Title
A Nexus Between Two Disruptions: A Multiscale Analysis of Transportation Electrification to Forecast the Impacts of Vehicle Grid Integration

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A Nexus Between Two Disruptions: A Multiscale Analysis of Transportation Electrification to Forecast the Impacts of Vehicle Grid Integration

by

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Committee in charge:

Professor Joan Walker, Chair
Professor Alexander Bayen
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Abstract

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University of California, Berkeley

Professor Joan Walker, Chair

In this dissertation, I present a body of work that advances our understanding of the technical and economic potential for vehicle grid integration based on a variety of methodological approaches that quantify the opportunity at multiple scales, across multiple geographies, and that cover scenarios with both personally owned plug-in electric vehicles (PEVs) and shared autonomous electric vehicles (SAEVs). The key research questions addressed in this dissertation include:

- How can charging infrastructure be cost-effectively deployed to maximize utilization and value to PEV drivers?
- How much flexibility exists in the charging demand from PEVs?
- What is the economic opportunity to manage the charging of PEVs to occur at lower cost time periods?
- How will fleets of electrified autonomous vehicles serving mobility on-demand differ in how they are managed to minimize the cost of charging or to serve as a source of electricity for buildings?

These questions are motivated by the fact that transportation electrification and emerging forms of mobility are dramatically changing how the transportation system is planned, operated, and analyzed. PEVs present new challenges and constraints around the siting and operation of refueling infrastructure. Electric load from PEVs can exacerbate grid congestion at either transmission or distribution scales if left unmanaged. Sharing and autonomy are changing mobility which will have unique implications for the grid integration of PEVs.

Meanwhile, there are strong social and environmental forces compelling planners, regulators, and private industry to electrify transportation as soon as possible. The transportation sector is the largest emitter of greenhouse gases in the United States. With the exception

of the great recession, emissions in the transportation sector have been growing for the last three decades, in contrast to the electric power and industrial sectors which have been on a downward trend in emissions. Transportation, therefore, represents one of the primary challenges to achieving deep decarbonization of the U.S. economy.

In the electric power sector, policy and economic forces are upending incumbent generation technologies (coal and natural gas) in favor of lower cost and lower carbon alternatives, particularly wind and solar power. As these intermittent renewable resources increase in capacity, the incidence of renewable energy (RE) curtailment increases due to time periods when supply is greater than demand and generators are turned down or shut off from the level that they would otherwise be producing. Curtailment raises the overall system cost of supplying electricity. In addition, some utilities must meet an energy production standard to satisfy state mandates for renewable production. Renewable curtailment forces utilities to either acquire more RE or introduce sources of grid flexibility to relieve the curtailment. One low cost strategy to mitigate these challenges is to manage the temporal profile of electricity demand to make use of the renewable resources when they are available.

PEVs are generally analyzed through modeling using one of two approaches, statistical modeling and activity-based modeling. Statistical models typically summarize or infer travel patterns from travel survey data and use them to characterize the need for PEV charging and the temporal opportunities to charge. The key disadvantage of such approaches is that they cannot account for the individual mobility constraints of travelers and they typically require an assumption that charging infrastructure is unlimited. Another common approach is to develop Markov Chain models of mobility and PEV charging. In these models, transitions between states are treated as random events. Because they lack a representation of the causal mechanism for these transitions, these models are difficult to generalize and their utility is degraded if applied in prospective contexts assuming a transportation system with dramatically different characteristics than present.

Activity-based models make use of travel diaries from surveys or GPS data logging which are then provided as input to mobility and charging simulations. Agent-based models are a subset of activity-based models, in so far as they treat travelers individually and require a representation of each individual's activity schedule in order to model the travel necessary to engage in those activities. What distinguishes agent-based models are two key features: 1) wrapping the individuals in a virtual environment (e.g. the transportation system) with detailed representation of transportation supply and 2) dynamically simulating the agents' interactions with the virtual environment and with each other. These interactions open the opportunity to model the choices of the agents based on empirical studies of human behavior as well as to make agent behavior contingent on the time-evolving state of their environment and other agents.

