%, 2%, and 5% for stations 1 – 5, respectively. Given this baseline scenario, the parameters of each single charging station are set as follows. Stations under heavy traffic have bigger capacity $S_2=S_3=8$ and $R_2=R_3=8$. Since station-1 is the nearest to congested regions, it has $S_1=6$ and $R_1=6$, while stations 4 and 5 that do not operate under heavy load, have $S_4=S_5=3$ and $R_4=R_5=3$. Moreover, the charge rate to satisfy one EV charging request is $\mu_1=\ldots=\mu_5=2$, while the charging rate from local energy storage unit is $\nu_1=\ldots=\nu_5=3$.

Next, we elaborate on the settings of the discrete event simulation. The overall charging requests (or arrival rate) is depicted in Figure 5.4. Customer demand to each station
is proportional to the traffic load calculated above; for example, for station-2 it is about $\lambda_2(t=6\text{am})=20 \times 0.5 = 10$. The charging station operator aims to provide service to the EVs with QoS guarantee $\delta = 0.05$ and dissatisfaction parameter $\xi = 0.1$. Based on these charging station specifications, the leader (system operator) solves equation 7.2 and starts the game when the arrival rate exceeds this threshold, which corresponds to the following thresholds for each individual station: $\vec{\lambda}^* = [10.3, 13.4, 13.4, 4.2, 4.2]$. Since it may be challenging (and possibly wasteful) to update arrival rates in real time, we set 15 minute intervals at which arrival rates are recalculated.

The pricing parameters are set as follows: in the absence of congestion, EVs pay the operator $p_{\text{normal}} = 4$, whereas if customers are blocked the operator rewards them with $p_{\text{block}} = 5$. As mentioned before, this cost is a penalty to the operator for poor service which can impact customer loyalty and its long term reputation. Also, to calculate blocking probabilities we set $\gamma_1 = 0.45$ and $\gamma_2 = 0.55$. For the $k$-th EV, $c_{\text{netv}}$ is a uniformly distributed random number in the interval $[0.5, 0.75]$ and $p_{\text{dis}}$ is a uniformly distributed random number (per unit of distance) in
the interval $[0.02, 0.05]$. We assume that driving duration is linearly correlated with distance (based on an average speed of 40 mph). Currently popular EV models (e.g. Nissan Leaf) exhibit $0.22\text{kWh/mile}$ energy consumption; thus, we set $p_{\text{drive}} = 0.03$ per unit of distance.

Next, we present the strategy of the leader. Since stations 1, 4, and 5 operate under light load, we set $\theta_1 = \theta_4 = \theta_5 = 0.5$ and vary the strategy parameters for the congested stations, namely $\theta_2$ and $\theta_3$, between $0 - 0.55$ for a generic rate of $\lambda = 40$. Note that $(\theta_2, \theta_3) = (0, 0)$ implies no congestion control at stations-2 and 3. As shown in Figure 5.5, with appropriate pricing parameters, the network of charging stations can accommodate up to 20% more EVs. Further, net revenue becomes constant after $\theta_2$ and $\theta_3$ exceeds 0.4. The reason is that the proposed congestion price already offers enough incentives for customer routing for the given set of system parameters. However, if the leader wants to route customers in order to accommodate a higher arrival rate, she needs to pick a higher $\theta$ parameter. The proposed decentralized control mechanism is simulated with the given set of parameters for three different scenarios.

In the first scenario, $\tilde{\theta}$ is set to 0, which implies no congestion control at any station. This case serves as a baseline scenario to evaluate the performance of the proposed control mechanism. Partial control is considered for the second scenario with the following strategy parameters $\bar{\theta} = [0.05, 0.5, 0.5, 0.05, 0.05]$. Note that stations-2 and 3 can fully route customers when there is
congestion, whereas the rest of the stations may not provide strong enough incentives to their customers to drive to stations further away. The final scenario provides strong incentives with all $\theta_n$ parameters set to 0.5. In Figure 5.6, the weighted-sum of blocking probabilities for all five stations and for the three scenarios is depicted. The weight of each station is proportional to the customer load each station serves. Note that with the proposed control mechanism more EVs can be served with the same amount of grid resources. To illustrate the effect, the busiest station (#2) is selected. Without customer routing, this station can not satisfy the QoS guarantee ($\delta=0.05$), but with the proposed mechanism it can provide high quality service. Note that in the partial control setting, station-2 lowers its blocking probability (depicted in Figure 5.7) since congestion control at the neighboring stations is weaker. Nevertheless, strong incentives to route customers to more distant stations exhibits the best performance both in accommodating more EVs and as shown in Figure 5.8 also leads to increased revenue for the operator.

Moreover, in order to show how the proposed pricing scheme balances the load, we quantify
the percentage of successfully routed customers. Figure 5.10 shows traffic shaping between charging stations. For instance, during the busiest hour 17.68% of station-2 customers accept to go to station-1. Note that since the proposed utility functions consider the physical distance of the stations, only a relatively small percentage of EV prefer to drive to distant stations. In Figure 5.9, the percentage of routed EVs from station-2 versus the pricing parameter $\theta_2$ is presented.

5.5 Conclusion

In this chapter, we introduced an admission control mechanism based on pricing signals to reduce congestion at a single charging station level. Next we presented a decentralized control for charging EVs over a network of charging facilities. It is assumed that the network operator has the first move advantage to incentivize selfish EVs to move to nearby stations, if necessary, to load balance traffic at each station. The preferences (spatial and temporal) of EVs are captured through utility functions and the system is modeled with Stackelberg game. It was established that not only this strategy can achieve better results in terms of blocking EVs from receiving service, but it also leads to a more efficient power/energy resource.
Figure 5.8: Total Revenue for the Charging Network

Figure 5.9: Traffic Shaping for Station-2
Figure 5.10: Traffic Shaping Among the Charging Facilities (at hour=4pm)
Chapter 6

Enabling Communication Technologies

The previous two chapters illustrated an approach to formalize the problem of optimal power and customer allocation in a small geographical area. Two types of customers; EV Fleets and selfish users, are considered. The realization of such a system approach requires the appropriate communication architectures and protocols to enable efficient and reliable information dissemination.

The performance of the overall system is thus dependent on the reliability of information dissemination. For this reason, connectivity, performance, reliability, and robustness becomes a central issue in making the system implementable.

In this chapter we identify the communication requirements for EV networks and survey on candidate technologies. The interdependency of communications, power grid, and EV charging is depicted in Figure 6.1.
6.1 Introduction

The EV population is going to hit several millions in the next decade [91]. EV batteries can be charged by any of the following methods; level-1 (garage charging), level-2 (park and charge), and DC fast charge (public). They are differed by the volume of electric current they use. Moreover, the popularity of each charging type will greatly be determined by the housing demographics [32]. For instance, in the early EV adapter cities, substantial portion of the population lives in multi-unit dwellings and EVs in this regions will most likely use public fast charging facilities.

Accordingly there is a growing interest in expanding the deployment of charging station networks. For instance, there is an attempt to build state wide charging station network in California. Similarly, Estonia is building the Europe’s largest fast-charging station network with two hundred nodes [13]. The number of EV charging stations is expected exceed 4 million in Europe and 11 million globally by year 2020 [94].

Despite the motivation, the mass marketing of EVs poses a variety of technical challenges. The current power grid does not have capabilities to accommodate EV demand (especially during peak hours). The grid is fragile and has been running close to its operating limits. The projected adoption of EVs is likely to stress the distribution network; increases power loses and voltage deviations and decreases transformer lifetime (high loading leads to high operating temperature) [91, 52, 40]. Moreover, [68] shows that only a few concurrent EV chargings can
lead to service interruptions. Since adding extra generation capacity (new power plants), or upgrading the power grid, is in most cases costly, system operators have to control and coordinate EV chargings intelligently.

The realization of such control techniques requires appropriate communication architectures. The two-way communications will enable reliable interaction between the grid and the drivers. At a minimum, mobile drivers need to access charging station location and pricing information. However, spatio-temporal variations in the customer demand may create instabilities between charging stations. Communication networks will allow grid operators to interact with customers to balance the load. This can be done by offering customers incentives to drive extra miles to neighboring stations. For garage charging applications, time-differentiated tariffs can motivate customers to charge during off-peak hours. However, implementation of such pricing scheme requires EVs to be fully equipped with the required communication modules. Smart grid applications for EVs also allow reverse power transfer (Vehicle-to-Grid (V2G)). Groups of stationary EVs can sell part of their stored energy during peak hours to alleviate the stress on the grid. Auction-based energy trading can be enable with integration of two-way communications [98].

6.2 Available Communication Standards and Technologies

In order support the aforementioned information exchange, we survey the related technologies and standards. As this is a new area some of the standards are either published or under development. We classify the communication standards and technologies into three groups: (1) the first group includes the technologies that are responsible for home charging applications and the message exchange between the EV and the charging equipment; (2) the second group includes the technologies for the mobile EV communication; and (3) the third group includes the standards for “inter-control center” communication.
6.2.1 Mobile EV to Control Center Communications

The network of charging facilities needs to be spatially distributed [30, 26], both due to operational limitations (e.g. transformer rating, line capacity etc.), as well as to meet a spatially distributed EV demand. However, the two may not be perfectly aligned, thus introducing the need that the network operator incentivizes customers to be rerouted to neighboring, but less congested stations. Hence, customer demand should be balanced among neighboring stations through the use of communication infrastructures. Thus the ability to share data for mobile EVs becomes a necessity. In Figure 6.2, we present an overview of message exchange in electric vehicle networks.

There are several wireless communication technologies that are projected to support “electric mobility”. Two strong candidates are cellular network communications and wireless mesh networks.

Cellular Network Communications

For the short term, ubiquitous public cellular networks can provide required communication coverage in a cost effective way. Moreover, cellular operators offer service solutions for smart grid applications. Power meter manufacturers embed communication modules to enable use of cellular communications. For garage charging and vehicle-to-grid applications data (e.g. power
usage, price etc.) is exchanged periodically (typically around every 10-15 minutes). Most cellular networks have sufficient capabilities to support required communication medium. Further, cellular networks have the following advantages: (1) Cellular communication technology is mature is enough to meet smart grid needs; (2) Since all cellular networks operate on licensed spectrum, there is no need to pay for unlicensed bands; and (3) Cellular networks are scalable enough to connect huge number of EVs.

Worldwide inter-operability for Microwave Access (WiMAX) is another strong candidate. WiMAX offers high capacity, wide coverage, low latency, low per-bit cost, and required quality of service capabilities. For example, garage charging applications generate small amount of traffic, but the projected number of connections is very high. For mobile EVs, high data rate is needed to support location based applications. In most cases, in-vehicle application require wide coverage, high throughput, and QoS support. WiMAX has required capabilities to handle the transmission of such data. On the other hand, public charging applications require mobility support. As the mobile user moves faster, the supported data rate decreases. In Figure 6.3, we compare wireless communication networks according to mobility and throughput. 2.5G, 3G, 4G (WiMAX and LTE) offer required connectivity for mobile EVs. IEEE P2030 Standard [8] presents possible communication interfaces. The connection to central controller, or telematics provider can be established by either equipment manufacturers OEMS or wide area communication.
Wireless Mesh Networks

Wireless Mesh Networks (WMNs) are qualified to deliver required connectivity to EV drivers and the power grid. Moreover, their low cost, high scalability, self-healing, and self-organizing nature along with mobility support makes WMNs a very strong candidate. WMNs can provide high bandwidth and seamless handover capabilities at high speeds (almost the same quality as third generation technologies) [103]. Also, WMNs are compatible with other networks: they can be integrated with other existing networks (e.g. IEEE 802.15 IEEE 802.16, cellular networks etc.). Further advantages of WMNs include its higher physical layer transmission rate than most cellular networks and coverage can be extended without using extra channel capacity.

Several companies already deployed WMNs for smart grid applications [14, 15]. As EV population continue to grow fast, the need for a dedicated communication infrastructure will become more important. Especially in urban environments, where “xG” networks are overloaded or not deployed yet, WMNs will become even more important. In [15] a medium city is successfully deployed with wireless mesh networks to support required connectivity to electric vehicles.

On the other hand WMNs have several disadvantages. In urban environments network coverage can be affected by interference and fading. Available bandwidth can reduce in the case of possible loop problems [56]. In order to enjoy benefits of WMNs, research efforts are being shown to solve complexity of these networks.

6.2.2 Inter-Control Center Communications

As shown in Figure 6.2, different regions are served by different service providers. Each control center monitors and controls registered customer demand at each charging facilities connected to him. Moreover, when a customer from another service territory requests service, control centers should be able to exchange information for authentication, billing, and location. Currently, all-electric range of most EVs is more than hundred miles [68]. This range enables drivers to go to different regions that are served by some other utility (e.g. Central Europe etc.). Hence the communication network should be able handle possible hand-offs situations.
At the present time, utilities employ IEC 60870-6/TASE.2 (International Electrotechnical Commission Telecontrol Application Service Element) communication standard for information exchange between control centers, utilities, and power pools [56]. However, additional communication features may be needed to keep track of mobile users.

### 6.3 Communication Requirements & Performance Metrics

The end-to-end communication requirements for EV network applications require highly available, reliable, and secure communications. Different applications, such as V2G, load shedding etc, may have different communication requirements. The use cases for EV applications serve as a starting point for communication requirements. A detailed use case analysis is presented in [34, 7]. Each use case scenario defines the end-users (e.g. customer, utility, EV, etc.), their types (e.g. individual, organization etc.), content, size, and the frequency of the required message exchange. In this section we discuss communication system requirements and associated performance metrics.
6.3.1 System Reliability and Availability

The successful management of EV networks requires extensive use of reliable and (highly) available communications. The loss of availability is going to terminate the grid to customer interaction. During these isolation periods, customers will not be able to receive electricity prices, hence cannot optimally adjust and schedule their electricity usage. In fact the cost of unavailability can be more severe. For instance, for garage charging scenarios, uncontrolled EV chargings may lead to unwanted peaks and overload some of the grid components, such as the distribution transformer.

Considering the aforementioned use cases, [63] explores the reliability requirements for home charging EV applications. The authors show that 11 different messages are used and the minimum reliability requirement varies between $98.8 - 99.5\%$. This variety is attributed to some messages, such as Vehicle Identification Number (VIN) information request, error messages related to EV charging rate, require high availability than other types.

The connectivity loss for mobile EVs is even more critical. Unavailability will refrain customers from locating and scheduling charging stations. Similarly, it may lead to suboptimal station selection both for customers (more expensive) and the grid operator (busy stations or long waiting lines may cause customer dissatisfaction) [28]. There are a handful of studies that quantify the cost of bad communication system performance. For instance, garage charging applications use AMI network. In a related study [87] presents a generic AMI communication network and perform availability analysis for each component (e.g. Home Area Network, 3G Network etc.). Moreover, it quantifies the cost of unavailability due to suboptimal power allocation.

Communication system availability models and the corresponding performance evaluation techniques have been very well studied in the literature [60, 80, 36, 44]. The availability of a communication system is the probability that the system works under normal operation conditions. Corollary, the availability ($A$) can be calculated from the ratio of the uptime of the system to the total operation time (uptime plus downtime). The operation of communication
systems are subject to failures due to a variety of reasons such as human errors, software or hardware faults, and damage from harsh environments. [44] presents an analytical approach to 3G (UMTS) cellular base station. They show that the availability of UMTS depends on the availability of four system components (Node-B, Radio Network Controller (RNC), Service Gateway Support Node (SGSN), and GPRS Gateway Support Node (GGSN)) and can be computed by:

\[ A = A_{Node-B} \times A_{RNC} \times A_{SGSN} \times A_{GGSN}. \]

The second group of approaches include modeling the system availability with continuous time Markov chains (CTMC) [60, 80, 36]. For instance in a telecommunication system failure and repair times of each component are assumed to be exponentially distributed and availability is calculated from the steady state probability distribution.

### 6.3.2 Quality of Service

The Quality-of-Service (QoS) needs are gradually increasing as the EVs gain widespread acceptance. Since centralized or decentralized control of EVs is done via price signals, degradation in communication system performance may cost. In [78], authors define QoS requirements for general smart grid communications using in terms of communication delays and outage probability.

The QoS requirements can be slightly different for mobile EVs and the grid operator. For instance, IEEE P2030 [8] states that an EV can afford to have a few seconds of latency to retrieve location, pricing, and availability information. However, in order to respond to the huge number of queries (approximate number depends on the EV penetration level) grid operator have to receive the information in a timely manner.

Even though today’s mobile broadband technologies (e.g. 3G/HSPA/EV-DO etc.) promise high-throughput and low latency communications, in some occasions there can be a degradation in the user experience. This is attributed to the network capacity saturation in some areas. For instance, [4] shows that customer demand is going to exceed network capacity, for most metropolitan areas, in the next years. This will force time critical data transfer from EVs to
**Table 6.1: Summary of Candidate Wireless Communication Networks [18]**

<table>
<thead>
<tr>
<th></th>
<th>Latency</th>
<th>Throughput</th>
<th>Security</th>
<th>Scalability</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>WiFi</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IEEE 802.11a</td>
<td>L</td>
<td>H</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td>IEEE 802.11b</td>
<td>L</td>
<td>H</td>
<td>M</td>
<td>L</td>
</tr>
<tr>
<td>IEEE 802.11g</td>
<td>L</td>
<td>H</td>
<td>M</td>
<td>L</td>
</tr>
<tr>
<td>IEEE 802.11n</td>
<td>L</td>
<td>H</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td><strong>3G</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UMTS/HSPDA</td>
<td>M</td>
<td>M</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>EVDO</td>
<td>M</td>
<td>M</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td><strong>4G</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LTE/HSPA+</td>
<td>L</td>
<td>H</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>IEEE 802.16e</td>
<td>L</td>
<td>H</td>
<td>H</td>
<td>H</td>
</tr>
</tbody>
</table>

Wireless Mesh Network can be implemented with WiFi nodes.

Low (L): Latency (<250ms), Throughput (<500Kbps), Scalability(<100nodes/backhaul node).

Medium (M): Latency (250ms-1s), Throughput (500Kbps-1,500Kbps), Scalability(<100-1000nodes/backhaul node).

High (H): Latency (>1s), Throughput (>1,500Kbps), Scalability(>1000nodes/backhaul node).

Compete with other bandwidth demanding applications such as video streaming and Voice over IP.

On the other hand, next generation mobile WiMAX/LTE technology can support necessary QoS requirements. More specifically, WiMAX offers four different QoS level namely (1) Unsolicted Grant Service (UGS); (2) Real-Time Polling Service (rtPS); (3) Non-Real Time Polling Service (nrtPS); and (4) Best Effort (BE). UGS can support low latency and low jitter and prioritize EV charging related data transfer. However, 4G technologies are not available everywhere. Also only limited variety of devices support 4G connectivity.

In some areas, wireless mesh networks have been deployed using IEEE 802.11 technology. The cost of building such infrastructure is relatively cheaper and does not require permission, since they function in the open 2.4GHz band. These networks can provide application access priority (starting from 802.11e and more recently with the 802.11g), but they do not guarantee any strict QoS. In addition, they have a limited range, which means that vehicles that want to communicate through them may be in a wireless blind spots.
6.3.3 Cyber-Physical Security

The power grid is vital to human life and with the integration of information systems, the power grid becomes a huge cyber-physical system. The grid’s unique nature poses new series of security challenges. The components of the power grid are vulnerable to variety of new cyber-security threats that could affect national security, public safety, and revenues.

There has been an increasing interest in smart grid security aspect [120, 79, 109, 83, 9, 2, 93, 35, 37, 76]. In [83], the authors presented cyber-physical security overview of smart grid communication infrastructure. [109] presented security threats for electric vehicle networks. They concluded that electric vehicle networks have the following security requirements: (1) Availability (discussed in the previous section); (2) Confidentiality (prevent attackers to obtain private information); (3) Integrity (block unauthorized users from changing the data); and (4) Authenticity.

If the security of the EV network communication is not provided at a high level, an adversary can impact the EV network in various ways. A hacker can route customers to a specific charging station to create chaos for drivers. Similar to a home appliance, the garage charging is also programmed to fill up EV battery when price is low. An adversary can launch an attack to inject negative prices to increase power usage (of automated appliances), which may result in a peak or spike in electricity usage. Similarly, price modification can cause instabilities in V2G energy trading.

In [76], the authors presented the security threats in physical layer of wireless communications for smart grid applications. Moreover, [37] defines the attack types for smart grid communication networks. They introduce three different kinds of smart grid attacks:

- **Data Injection:** The attacks in this category falsify the meter measurements (e.g. garage charging) to mislead the power grid operator. The main purpose of this type of attacks is to create revenue loss.