In the electric power and grid modeling domain, load from PEVs are typically represented as static or derived from very rudimentary estimation techniques. Studies either ignore flexibility entirely or they make simplistic assumptions about the timing and degree to which PEV load can be shaped. The inaccuracy in these modeling choices have had a relatively low impact in the recent past due to the still relatively low penetration of PEVs in the national vehicle fleet. But within a decade it will no longer suffice to ignore or simplify PEV load, which could eventually make up more than 20% of U.S. electricity demand.

This dissertation addresses these gaps by coupling models of electric mobility and the grid at multiple scales. Each paper presented in this dissertation was produced in collaboration with co-authors across multiple projects and contexts. I employ reduced-form models in the context of optimization to solve the charger scheduling and vehicle mobility problems, as well as detailed agent-based models that simulate context-specific traveler behaviors and the dynamics of resource-constrained charging infrastructure.

To address the infrastructure siting problem, I develop a spatially explicit agent-based simulation model that represents charging infrastructure, charging behavior, competition for scarce chargers, and driver adaptation. A differential evolution and a heuristic optimization scheme are employed to find a cost-effective distribution of charging infrastructure.

I then address the question of flexibility in two ways. First I develop a scheme for optimizing the charging profiles of individual PEV drivers based an objective that simultaneously considers the costs of charging and the benefits associated with providing ancillary services to the grid. Then I employ a much higher fidelity approach to simulate both the electrified mobility system as well as the power sector. I develop the BEAM modeling framework (Behavior, Energy, Mobility, and Autonomy), which is an agent-based model of PEV mobility and charging behavior designed as an extension to MATSim (the Multi-Agent Transportation Simulation model). I apply BEAM to the San Francisco Bay Area and conduct a preliminary calibration and validation of its prediction of charging load based on observed charging infrastructure utilization for the region in 2016. I link the BEAM model with PLEXOS, an industry standard production cost model that accurately characterizes grid dispatch constraints.

Finally, I consider the impact of grid-integrated fleets of SAEVs providing mobility on-demand. In two separate studies I develop models to consider how such fleets could be used to serve building energy demand during power outages as well as a more general analysis of the battery and charging infrastructure requirements to serve nationwide mobility.

The key findings across all of this work are the following:

- In today's energy markets, PEV flexibility can reach values of \$155/year/vehicle for NYISO and \$98/year/vehicle for CAISO. The annual cost savings due to optimizing dispatch come more from savings on the price of energy (74% in CAISO and 61% in NYISO) but providing ancillary services (in the form of regulation) also contributes value to the solution (26% in CAISO and 39% in NYISO).

- When we project the energy market of California to a future year when renewables make up 50% of the annual energy produced, PEV flexibility is even more beneficial to the power sector, primarily in lowering grid operating cost and the amount of RE that must be curtailed to avoid over-generation when supply and demand are mismatched. For example, if treated as flexible loads, 2.5 million smart charging PEVs avoid 50% of incremental system operating costs annually and reduce renewable energy curtailment by 27% annually relative to when the same number of unmanaged charging PEVs are added to the grid.

- When SAEVs serve power to buildings during an extreme outage, the fleet can generate 32%-40% more revenue than is earned serving mobility alone. While the overall value of providing on-demand power depends on the frequency and severity of power outages, the results show that serving power demand during large-scale outages can provide a substantial value stream, comparable to what can be earned providing grid services.

- All mobility in the United States currently served by 276 million personally owned vehicles could be served by 12.5 million SAEVs at a cost of $0.27/vehicle-mile or $0.18/passenger-mile. The energy requirements for this fleet would be 1142 GWh/day (8.5% of 2017 U.S. electricity demand) and the peak charging load 76.7 GW (11% of U.S. power peak).