- **Vulnerability:** This type of attack is caused by the failure of a communication channel
Table 6.2: Overview of Communication Standards for Electric Vehicle Networks

<table>
<thead>
<tr>
<th>End Users</th>
<th>Application</th>
<th>Name of Standards</th>
</tr>
</thead>
<tbody>
<tr>
<td>EV-EVSE</td>
<td>Energy Transfer-Garage Charging</td>
<td>SAE J2293, SAE J2836/1, SAE J2847/1, SAE J2836/2, SAE J2847/2, SAE J2836/3, SAE J2847/3, SAE J2836/4, SAE J2847/4, SAE J2931, IEC 61851-23, IEC 61851-24</td>
</tr>
<tr>
<td>EVSE - Energy Management Unit (EMU)</td>
<td>Home Area Network</td>
<td>Zigbee, 802.11, HomePlug</td>
</tr>
<tr>
<td>Customer (EMU) - Grid</td>
<td>Garage Charging, Load Shifting, Valley Filling, Energy Trading</td>
<td>PLC, 3G/4G/WiMAX, WMN, TV White Space, DSL, Cable</td>
</tr>
<tr>
<td>Mobile EV - Control Center</td>
<td>Public Charging</td>
<td>3G/4G/WiMAX, WMN</td>
</tr>
<tr>
<td>Inter-Control Center</td>
<td>Public Charging</td>
<td>IEC 60870-6/TASE.2</td>
</tr>
</tbody>
</table>

or a device. Information on the feedback channel can be unsynchronized due to erroneous communication links.

- **Intentional:** In this type, the attacker has the full knowledge of network topology. It can be carried out by targeting the node with the highest degree with a denial-of-service attack.

Several organizations including IEEE (1402-2000, IEEE Guide for Power Substation Physical and Electronic Security), North American Electrical Reliability Corporation - Critical Infrastructure Protection (NERC-CIP), National Infrastructure Protection Plan (NIPP), and NIST (National Institute of Standards and Technology) [79]. In the second volume of NISTIR 7628 [2], NIST documents a comprehensive overview of guidelines for smart grid cyber security. This documents contains several use cases concerning the security issues with EV chargings. In [35], the authors evaluated the effectiveness of NISTIR framework for an electric vehicle charging
Table 6.3: Communications Needs and Requirements for All Three Types of EV Charging Applications

<table>
<thead>
<tr>
<th>Application</th>
<th>EV Perspective</th>
<th>Grid Perspective</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Communication Needs</td>
<td>Communication Needs</td>
</tr>
<tr>
<td>Public Charging</td>
<td>Locate and reserve charging station.</td>
<td>High availability, service differentiation may be required.</td>
</tr>
<tr>
<td>Residential Charging</td>
<td>Respond to price updates to minimize charging cost</td>
<td>Part of AMI network (see [72])</td>
</tr>
<tr>
<td>Energy Trading via V2G</td>
<td>Sell part of stored energy to make profit or use stored energy during peak hours</td>
<td>High security and availability</td>
</tr>
</tbody>
</table>

infrastructure case. They claim that NISTIR 7628 framework is not strong enough in device authorization and protecting the location privacy of mobile EVs.

6.3.4 Scalability

As the EV population is continuously going to increase for the next couple of decades, the underlying communication networks should be scalable enough to support required functionalities. Such scalability concerns can be alleviated by employing IP based network designs. Considering the big smart grid picture on mind, it is very likely that required communication networks will be based on IPv6. Moreover, IP-based solutions offer huge cost savings in deployment and maintenance [119].

6.3.5 Capacity

Since EV applications generates data traffic, the underlying communication networks should be have enough capacity to meet minimum communication requirements. For mobile EVs,
the required capacity can be measured in bits-per-second. However, for residential charging applications, the communication capacity is more likely to be measured in the maximum number of advanced meters (or smart meter) that it can support at a time (since most messages types/lengths are standard).

In a related study [67], researchers analyze the capacity of a linear chain network topology for an AMI network. They also compute the required network capacity for different amount of nodes, varying message lengths and meter reading periods (e.g. every 10 or 15 min.). They also extend their study for larger networks with different communication infrastructures.

On the other hand, capacity comes at the expense of cost. Capacity planning is a critical step as it includes trade-offs that could affect the success of EV applications. Initial deployments may seem easy and does not require high capacity networks, since EV population will be low. This will allow utilities to have a good head start with low installation cost. However, short term solutions are likely to fail to scale. Hence, the expected exponential growth in EV population may force utilities to replace the entire communication network.

### 6.3.6 Interoperability

The proper functioning of EV related applications depends on different entities such as power system and communication system to work together. According to the U.S. Independence and Security Act (2007) the National Institute of Standards and Technology (NIST) is appointed to be the main global coordination of such smart grid interoperability.

In its framework [51], NIST identifies the domains of the smart grid as; customers, markets, service providers, operations, bulk generation, transmission, and distribution. NIST conceptual framework also provides the required information exchange between these domains. EV application are unique in the sense that they bridge most of these domains. For instance, home charging deals with distribution network and the service provider, V2G deals with markets, and public fast charging is related to bulk transmission and customers.

IEEE P2030 Smart Grid Interoperability Series of Standards aims to establish an interoper-
ability framework to develop IEEE based standards on power system applications and control through the use of communication infrastructures. The first of this series IEEE Std 2030 (2011) presents communication and information networks interfaces for different domains of the smart grid. Moreover, this reference model presents the communication requirements for each interface (e.g. security, availability, latency etc.).

In addition, IEEE P2030.1 Working Group [16], develops a draft guide for electric-sourced transportation infrastructures. Also, P2030 Task Force-3 defines communication requirements between devices in the smart grid. They are going to describe the Network, Transport, and Session layers (from OSI reference model). Recently, IEEE has established a new technical advisory group (IEEE 802.24) which will work with multiple IEEE 802 working groups standards of which are very essential for smart grid communications [17].
Chapter 7

Towards a More Realistic Model: Decentralized Control Under Communication Uncertainty

7.1 Introduction

This chapter consolidates the ideas and the frameworks presented in the previous three chapters and proposes a more realistic modeling approach. Our assumption of self-interested users continues and there will be several upgrades to decentralized control framework presented in Chapter 4. First, optimal power allocation framework that considers mobile EV demand, QoS constraints, and grid constraints, is integrated. Moreover, a few upgrades are made to Electric Vehicle Admission Control framework that will be explained in the next sections.

The performance of the routing scheme is highly coupled with the underlying communication network. In order to quantify the communications system performance, we propose a Markov-Modulated Poisson Process based model. We examine four scenarios of increased complexity that gradually approximate real world experiences. The obtained results show that the proposed framework leads to substantial performance improvements in terms of the aforementioned goals,
when compared to current state of affairs. Further, we show that as the EV population increases, the network operators will need better communications technology to handle additional demand.

7.2 A More Realistic Electric Vehicle Admission Control

In section 5.2, we introduce a basic Electric Vehicle Admission Control framework. However, in real life, blocked customers may not leave the system immediately. On the contrary, a certain percentage of them is expected to wait some time and re-try the system by entering the pricing block again. Hence, in this section in order to model such cases, we upgrade the basic admission control mechanism proposed in chapter 5. Moreover, the underlying communication network in chapter 5 is assumed to be perfect. However, this is not the case in real systems as they are prone to random failures. Hence, we also consider imperfect communication system and consider the customer actions during communication uncertainties.

System Parameters

Next, we explain the dynamics of the upgraded admission control mechanism employed at a single station level. Similar to previous case, if there is no congestion it is assumed that each
Table 7.1: Systems Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_{EV}(t)$</td>
<td>EV arrival rate (charge request) to the nearest station.</td>
</tr>
<tr>
<td>$\lambda_{AC}(t)$</td>
<td>EV arrival rate who accepted the price at the nearest station.</td>
</tr>
<tr>
<td>$\lambda_{R}(t)$</td>
<td>Arrival rate of routed (from neighboring stations) customers.</td>
</tr>
<tr>
<td>$\lambda_{BL}(t)$</td>
<td>Arrival rate of blocked customers–specific percentage of EVs retry the system.</td>
</tr>
<tr>
<td>$\lambda_{RB}(t)$</td>
<td>Arrival rate of blocked routed customers –specific percentage of EVs retry the system.</td>
</tr>
<tr>
<td>$B_{EV}$</td>
<td>Blocking probability of customers (who pick the nearest station).</td>
</tr>
<tr>
<td>$B_{RB}$</td>
<td>Blocking probability of the routed customers.</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>Availability of the communication system.</td>
</tr>
<tr>
<td>$p_{normal}$</td>
<td>Normal price accepted by every driver. The same price at each station.</td>
</tr>
<tr>
<td>$p_{congestion}$</td>
<td>Congestion price depends on the station load.</td>
</tr>
<tr>
<td>$p_B$</td>
<td>Penalty paid for blocking a customer. Alleviates customer frustration.</td>
</tr>
<tr>
<td>$\delta$</td>
<td>QoS target may be different at each station.</td>
</tr>
<tr>
<td>$\lambda^*$</td>
<td>Maximum allowable arrival rate to support QoS calculated by equation 7.2.</td>
</tr>
<tr>
<td>$c_{k_{inect}}$</td>
<td>Minimum amount of desired savings to accept routing.</td>
</tr>
<tr>
<td>$c_{k_{near}}$</td>
<td>Cost to drive to nearest station.</td>
</tr>
<tr>
<td>$d_k$</td>
<td>Distance vector for each customer k.</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Vector of price tuning parameter for each station set by station operator.</td>
</tr>
<tr>
<td>$S, R, \mu$</td>
<td>Single station parameters. Denotes grid power, energy storage size, and EV charging rate respectively.</td>
</tr>
<tr>
<td>$S_{\text{limit}}$</td>
<td>Maximum power that can be drawn by a single station.</td>
</tr>
</tbody>
</table>

Customer chooses to go to the nearest station to receive service. In the EVAC model (depicted in Figure 7.1), the arrival rate for each EV is represented by $\lambda_{EV}(t)$. Each customer enters the pricing block, and $\lambda_{AC}(t)$ is the proportion of the arrival rate that accepts the offered price. Similarly, $\lambda_{R}(t)$ is the arrival rate for routed vehicles from neighboring stations and $\lambda_{AD}(t)$ is the arrival rate of admitted EVs. On the other hand some customers may choose to go to busy stations and may not get service. In order to distinguish customer weights, two types of EV blocking probability are defined: (i) $B_{EV}$: blocking of EVs who come to the nearest station (ii) $B_{RB}$: blocking of a routed EV. Further, when a customer is blocked it is assumed that he will wait some random time and going to retry the pricing block. Overall one third of the customers are assumed to retry and the rest is assumed to leave the system. $\lambda_{BL}(t)$ and $\lambda_{RB}(t)$ represents
the arrival rate for customers who retry the system.

**QoS and Pricing Block**

The blocking probability is the same as the previous version: the performance metric is denoted by \( P_{BT} \) as the weighted sum of the two blocking types: \( P_{BT} = \gamma_1 B_{EV} + \gamma_2 B_{RB} \) where \( \gamma_1 + \gamma_2 = 1 \). However, the pricing block has new components. Pricing \( P(t) \) works as follows. Let,

\[
\tilde{\lambda}_{EV} = \lambda_{EV}(t) + \lambda_{BL}(t) + \lambda_{RB}(t)
\]

(7.1)

then unless the arrival rate \( \tilde{\lambda}_{EV}(t) \) exceeds a certain threshold \( \lambda_{EV}^* \) which is related to the QoS target, the station offers normal price (the same at each station) \( p_{normal} \) that is acceptable by each customer. During a congestion period (when QoS target is violated), \( \tilde{\lambda}_{EV}(t) > \lambda_{EV}^* \), the station owner adjust prices accordingly and offer *congestion price* \( p_c > p_{normal} \), so that EVs will potentially prefer to go to neighboring (also less busy) stations. Note that the “peak hour” price is based on actual customer load on the system.

The threshold at which station operator starts to offer congestion prices. Given the serving capacity of a particular charging station (grid power-\( S \), energy storage size-\( R \), and its technology parameter \( \nu \)), the optimal arrival rate is defined as the maximum arrival threshold that the station performance stays within the QoS target \( \delta_{max} \). This can be calculated by

\[
\lambda_{EV}^* = \arg \max_{\tilde{\lambda}_{EV}} (P_{BT}(\tilde{\lambda}_{EV}) \leq \delta_{max})
\]

(7.2)

Note that QoS target \( \delta_{max} \) is specified in the Service Level Agreement (SLA). Now let us define the pricing policy employed in the Pricing Block \( P(t) \). As depicted in Figure 7.1, the pricing block \( P(t) \) determines the percentage of customers who accept the offered price at time \( t \). That is

\[
(\lambda_{EV}(t) + \lambda_{BL}(t) + \lambda_{RB}(t))P(t) = \lambda_{AC},
\]

(7.3)
which yields

\[
P(t) = \frac{\lambda_{AC}}{\lambda_{EV} + \lambda_{BL} + \lambda_{RB}} \leq \frac{\lambda_{EV}^*}{\lambda_{EV}}
\]  

(7.4)

This indicates that the percentage of customers who would accept the offered price is inversely proportional to the load on the system. Thus, as the arrival rate \( \bar{\lambda}_{EV} \) increases, the station operator will increase the prices and less customers will accept the price. Note that \( D(p_{normal}) = 1 \) meaning that all customers accept this price. It is well-known that demand functions describe the sensitivity of customers to the price changes, that is

\[
p(t) = D^{-1} \left( \frac{\lambda_{EV}^*}{\lambda_{EV} + \lambda_{BL} + \lambda_{RB}} \right)
\]  

(7.5)

where \( \frac{\lambda_{EV}^*}{\lambda_{EV} + \lambda_{BL} + \lambda_{RB}} \) is the load on the system. Various demand functions –for services providing QoS in congested networks– have been proposed in the literature. In this work, we use the demand function proposed in [50]. Then, \( p(t) \) the price at time \( t \) becomes:

\[
p(t) = \begin{cases} 
p_{normal} & \text{if } \bar{\lambda}_{EV}(t) \leq \lambda_{EV}^* \\
p_c = p_{normal} \left\{ 1 + \theta \sqrt{-\log \left( \frac{\lambda_{EV}^*}{\lambda_{EV} + \lambda_{BL} + \lambda_{RB}} \right)} \right\} & \text{if } \bar{\lambda}_{EV}(t) > \lambda_{EV}^* \end{cases}
\]  

(7.6)

When congestion occurs in a charging station \( \bar{\lambda}_{EV}(t) > \lambda_{EV}^* \) resource pricing according to the customer load will improve the QoS deteriorations.

### 7.3 Resource Allocation in a Network of Fast Charging Stations

As the limitations of the power grid prevent charging stations from providing more serving capacity, grid operators have to consider the spatio-temporal customer demand to optimally allocate the available grid power. Let us assume that \( N \) charging stations are employed in a serving area and let \( l = 1, 2, ..., N \) be the index set and \( \mathcal{N} \) be the set of charging stations.
Further, let $S_{\text{max}}$ be the maximum portion of generation capacity that the utility can provide to charging network. Then considering the spatial distribution of vehicles and the discretization assumption at each charging station, network operator aims to maximize the serving capacity by optimally allocating the power resources. To this end, network owner solves a two phase resource allocation problem:

**Phase-I**

\[
\begin{align*}
\min_S & \quad \sum_{i \in l} P_b^{(i)}(\lambda_i, S_i, R_i) \\
\text{s.t.} & \quad \sum_{i \in l} S_i \leq S_{\text{max}} \\
& \quad \delta_{\text{min}} \leq P_b^{(i)}(S_i, R_i, \lambda_i) \leq \delta_{\text{max}} \\
& \quad S_i \in \mathbb{Z}^+, \delta_{\text{min}}, \delta_{\text{max}} > 0 \\
& \quad R_i \text{ and } \lambda_i \text{ are given, } \forall i \in l
\end{align*}
\]

(7.7)

Further, given any set of station locations and the EV spatial distribution, arrival rates for each station ($\lambda_i$) can easily be calculated from a discrete event simulation [30]; details given in the next sections. Also note the blocking probability has a lower bound $\delta_{\text{min}}$ (typically around 0.01%) which prevents capacity planners from over-provisioning serving capacity. However, in reality, the result of the optimization problem ($\tilde{S}$) is constrained by the power grid operation limitations. Hence another constrained $S_i \leq S_{\text{limit}}$ which dictates the upper limit for the grid power that can be drawn, is introduced. Then, if $\sum_{i \in l} S_i < S_{\text{max}}$, meaning that one or more stations cannot get optimal $S$ due to power grid limitations, the excessive power,

\[
S_{\text{excess}} = S_{\text{max}} - \sum_{i \in l} S_i
\]

(7.8)

is allocated among the neighboring stations inversely proportional to the physical distance between stations.

Let $\Psi \subset \mathcal{N}$ be the subset charging stations which have excessive power. Suppose that station
$j \in \Psi$ has excessive power $S_j^{\text{excess}}$. Then in Phase-II a neighboring station-$k \in N \setminus \Psi$ gets an extra $S_{kj}^{\text{extra}}$ amount of power from station-$j$, that is:

**Phase-II**

$$S_{kj}^{\text{extra}} = \left[ S_j^{\text{excess}} \omega_k \right], \text{where } \omega_k = \frac{1}{d_{kj}^2} \left( \sum_{z \in N \setminus \Psi} \frac{1}{d_{zk}^2} \right)^{-1} \tag{7.9}$$

where $d_{zj}$ is the physical distance between stations $z$ and $j$. A simple example follows to better clarify this point. Assume four stations serve a neighborhood, and station-1 has excessive power of six units. Other three stations do not have excessive power and they will share six units of power according to equation 7.9. Let us assume that $d_{21} = 1$, $d_{31} = 2$, and $d_{41} = 2$ units of distance. Then, the excess power would be allocated as $S_{21}^{\text{extra}} = 4$, $S_{31}^{\text{extra}} = 1$, and $S_{41}^{\text{extra}} = 1$. Notice that the power allocation is inversely proportional to the inverse of the square of the physical distance. The main reason is that in the event of congestion, offering enough incentives to customers in order to convince them to drive distant miles could be a challenging task. Thus, since closer station (in this case station-2) will serve most of the station-1’s customers, it gets a bigger portion.

### 7.4 Decentralized Control

The decentralized framework provided in Chapter 5 will also be employed here: the charging network owner acts as a *leader* who can commit to a strategy before *followers* (customers) can pick their strategies. In this respect, a Stackelberg game (leader-follower game) is employed to model this system. First, we define the game in its strategic form

$$\Gamma = \{ \mathcal{N} \cup \mathcal{K}, \{ \vec{p}_k \}, \{ X_{k \in \mathcal{K}} \}, \{ U_{n \in \mathcal{N}} \}, \{ U_{k \in \mathcal{K}} \} \} \tag{7.10}$$

where $\mathcal{N} = \{1, \cdots, N\}$ is the set of charging stations and $\mathcal{K} = \{1, \cdots, K\}$ the set of EVs that require charging at a given time. The strategies of each set of players are as follows. $\{ \vec{p}_k \}$ denotes a $1 \times N$ price vector offered by the charging network operator. Note that to set the
pricing vector station operator also need to set $\{\theta\}$ for each station. The rationale behind setting this parameter stems from the fact that in order to convince people to change their electricity consumption during rush hours, or in our case where to charge their EVs, the ratio of peak-to-off-peak hour should be some positive number that is greater than one [48]. The parameter $\theta$ is set to maintain such incentives for customers. The EVs strategy, $X_k$, is to pick a charging station from $\mathcal{N}$. $U_n$ and $U_k$ are the utility functions that represent the payoffs for the both players. The game in its extensive form is given in Figure 7.2. Next, we describe the components of the game in detail. The formulations for the game theoretic approach is given in section 5.3, however the algorithm to solve the routing mechanism is updated as the communication uncertainties need to be considered as well. Hence, the algorithm to solve the new load balancing mechanism is presented in Algorithm 2.