In total, this body of work contributes new insights into the opportunity for electric mobility to reduce the cost of operating the electric grid, enabling deeper and faster adoption of renewable power in the electric sector, and providing reliable mobility to travelers in the transportation sector. The domain of vehicle grid integration is still relatively new, there are many areas of research that require additional attention, such as increased research on traveler preferences around PEV charging, the intersection between electric mobility and the distribution grid, electrification of medium and heavy duty vehicles, as well as properly incentivizing electric vehicles to ride hail drivers in the gig economy.

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Dedication

This dissertation is dedicated to my family: to Jillian, Ruby, Coraline, who sacrificed to support my pursuit of a doctorate degree and whose love kept me fed throughout; to Ibby who cared for my children when I couldn't; to my mother Mary who supported me every step of the way; and to my father Tom who didn't live to see me complete but made his pride and love clear in his final years.

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This dissertation is the result of six collaborations with incredibly intelligent, passionate, and creative partners: Rashid Waraich, Julia Szinai, Anand Gopal, Laurel Dunn, Andrew Harris, Alexei Pozdnukhov, Brian Gerke, Nikit Abhyankar, Sangjae Bae, Max Gardner, Gordon Bauer, Jefferey Greenblatt, Alan Jenn, and Andrew Campbell.

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Chapter 1

Introduction

The transportation sector is undergoing major transformations through electrification and new forms of mobility. Plug-in electric vehicles (PEVs) require an entirely new form of refueling and introduce an entirely new load to the electric system. Charging infrastructure must be deployed to support mobility and the adoption of PEVs. As transportation becomes increasingly coupled to the power sector, transportation planners must account for the evolving dynamics of electricity markets and grid planners must account for the evolving dynamics of human mobility. The nature of mobility is changing as well, through shared vehicles, shared rides, and vehicle automation.

These changes require new approaches to system planning, operation, and analysis. This dissertation is a compilation of several unique approaches to addressing these challenges, with a particular emphasis on the integration of PEVs with the electric grid.

1.1 Trends and Policy Context

In 2017, the transportation sector became the largest emitter of greenhouse gases in the United States, overtaking emissions from the electric power industry [201]. With the exception of the great recession, emissions in the transportation sector have been growing for the last three decades, in contrast to the electric power and industrial sectors which have been on a downward trend in emissions. Transportation, therefore, represents one of the primary challenges to achieving deep decarbonization of the U.S. economy [182].

Electric Vehicle Adoption

PEVs represent a significant opportunity for nations to reduce emissions of both air pollutants and greenhouse gases, in addition to reducing their dependency on foreign sources of energy. Electric vehicle adoption passed 2 million vehicles in 2016, with China overtaking the United States as the leading market for PEV sales. By 2030, global projections range from 60 to 200 million electric vehicles will be on the roads [183]. Within the United States, California dominates in PEV adoption, with over half of the national stock [184]. In addition, California is on a trajectory to meet or exceed a 2012 Governor mandate for 1.5 million PEVs on the road by 2025 [185] [186] [187] [44]. California therefore serves as an excellent case study for analyzing how PEV adoption will intersect with complementary initiatives to decarbonize the electric sector.

Charging Infrastructure

Public PEV charging infrastructure is a critical component to accelerate the adoption of PEVs [202] [203] [204], however there is a weak business case for the private sector to invest in chargers [205]. Governments across the world have therefore initiated campaigns to support the planning and installation of charging infrastructure to varying degrees.

In the United States, the U.S. Department of Energy has established a workplace charging challenge to the nation to support PEV adoption [42], but the most aggressive policy initiatives are occurring at the state level. For example, California has been supporting PEV uptake by funding statewide and regional planning efforts for PEV readiness [46] and implementing projects including the installation of electric vehicle charging stations (EVCS) throughout the state [50] [188] [189]. More recently, Volkswagen has committed to investing $2 billion nationwide in charging infrastructure as a part of the settlement over the emissions control fraud [249].