7.5 Numerical Results

In this section, we illustrate the proposed resource allocation and EV routing scheme. The charging station layout and the spatial distribution assumptions are the same as the previous case and presented in figure 5.10 and equation 5.16. As depicted in this figure, half of the EV population resides in the lower left of the area (e.g. downtown region etc.) under consideration, while the remaining half in the rest of the area. Given this spatial distribution of customers and
Algorithm 2 Decentralized Control

Require: $\theta \geq 0$, $|\mathcal{N}|, |\mathcal{K}| \in \mathbb{Z}^+$

for customer-$k \leftarrow 1$ to $K$ do
  if available communication then
    network owner offers $\bar{p}_k(\theta) \in \mathbb{R}^\mathcal{N}$ to Eq.(5.13)
    calculate utility $\bar{U}_k \in \mathbb{R}^\mathcal{N}$
    pick station $n = \text{indexOf}(\min(\bar{U}_k))$
    enter station, set $\bar{e}(n) = 1$
    if gets service then
      set $\bar{q} = \bar{e}(n)$, $\bar{q}_B = \bar{0}$
    else
      set $\bar{q} = \bar{0}$, $\bar{q}_B = \bar{e}(n)$
    end if
  else
    pick station-$n$ w.p. $\mathbb{P}\{X_n = n\}$ (eq.7.19)
    enter station, set $\bar{e}(n) = 1$
    if gets service then
      set $\bar{q} = \bar{e}(n)$, $\bar{q}_B = \bar{0}$
    else
      set $\bar{q} = \bar{0}$, $\bar{q}_B = \bar{e}(n)$
    end if
  end if
end for
in the absence of a decentralized control mechanism, EV demand for each charging node would be 1%, 50%, 42%, 2%, and 5% for stations 1 – 5, respectively. As a baseline scenario we assume that no allocation or customer routing of any kind takes places. To begin with, let us assume that the utility company can provide $S_{\text{max}} = 39$ units of power and the distribution grid constraint $S_{\text{limit}} = 13$. For the baseline scenario stations get $\vec{S}_i = [7, 8, 8, 8, 8]$ respectively. In this case the blocking probability performance of five stations would be $\vec{B}_i = [\sim0, 0.46, 0.36, \sim0, \sim0]$. This entails to a highly undesirable situation; stations 2 and 3 performs a very bad service, whereas neighboring stations are over-provisioned and the serving resources are wasted. Our two step framework, optimal resource allocation and customer routing will improve the system performance, hence the percentage of served customers significantly. Details are presented next.

Given the customer demand for each station as the baseline scenario, the serving capacity is allocated among the stations according to equations (7.7) and (7.9). Then the optimal resource allocation would be $\vec{B}_i = [6, 13, 13, 3, 4]$. Note that due to power grid constraints, the excess power $S_2^{\text{excess}} = 5$ and $S_3^{\text{excess}} = 2$ is allocated to stations 1, 4, and 5 as [5, 1, 1]. Moreover, the charge rate to satisfy one EV charging request is $\mu_1 = \ldots = \mu_5 = 2$, while the charging rate from
local energy storage unit is \( \nu_1 = \ldots = \nu_5 = 3 \). Also, each station employs an energy storage size of \( R_i = 8, \forall i \in \mathcal{N} \).

The details of the discrete event simulation is presented next. The network-wide charging requests (or arrival rate) is depicted in Figure 7.3. EV demand at each station is proportional to the traffic load calculated above; for instance, for station-2 it is about \( \lambda_2(t=8\text{am}) = 40 \times 0.5 = 20 \). The charging station operator aims to provide service to the EVs with QoS guarantee \( \delta = 0.05 \) and dissatisfaction parameter \( \xi = 0.1 \) for all customers. Based on these charging station parameters, the leader (system operator) solves equation 7.2 and initiates the routing game only when the arrival rate exceeds this threshold, which corresponds to the following thresholds for each individual station: \( \tilde{\lambda}_i^* = [6.7, 23.4, 23.4, 3.3, 5.0] \). Since it may be challenging (and possibly wasteful) to update arrival rates in real time, we set 15 minute intervals at which arrival rates are recalculated. Just to clarify how resource allocation improves the system performance, let us compare it with baseline scenario at 4pm according to weighted sum of overall system performance using the formula given below:

\[
\sum_{i \in \mathcal{I}} w_i B_i, \text{ where } w_i = \frac{\lambda_i}{\sum_{i \in \mathcal{I}} \lambda_i}
\]

where \( \lambda_i = \tilde{\lambda}_{EV} \). Then, the weighted sum of the baseline scenario and the power resource allocation would be 0.38 and 0.10 which leads to more efficient use of grid resources.

The details of the customer routing framework is discussed next. In the absence of congestion \( (\lambda_i < \lambda_i^*) \), customers pay the operator \( p_{\text{normal}} = 4 \) units, whereas if EVs are blocked the operator rewards them with \( p_{\text{block}} = 6 \). As mentioned before, this cost is a penalty to the operator for poor service which can impact customer loyalty and its long term reputation. Also, to calculate blocking probabilities we set \( \gamma_1 = 0.45 \) and \( \gamma_2 = 0.55 \). For the \( k \)-th EV, \( c_{k,\text{inact}} \) is a uniformly distributed random number in the interval \([0.75, 1.0]\) and \( p_{\text{dis}} \) is a uniformly distributed random number (per unit of distance) in the interval \([0.02, 0.05]\). We assume that driving duration is linearly correlated with distance (based on an average speed of 40 mph). Currently popular EV
models (e.g. Nissan Leaf) exhibit 0.22 kWh/mile energy consumption; thus, we set $p_{\text{drive}} = 0.03$ per unit of distance.

Next, the strategy of the leader (setting the tuning parameter vector $\theta$) is given. As stations 1, 4, and 5 operate under light traffic, the operator is motivated to shape excessive demand at stations 2 and 3 and route customers to these stations. For the given arrival rate at $(\lambda(t = 4pm))$, we set $\theta_1=\theta_4=\theta_5=0.5$ and investigated how $\theta_2$ and $\theta_3$ affects the blocking probability at these stations. As depicted in Figure 7.4 station-2 and 3 violate $\delta_{\text{max}} = 0.05$ QoS policy, however station operator increases $\theta_2$ and $\theta_3$ to set the congestion prices and start routing customers to neighboring stations. Our customer routing framework enables stations to meet SLA agreements. Note that $\theta_2, \theta_3 > 0.4$ does not lead to further reduction in blocking probability because the neighboring stations also hit $\lambda^*$ and does not accept more customers. Similarly, Figure 7.5 shows the load balancing framework. Notice that for low customer demand there is no need for customer routing scheme because the regional serving capacity resources suffice the demand. On the other hand as stations become more congested customers are routed to neighboring stations. One important point of consideration is that since station-1 is physically more close to congested stations 2 and 3, more customers accept (almost 11% of the population) to go to this station. The proposed decentralized control mechanism is simulated with the given set of parameters and compared to baseline and power allocation scenarios. The performance of the most congested station (station-2) is presented in Figure 7.6. It can be seen that the percentage of served customers can be increased significantly by employing proposed framework. We further compare the network-wide weighted-sum of blocking probabilities and the net revenue. In Figure 7.8 and the details will be explained in the next section. The main finding of this result is that as the network operator optimally allocates grid resources and do load balancing, the utilization of each charging station will increase, and hence more customers will be served with the same amount of grid resources. A parallel finding is depicted in Figure 7.9, by employing proposed framework network operator increases her profit tremendously.
7.6 Communication System Performance

The successful deployment of the coordination mechanism discussed in the previous section, heavily depends on the availability of the necessary communication infrastructure to ensure reliable information dissemination. In our framework, mobile EVs use wireless communication technologies to locate and retrieve pricing information. On the other hand, wireless communications enable the network operator to monitor station usage, update prices and forward them to EVs. Hence, it is crucial to identify the communication system requirements and quantify its impact on the performance of the charging stations. In Chapter 6, we discuss candidate communication technologies. In this section, we propose a Markov Modulated Poisson Process (MMPP) based stochastic model to quantify the cost of the communication system performance. Finally, we present a case study complementing the one discussed in section 7.4. The primary performance concern of the candidate technologies is the system availability as 3G and 4G technologies can easily support the required bandwidth and the proposed coordination framework can handle medium level latency (a few seconds) [8]. On the other hand, the proliferation of mobile internet users leads to significant deviations of the user experience from theoretical
results. To that end, measurement based studies can provide more insights in the availability performance of aforementioned communication technologies. There are only a handful of measurement based studies that focuses on the performance of the wireless network (Wi-Fi, 3G (UMTS), EV-DO, and WiMAX) [88, 89, 24]. [89] presents an architecture to improve end user experience by exploiting; (i) channel diversity, (ii) wireless network service provider diversity, and (iii) technology diversity (UMTS, CDMA, etc.). Their results shows that the proposed Mobile Access Router architecture decreases the blackout periods considerable and increases average throughput. In addition, [88] shows the results of a city-wide mobile internet experimentation results. The mobile nodes in their test bed employs both EV-DO and WiFi interfaces. Their focus is on measuring the signal latency and TCP throughput performance.

The theme of the study presented in [24] is closest to our communication framework. A measurement study was undertaken to evaluate the performance of mobile Internet access with 3G (UMTS) and Wi-Fi networks. Measurements were obtained in Seattle, San Francisco, and Amherst. Across all cities, the average availability of 3G and WiFi is 87% and 11% respectively.
The details of the study’s findings are presented in Table 7.2. In addition, it is established that unavailability of communications for intervals of 50 seconds is 5% for a small city like Amherst. The study also proposed a hybrid framework to improve the availability of 3G by augmenting it with WiFi.

Table 7.2: Availability Performance of Wide Area Wireless Technologies [24]

<table>
<thead>
<tr>
<th>Technology</th>
<th>Amherst Average Peak</th>
<th>Seattle Average Peak</th>
<th>San Francisco Average Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>3G (UMTS)</td>
<td>90% 85.5%</td>
<td>82% 79%</td>
<td>89%</td>
</tr>
<tr>
<td>WiFi</td>
<td>12% 10%</td>
<td>10% 8.5%</td>
<td>11%</td>
</tr>
</tbody>
</table>

7.6.1 The Cost of Unavailability of the Communications System

As previously discussed, loss of communications will terminate the EV to grid interaction. During blackout periods, customers will not be able to retrieve pricing information which would
lead to suboptimal charging station selection. For instance, if an EV does not receive any pricing signals, he will just choose to go to nearest station-$n \in \mathcal{N}$. However, if the station is congested while there is an idle neighboring station, that particular customer will pay extra money. In the same scenario, blocking that customer will have a cost to the network operator. Then the total cost of communication system unavailability becomes:

$$Cost_{\text{Communication Unavailability}} = Cost_{\text{Suboptimal Station Selection}} + Cost_{\text{Blocking Customer}}$$  \hspace{1cm} (7.12)

Let us assume that $cost_{min}$ is the maximization of the customer utility presented in equation 5.13 when the communications system is properly functioning. When it is unavailable, an additional cost would occur if the customer pays congestion price $p_c$ to the nearest station instead of paying $cost_{min}$; hence, the corresponding cost would be

$$Cost_{\text{Suboptimal Station Selection}} = p_c - cost_{min}$$  \hspace{1cm} (7.13)

which is lower bounded by zero. On the other hand the expected cost of rejecting a customer depends on the blocking probability performance of the nearest station-$n$ that is

$$P^n_B = f(S^n, R^n, \nu^n, \lambda_{AC}(t))$$  \hspace{1cm} (7.14)

Then the expected cost of blocking a customer becomes

$$\mathbb{E}(Cost_{\text{Blocking Customer}}) = P^n_B p_B$$  \hspace{1cm} (7.15)

where $p_B$ is the penalty paid to blocked customer. Next we explain our performance evaluation framework.
Figure 7.7: MMPP Model for Communication System Performance. Note that rates $\alpha_{i,j}$ and $\beta_{i,j}$ represent generic transition rates.
7.6.2 Performance Modeling

Communication system availability models and the corresponding performance evaluation techniques have been very well studied in the literature [60, 80, 36, 44]. The availability of a communication system is the probability that the system works under normal operation conditions. Corollary, the availability \( A \) can be calculated from the ratio of the uptime of the system to the total operation time (uptime plus downtime). The operation of communication systems are subject to failures due to a variety of reasons such as human errors, software or hardware faults, and damage from harsh environments. [44] presents an analytical approach to 3G (UMTS) cellular base station. They show that the availability of UMTS depends on the availability of four system components (Node-B, Radio Network Controller (RNC), Service Gateway Support Node (SGSN), and GPRS Gateway Support Node (GGSN)) and can be computed by:

\[
A = A_{\text{Node-B}} \times A_{\text{RNC}} \times A_{\text{SGSN}} \times A_{\text{GGSN}}.
\]

The second group of approaches include modeling the system availability with continuous time Markov chains (CTMC) [60, 80, 36]. For instance in a telecommunication system failure and repair times of each component are assumed to be exponentially distributed and availability is calculated from the steady state probability distribution. In this work we also follow a similar approach and represent the communication system using CTMC. The details are given next.

7.6.3 MMPP Model

Let us assume that \( N \) independent base station serve \( N \) geographically clustered regions. On the other hand, the communication between stations and the network operator is provided via wireline communications, so even if the customers associated with a particular stations could not retrieve a global pricing information, customers at other regions can still learn the charging prices of that station, and may be routed if needed. As presented in the previous section the steady state solution of the Stackelberg game depends on the disseminated pricing information. Hence, the solution of the decentralized control mechanism depends on the “health” or availability of the communication system. We assume that communication system failure rate
is $\alpha_i$ and repair rate is $\beta_i$ (both exponentially distributed) for communication network $i \in N$. For instance the probability of being “healthy” of a particular communication can be calculated as $\frac{\alpha_i}{\alpha_i + \beta_i}$. The corresponding CTMC represents each possible state of the communication system availability with the following state space $\Delta = \{(\tau_1, \tau_2, ..., \tau_N), \tau_i \in (0, 1), 1 \leq i \leq N\}$ and the total number of states is $2^N$. For instance state $(0,0,0,...,0)$ represents when all the system up and available. Similarly state $(1,1,1,...,1)$ represents that all stations are unavailable. The corresponding Markov chain is depicted in Figure 7.7. Note that each column, starting from the right of the initial state, represents the number of unavailable base stations (column one shows states with one base station unavailable, etc.).

$$Q = \begin{pmatrix}
\bar{a}_{11} & \alpha_1 & \alpha_2 & \cdots & \alpha_{N+1} & 0 & 0 & 0 & \cdots & 0 \\
\beta_1 & \bar{a}_{22} & 0 & \cdots & 0 & \alpha_2 & \alpha_3 & 0 & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
\beta_{N+1} & 0 & \cdots & 0 & \bar{a}_{NN} & \alpha_{N-1} & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & 0 & 0 & \cdots & 0 & \beta_1 & \cdots & \bar{a}_{\kappa} \end{pmatrix}$$  \hspace{1cm} (7.16)

It is easy to see that a unique steady state distribution would exist which can be calculated by solving:

$$\bar{\pi}Q = 0 \quad \text{and} \quad \bar{\pi}e = 1$$  \hspace{1cm} (7.17)

where $e$ is a column vector whose elements are all equal to 1, and $Q$ is a $2^N \times 2^N$ matrix containing the transition rates and $\bar{\pi}$ a vector of length $2^N$ containing the steady state probabilities. Note that the elements of $Q$ satisfy $\alpha_{ab} \geq 0$ for $a \neq b$ and $\alpha_{ab} = -\sum_{a=1,b\neq a}^{2^N} q_{ab}$ for all $a = 1, 2, \ldots, 2^N$. The performance of the decentralized control mechanism depends heavily on the availability of the underlying communication network. Hence for at each state of the CTMC, the Stackelberg game reaches different customer allocation equilibrium due to available information. The variations of the arrival rates for each station are modeled by a Markov Modulated Poisson
Process, at each state the steady state solution is of each station is represented by the vector \( \mathbf{J}_i = [\lambda_1, \lambda_2, \ldots, \lambda_N] \). For instance when the base station serving the station-2 customers is down, then the game will be played by the customers of stations 1, 3, 4 and 5.

In this case, the percentage of cost due to unavailability can be calculated by taking the ratio of the expected revenue \( (\mathcal{P}_i, i \in N) \) obtained at each state and the revenue obtained at state-1 \( (\mathcal{P}_1) \) when there is a perfect communication. Also note that the very rightmost state in the Markov chain corresponds to the case without any control mechanism. Then,

\[
\text{RevenueLoss} = \frac{1}{\mathcal{P}_1} \sum_{i=1}^{N} \bar{\pi}_i \mathcal{P}_i
\]

(7.18)

### 7.7 Case Study

In order to quantify the performance of the communication system, we run a discrete event simulation with the same set of parameters from the previous section, this time by considering the communication system performance. When the communication system is unavailable EVs will simply go to the nearest station. However, customers in the borders may not exactly choose the nearest station. Hence we assume that those customers will choose the station at random and the corresponding station selection probabilities depend on the physical distance of customer to each station. Further, the set of stations considered for this selection includes the ones whose distance is at most 25% more than the nearest station. Let \( \Omega \subset N \) be the subset of such stations and \( d_n, n \in \Omega \) is the distance of a customer to station \( i \). Then the probability of choosing station-\( i \) can be calculated as

\[
\mathbb{P}\{X_n = n\} = \frac{1}{d_n} \left( \sum_{i \in \Omega} (d_i)^{-1} \right)^{-1}
\]

(7.19)

In the first set of simulation, we quantify the performance of the communication in terms of the increase in the blocking probability for all four cases. The rates for the MMPP model are calibrated from [24]. For stations 1, 4, and 5 \( \frac{\alpha_{4,5}}{\alpha_{1,4,5} + \beta_{4,5}} = 0.05 \). Since this rate will be higher for
more dense regions, for busy stations 2 and 3 \( \alpha_{2,3} + \beta_{2,3} = 0.1 \). As presented in Figure 7.8 as the resource and customer routing capabilities increase the weighted sum of the blocking probabilities decrease and the more customers can be served with the same amount of grid resources. Also note that even for moderate customer arrival rate (given in Figure 5.4) the loss of communication considerably degrades the blocking probability performance. Similarly, we compare our resource allocation and decentralized control framework for net revenue calculations. As presented in Figure 7.9 the network operator maximizes her revenue when she can optimally route customers under perfect communication scenario. Our decentralized control mechanism increases the network revenue tremendously. Next we investigate the relationship between the EV population and the communications system performance. As the EV population increases, the communication of pricing information in a timely manner will become more prominent in order to optimally balance the load at each station. In our scenario since stations 2 and 3 gets the majority of the customer by default, the congestion at these stations will not be alleviated if the communication system is down. The corresponding results are depicted in Figure 7.10; the
revenue of the station operator decreases as the EV population increases. Further we evaluate the revenue loss for three different ($\alpha_1=\alpha_2=0.05$, $0.10$ and $0.15$) communication system performances. The results indicate that as the EV penetration increases network operator needs to employ a better communication network in order to manage excessive EV load.

Figure 7.9: Comparison of Station Operator’s Net Revenue

Figure 7.10: Revenue Loss vs EV Population
7.8 Conclusion

In this paper, we introduce a Stackelberg game theoretic based control mechanism to manage a population of self-interested mobile EVs. The aim of the leader (Network Operator) is to serve more customers with the same amount of grid resources, while the goal of the EV followers (EV drivers) is to get the charging service at a minimum cost. Utility functions are developed to represent the behavior of both parties. Further we investigate the performance of the underlying enabling communication technology. We present a methodology to quantify the cost of communication unavailability. We conclude that as the EV population increases, the performance of the communication system will be more crucial. Hence, networks operators may need to use dedicated communication technologies such as Wireless Mesh Networks, instead of shared cellular communication.
Chapter 8

Capacity Planning at Large Scale Charging Stations: A Stochastic Modeling Approach

8.1 Introduction

In the past chapters, we present a stochastic modeling approach to electrification of transportation. We consider three main blocks: first we propose a small scale fast charging station architecture. In the second part, we present optimal load balancing and customer routing frameworks in a network of charging stations, and finally in the third part communication system performance is considered.

In this chapter we extend our modeling framework to large scale charging stations. Such facilities are essential for the mainstream adoption of EVs/PHEVs, and probably represent the only option for drivers living in densely populated areas. They could also provide complementary service to extend the EV range for drivers who also have access to domicile charging. On the other hand, since these stations will mainly operate during the day, stochastic customer demand exerted on the power grid may threaten its reliability. Hence, the problem of electric
power resource provisioning should be carefully considered. In this study, we propose a capacity planning framework by exploiting the stochastic behavior of customer demand at each charging slot in large capacity stations. Our framework assigns a constant power to each charging slot. Thus, aggregated stochastic demand is approximated by a deterministic quantity, at the price of denying service to a very small percentage of customers. Our model leads to significant savings in power provisioning and provides critical insights about the design of charging station.

The deployment of such charging facilities is not merely a matter of equipping existing ones with the necessary chargers. As a number of studies have shown, a large scale EV charging station can be equipped with either level-2 single or three phase or fast DC charging technology [45]. All these technologies represent large additions to the existing power grid. For instance, during a 30 minute period, level-2 single phase (3.3kW), level-2 three-phase (6.6kW), and DC fast charge (50kW) can enable a typical EV to drive 5.5, 11, and 83.4 miles, respectively [85].

On the other hand, such infrastructure is critical to EV adoption, since according to a recent survey [86], even with the current adoption level, 30% of vehicles use public charging regularly and 40% of EV drivers travel farther than their all-electric-range and hence need to use public charging to complete their daily trips.

Electric power provisioning for charging facilities is a critical step. Roughly a 22-mile electric drive requires the same amount of energy consumed in one day in a typical household. Given that to some extent, the power grid has been running close to its operating limits, in the longer run expanded capacity will be required. For example, in [57] it is argued that if just 5% of all EVs charge simultaneously at fast charging stations, 5 GW of extra power would be needed by year 2018 in the VACAR region (Virginia - North Carolina - South Carolina). Similarly, [68] shows that if each of the NERC regions were to have 25% EV penetration by year 2030, each territory would need a 5.5% increase in power generation.

A parallel concern includes the corresponding upgrades of the distribution network; for instance, utilities are likely to replace aging transformers especially in areas with large charging facilities to accommodate expanding power demand. Hence, sizing the distribution network
for supplying power to large scale charging facilities is of key importance. Over-provisioning by considering peak loads would be conservative and utterly expensive; on the other hand, undersizing would lead to overloads and ultimately grid failures. Controlling EV chargings in a large scale facilities has been the subject of study in numerous papers (see e.g. [38, 111, 73] and references therein). Specifically, authors of [38] consider a large scale EV charging facility and proposes a deadline scheduling algorithm with a pricing based admission control. Researchers in [111] use swarm optimization techniques to allocate power to customers in large scale charging stations, while the work presented in [73] proposes an energy management system to control the demand of large number of EVs parked in a municipal parking deck. These studies assume that charging takes a fairly long amount of time (between 3-5 hours). Hence, the primary goal is to optimize power flow and maximize station profit by serving as many customers as possible. In this work, we assume that charging lasts a relatively short period (less than 30 minutes on average) and we focus on maximizing the number of EVs served over a long time horizon, while accounting for the stochasticity of customer demand.

The proposed framework is rooted in teletraffic theory, where the problem of providing statistical quality of service guarantees to broadband network traffic was addressed [69]. Early models focused on sizing communications links for voice traffic. However, as packet switched networks became prevalent, the focus shifted on developing admission control algorithms that control the packet loss probability [71]. The model considered in this study has similarities to bufferless multiplexing of communication network traffic resources. There has been extensive work on this subject and the main approaches to calculate the required loss probabilities are: (i) those based on queueing theoretic models that can provide exact results under certain simplifying assumptions and (ii) those based on approximate fluid models. In this paper, we adopt the former approach but consider a bufferless system, which is reasonable given the long service times faced by arriving EVs. The latter assumption simplifies the calculations for the key performance metric of blocked EVs.

1In teletraffic theory loss probability represents the percentage of cells or packets that are dropped or rejected. In this paper this metric represents the percentage of customers that cannot get service.
8.2 Problem Formulation

8.2.1 System Description

Consider a large scale EV charging station comprising of \( i = \{1, 2, ..., N\} \) charging slots. The total aggregated power drawn from the grid is \( P \). EVs arrive to the facility according to a Poisson process of rate \( \lambda \) [30]. During service, a customer at charging slot \( i \) draws constant power \( R_i \) to fill up the EV battery. Currently, there exists an array of EV models with different battery sizes [27]. Thus, we further assume that service durations (charging) are independent and exponentially distributed with parameter \( \mu \). Hence, each charging slot can be modeled as a two state (On/Off) continuous time Markov chain, with the On state representing EV charging and the Off state when the slot is unoccupied. This is depicted in Figure 8.1. Note that under the above stochastic assumptions on the EV arrival and service process, the long term probability that slot \( i \) is in the On state is \( p_i = \lambda_i / (\lambda_i + \mu_i) \). In the remainder of the chapter, for ease of presentation we assume that the Markov chain operates in discrete times, since a number of calculations simplify considerably. However, as shown in [74], the obtained results are very similar to the continuous time process.

Define by \( X_i(s) \) the amount of power drawn by charger-i in time period-s. Since the time slots are interchangeable (i.e. \( p_i = p \) for charging slots \( i \)), then the distribution of \( X_i(s) \) is given
by:

\[ X_i = \begin{cases} 
R_i, & \text{with probability } p \\
0, & \text{with probability } 1 - p 
\end{cases} \]  

(8.1)

Note that from a capacity planning point of view, the worst case approach would be to allocate the peak rate \( R_i \) to each charging slot, that is the total power allocated to the facility is \( P = \sum_{i=1}^{N} R_i \). However, note that the expected power is given by

\[ \sum_{i=1}^{N} R_i p_i < P, \]  

(8.2)

provided \( 0 < p_i < 1 \) for all \( i \). The question is whether the expected power is a good guideline for provisioning the charging facility or one needs to determine some other level. To address this question, we would look for a level of power provisioned by the grid, that the actual EV demand would rarely exceed. This is the concept of effective power derived next.

### 8.2.2 Determining Effective Power

As previously discussed, we are interested in calculating effective power \( R_{ef} \), so that the charging facility can serve \((1 - \epsilon) \times 100\%\) of the customers in the long run. Typical values for \( \epsilon \) range between \(10^{-4} - 10^{-5}\) and correspond to the probability that an arriving EV would be denied service (depicted in Figure 8.2). Note that this blocking probability would serve as our quality of service (QoS) metric. We are interested in the long term fraction of time slots that EV demand for power exceeds the allocated amount of power \( R_{ef} \). Since, the \( X_i(s) \) are independently distributed, they form a stationary and ergodic process, we obtain

\[ \lim_{t \to \infty} \frac{1}{t} \sum_{s=0}^{t-1} \left\{ \sum_{i=1}^{N} X_i(s) > R_{ef} \right\} = P \left\{ \sum_{i=1}^{N} X_i > R_{ef} \right\}, \]  

(8.3)

where \( 1_{(\cdot)} \) denotes the indicator function. Since all charging slots are identical, we can write \( R_{ef} = Nr \).
We are then interested in finding $r$ such that the following holds:

$$P\left\{ \sum_{i=1}^{N} X_i > Nr \right\} \leq e^{-\delta}$$

(8.4)

Applying Chernoff’s bound [69], we obtain

$$P\left\{ \sum_{i=1}^{N} X_i > Nr \right\} \leq e^{-NA(r)}$$

(8.5)

where,

$$A(r) = \sup_{\theta > 0} \left\{ \theta r - \log E\{e^{\theta X}\} \right\}$$

(8.6)

is the rate function. Here, $\theta$ is a positive parameter that maximizes the rate function. We call the parameter $r$ the effective power of charging slot $i$. It is worth noting the direct analogy to the concept of effective bandwidth in teletraffic theory. The properties of the rate function $A(r)$ are as follows:

1. Function $f(\theta, r) = \theta r - \log E\{e^{\theta X}\}$ is convex in $r$ and concave in $\theta$. The proof is trivial, effective power $r$ and function $f(\cdot)$ have linear relation which is convex. For the second part, proving the convexity of the $log \ E(\cdot)$ would be enough. To do so, one can apply the definition of convexity and the proof can be completed using Hölder’s Inequality (see [33]).
2. As a corollary, the supremum over $\theta$ can be achieved and located through a search process.

3. For stability, the effective power is greater than or equal to the expected power demand ($r \geq \mathbb{E}(X)$) and less than or equal to the peak power demand $R$.

4. Note that the rate function $A(r) > 0$ for $r > \mathbb{E}(X)$ and $A(\mathbb{E}(X)) = 0$. To prove this property we take the derivative of $f(\theta, r)$ with respect to $\theta$ at the origin ($\theta = 0$);
$$\left. \frac{\partial f(\theta, r)}{\partial \theta} \right|_{\theta=0} = r - \mathbb{E}\{X\}$$. The derivative will be positive since $r > \mathbb{E}(X)$, hence $A(r) > 0$. For the second case, $r = \mathbb{E}(X)$, then the slope will be zero at the origin and since $f(\cdot)$ is concave in $\theta$, supremum will occur at the origin, thus $A(\mathbb{E}(X)) = 0$.

Next, we are interested in investigating the behavior of the obtained probability bound $(P \left\{ \sum_{i=1}^{N} X_i > Nr \right\})$. Cramer’s theorem guarantees that for very large $N$, the obtained bound would be tight, while for relatively small $N$ it can become fairly loose [74]. This is the primary reason, we are considering large scale charging facilities in this study.

### 8.2.3 Multiplexing Gains

Next, we formally define the benefits of using effective power to allocate grid power to a large scale EV charging facility. Note that as the number of charging slots goes to infinity then the effective power per charging slot approaches the mean slot demand $pR$. The advantage of using this framework is to either decrease the number of charging slots so that overall physical space of the charging facility can be reduced or serve more customers with the same amount of charging slots. This multiplexing gain is defined as:

$$\frac{\# of \text{ chargers employed with statistical QoS}}{\# of \text{ chargers employed if each slot is provisioned at its peak rate}} \quad (8.7)$$

Since for very large $N$, the required capacity will be $pR$ (mean demand), the multiplexing gain can not exceed

$$\frac{P/(pR)}{P/R} = \frac{1}{p} \quad (8.8)$$
8.3 Numerical Results

In this section, we will present three different types of examples. We start by exploring the system dynamics and present generic evaluation and guidelines. The second example is from the capacity planning point of view; given the EV population of a region, we use effective power allocation to calculate the required capacity of the charging station. We also calculate the relation between number of charging facilities and gains with statistical multiplexing. In the third example, we introduce a profit model which captures the cost of required upgrades in the distribution network.

8.3.1 Toy Example-I

Next, we present sample calculations on how to compute the effective power for a large scale EV charging station. Let us assume that there are 100 charging slots available in the facility. During service, each charger draws 3.3 units of constant power (this can be considered as a single phase level-2 charger). Also assume that for each slot $i \in \{1, 2, ..., 100\}$, $R_1=R_2=\cdots=R_{100}$. Further,
The concavity property of the rate function is used to calculate the effective power. The optimal \( \theta \) that maximizes the rate function can be calculated as follows:

\[
\frac{\partial f(\theta, r)}{\partial \theta} = 0 \rightarrow \theta^* = \frac{1}{R} \log \left( \frac{r(1 - p)}{p(R - r)} \right)
\]  

Then, the rate function is derived as:

\[
A(r) = \frac{r}{R} \log \left( \frac{r(1 - p)}{p(R - r)} \right) - \log \left( 1 - p + \frac{r(1 - p)}{R - r} \right)
\]  

Using the equation \( \delta = NA(r) \), effective power \( r \) is calculated as 1.931 units. Instead of allocating \( 3.3 \times 100 = 330 \) power units to charging station, using statistical multiplexing \( 1.931 \times 100 = 193.1 \) units of power will provide the charging service with 0.1% loss probability. Note that this approach leads to 41% of savings in the total required power. This is depicted in Figure 8.3. Also note that the rate function varies between the mean and peak customer demand.

Next, for a given total grid power, we are interested in calculating the total number of charging slots that can meet the QoS requirements. Assume that total power \( P = 100 \), the QoS target \( \delta = 6.9 \), and the same set of parameters are used. Then, the effective power for each charger is \( r = 2.23 \) and \( 100/2.23 \approx 45 \) chargers can be employed, whereas in the previous case only \( 100/3.3 \approx 30 \) chargers can be employed.

We proceed to compute the effective power for varying QoS parameter \( \delta \) and probability of being at ON state (or customer arrival rate). In Figure 8.4, \( \delta \) is varied between 1 – 30 and \( p \) is varied between 0.1 – 0.9. Note that for \( \delta \) greater than 7 or 8 is already very small blocking probability, but further increments of \( \delta \) shows the asymptotic behavior the effective power. When the ON duration is high (\( p=0.9 \)), effective power converges to peak demand (\( R=3.3 \)). Similarly, when the QoS requirement is very stringent, effective power also gets closer to peak demand.
8.3.2 Toy Example-II

Our second example considers a capacity planning case with more tuned parameters. Let us assume that the total EV population in a city or a neighborhood is 50,000. This type of data can easily be obtained from customer surveys [86]. The daily operation of the charging facility operates is 10 hours. Hence roughly 5000 EVs/hour will be the arrival rate. The ON period is a function of the charging technology. Different charging standards and technologies exists respect to the electric power used, explicit details are presented in [59]. We assume that each EV wants to get enough charge to complete their tour (e.g. go home or work). Hence depending on the size of the battery pack, we assume that average charging service takes 0.5 hours. Peak customer demand for each charger is \( R = 6.6 \) units of power. For stability arrival rate and the charging duration is roughly the same, that is \( \lambda \approx \mu \).

Given these statistics, we are interested in computing the total number of chargers required.
to meet the projected customer demand. Such insights will be very handy in capacity planning and constructing the required physical space. As a baseline scenario, we present a naive approach to calculate the required number of chargers. Given the above assumption, 5000 = N_{naive} \mu, then the required number of chargers would be 2,500.

However, using statistical multiplexing, one can reduce the required number of chargers considerable. For instance, suppose that QoS requirement is \delta = 5 (0.6\% blocking probability), then using the previously described method, we calculate the effective power as 4.412 units. Thus, instead of employing 2,500 chargers, with effective power this number drops roughly to 1671 chargers. This approach reduces the infrastructure cost, assuming a linear relation, by 33%.

In Figure 8.5, we present the percentage of savings respect to baseline scenario for \delta = 3-8. Note that this range of QoS is already reasonable. Note that parameter \delta is usually determined in customer to utility contracts.

Employing a huge charging lot to serve all of the EV demand in one place may not be
practical everywhere. Hence, charging stations may need to be spatially distributed. Let $K$ represent the number of stations such that total EV demand is uniformly allocated to each charging facility. It is assumed that, reducing the required charger by one leads to $\frac{1}{B_0}$ of savings. We calculated the savings for $\delta=1-8$, $p=0.5$ and for $K=1$, 2, 5, 10, 20, 50, 100, and 250.

In Figure 8.6 monetary savings relative to baseline scenario is presented. Note that $K=1$ case leads to higher savings since the number of multiplexed chargers is the highest. This can also be confirmed from equation 8.3 which concludes that as the number of multiplexed users increase, the effective power approaches to mean demand. Corollary, this leads to an increase in the total savings. Cases $K=100$ and 250 corresponds to small scale EV charging stations. This result shows that even for stations with small capacity this method can be applied. On the other hand, monetary savings shown in Figure 8.6 may be higher since the proposed model may eliminate the need of upgrading distribution grid components. These upgrades vary case-by-case and depends on the load on the distribution network.

Figure 8.6: Total Savings for Different Number of Stations
8.3.3 Profit Model

Next, we proceed to present a profit model, that uses financial principles and relates pricing and cost parameter to the stochastic system’s parameters. This model provides guidance for choosing the size and number of charging stations. The profit model has the following principles: the charging station’s owner obtains revenue from each served customer. On the other hand, a cost (penalty) is paid for every blocked EV/PHEV, because it leads to dissatisfied customers and degrades the reputation of the station and it enables to control the QoS to foster EV adoption [30].

Let \( R_{EV} \) be the revenue obtained per EV/PHEV and \( R_{Blocking} \) denote the cost per blocked EV/PHEV. Also as the number of the charging slots increase, there will be a cost related to the size and required upgrades in distribution network. This is captured with the third component of the profit function shown below:

\[
P = \phi(1 - e^{-\delta})R_{EV} - \phi e^{-\delta} R_{Blocking} - C e^{N/\zeta} \tag{8.11}
\]

\( P \) is the profit per station and \( \phi \) is the population of customers. \( N \) represents the number of charging slots in one station, \( C \) is the cost parameter related to size of the station, and \( \zeta \) is the tuning parameter. Next we evaluate the profit function for following set of parameters. Pricing parameters are set to \( R_{EV}=1.0 \) and \( R_{Blocking}=1.25 \). \( C \) and \( \zeta \) are set to 1 and 200 and \( \phi=5,000 \). We calculated \( N \) for varying \( \delta \) and different number of stations.

The evaluation results are depicted in Figure 8.7. It can be seen that the proposed profit model forces station operators to provide QoS around \( \delta=5-7 \). On the other hand, picking a \( \delta \) beyond this range does not bring any benefits, since the extra revenue obtained is canceled by the cost of adding extra equipment that is captured by the last term in equation 8.7.

Assuming that the station operator picks a reasonable QoS target, we then are interested in the optimal size of the charging station. Employing a huge charging facility enjoys the multiplexing gains derived by the theory, but on the other hand, such a facility would require
large physical investments. Further, concentrating charging of EVs in a single facility may have secondary adverse effects in the form of increased traffic congestion. On the other hand, distributing the total demand to a large number of stations may eliminate the need of huge investments, but the multiplexing gain will not be as high as before. Since the total population \( \phi \) and QoS target \( \delta \) is constant, the profit depends on the \((N,K)\) combination. We further evaluate the profit model for different number of charging stations. We assume that total population is divided by \( K = 1, 20, 50, \) and 250. As depicted in Figure 8.7, the maximum profit is obtained when each station employs \( N = 200 \) chargers.

### 8.4 Conclusions

In this chapter, we address the problem of electric power provisioning for large scale EV charging stations. We model the customer demand at each charging slot with an On-Off process. Then, we introduce the concept of “effective power” that is strictly less than the peak power demand during On periods. This notion significantly reduce the required power resources when compared
to the baseline scenario (allocating peak rate to each charging slot).
Chapter 9

Conclusions

9.1 Summary of Findings

The main contribution of this report is to propose a system level stochastic modeling approach to future electric transportation system. The system is layered into three; design, control, and communications.

The contribution of the first layer which is explained in Chapter 2 and 3 can be enumerated as:

- We proposed stochastic design of a fast charging station. Performance, blocking probability is used to dimension the system resources. Such an approach proposes an alternative way to size energy storage systems.

- The proposed architecture ensures grid reliability. It further smooths stochasticity of the customer demand which leads to savings in the unit cost of power resource.

- The proposed economic model motivates station operator to meet QoS targets, and hence in return, it enables to control the QoS to foster EV adoption. This approach is very essential for customers to gain confidence and beat range anxiety.

- We proposed a metric to compare energy storage technologies respect to their technological
parameters. This methodology leads to optimal choice of charging strategy to maximize number of customers served. Since the choice of the energy storage is mostly project-dependent, our approach attacks this problem from performance evaluation point of view.

As a second phase, we assume that number of proposed charging stations constitute a network of fast charging stations. However, power grid refrains network planners to put required number of charging stations. Also the utilization of charging stations depends on the spatio-temporal variations in the customer demand. Hence in layer two we propose a control mechanism to balance the load by routing them to less busy stations. The main contributions can be listed as:

- We evaluated GPS traces of a large Metropolitan city in the US to gain more insights in how the spatial distribution of EVs affect the load at each facility.

- In order to maximize the percentage of served customers, we proposed a electric power allocation framework; stations under heavy load and stringent QoS targets get more power resources.

- Next, we proposed customer allocation mechanism. Central authority assigns EV fleets to neighboring stations to balance the load at each station. We compared this case to no allocation case, and showed that significant savings are made by customer and power allocation.

- For self interested EV drivers we proposed a decentralized control mechanism based on game theory. We proposed an admission control mechanism based on pricing which is a function of the load in the system.

- We modeled customer behavior with utility functions that has three components; price paid to get service, distance to charging station, and dissatisfaction with the extra miles traveled. Our proposed model showed that percentage of EVs can be increased significantly.
The realization of above control mechanism requires connectivity between EV drivers and the power grid. Hence, in Chapter 6,

- We addressed the challenges introduced by the EV chargings to the power grid.
- We identified the communication needs to reach projected EV roll-out.
- We surveyed on the communication requirements, standards, and candidate technologies that could serve EV networks smart grid applications.

The performance of the control layer is highly coupled with the underlying communication system performance. Hence, in Chapter 7,

- We propose a MMPP based model to quantify the affects of bad communication system performance.
- We further show that as the EV population flourishes, the network operators need to upgrade their communication technology to support critical information exchange.

We extended our modeling approach to large scale EV charging stations and proposed capacity planning framework. In Chapter 8,

- We considered a charging station equipped with a large number of charging slots. Customer demand at each slot was modeled as a two-state On-Off continuous time Markov process. We introduced the concept of effective power for different levels of customer satisfaction (as outlined below) for each charging slot.
- The effective power which was a deterministic quantity acts as a surrogate for the actual aggregate stochastic demand. By using the concept of effective power, we showed that it can lead to savings regarding distribution network investments.
- We provided general guidelines for power resource provisioning and capacity planning which was very critical in the design of charging facilities.
REFERENCES


[8] Ieee draft guide for smart grid interoperability of energy technology and information technology operation with the electric power system (eps), and end-use applications and loads. IEEE P2030/D5.0, February 2011, pages 1 –126, 10 2011.