In Europe, the government of the Netherlands has supported EVCS through tax incentives with an ultimate goal of installing over 20,000 public EVCS nationwide by 2015 [55]. Dutch electric utilities have supported the effort by installing and operating infrastructure, investing in over 4000 chargers by 2013 [57]. In Norway, the government has subsidized EVCS, resulting in nationwide deployment of over 1300 chargers [52]

In China, a national PEV plan was released in 2012 targeting 500,000 PEVs by 2015 and 2M by 2020 [61]. The plan emphasized charging infrastructure deployment pilots in cities through scientifically determined locational distribution. The cities of China are adopting their own goals. For example, Shenzhen is aggressively supporting charging infrastructure development with policies targeting installation of over 25,000 EVCS to support vehicle adoption [62].

Renewable Energy Integration

While efforts to support PEV adoption accelerate worldwide, there are corresponding efforts to decarbonize the electric sector. In California, the State Renewable Portfolio Standard (RPS) mandates half of electricity consumption be met by renewable resources by 2030 [190]. Wind and solar photovoltaic (PV) sources are the majority of renewable resources on the California grid, whose intermittency requires greater use of flexible generators, flexible demand, energy storage, and the curtailment of renewable generators to ensure a reliable supply of electric power [191] [67] [192].

As intermittent renewable capacity increases, the incidence of renewable energy (RE) curtailment increases which raises the overall system cost of supplying electricity [67]. In addition, utilities must meet an energy production standard to satisfy the RPS, so renewable curtailment forces them to either acquire more RE or introduce sources of grid flexibility to relieve the curtailment. [167]

Shared Electrified Automated Mobility Services

Self-driving vehicles are already on the roads, serving passengers in the United States without a human backup driver in the vehicle [211]. In addition, the leading developer of vehicle automation technology, Waymo, has entered an agreement to purchase 20,000 electric vehicles by 2020 [212]. While there is still a great deal of uncertainty in the impact that automated vehicles (AVs) will have on the transportation system in the coming decades [213] [215], there is little doubt that they will soon be a part of the transportation system and could dramatically disrupt conventional modes of mobility.

There are a wide variety of business models that could make use of AVs [206]. The particular business models that are successful will depend on their relative cost structures [207], regulatory burden [229], consumer acceptance [230], and a host of other factors. There is growing consensus, however, that without sharing rides, i.e. more than one passenger per vehicle, the end result of vehicle automation could increase undesirable outcomes like vehicle miles traveled, congestion, energy consumption, and emissions [214] [216] [228].

1.2 Analytical Approaches

PEVs are generally analyzed on two time scales. Long-term studies project adoption, vehicle miles travelled and the resulting energy, economic, and climate impacts from aggregations of PEVs. Other studies focus on short-term operation of PEVs, usually over the course of one day or one week [180]. Short time scales are necessary to resolve the evolving dynamics around PEV refueling and grid interactions; they are therefore the focus of this dissertation.

Short-term PEV models generally fall into one of two groups: statistical models and activity-based models. Within these broad categories, there are numerous variations and examples which are described in brief below.

Statistical Models

Statistical models typically summarize or infer travel patterns from travel survey data and use them to characterize the need for PEV charging and the temporal opportunities to charge [231] [232][233]. The key disadvantage of such approaches is that they cannot account for the individual mobility constraints of travelers and they typically require an assumption that charging infrastructure is unlimited.

Another common approach is to develop Markov Chain models of mobility [250], PEV charging [236], or both [235]. In these models, transitions between states are treated as random events. While these models can yield mobility and charging distributions that accurately reproduce observations, they often lack a representation of the causal mechanism for the transitions between states. These models are therefore difficult to generalize and their utility is degraded if applied in prospective contexts assuming a transportation system with dramatically different characteristics.

One notable exception to these problems are input/output hidden Markov models [234] which infer hidden states (such as activity purpose) and transition as well as emit conditioned on more than just the present state (e.g. transition and emission probabilities could be dependent on time of day and distance from home). As these models progress and data becomes more available, they will be capable of modeling stochastic behavior in a manner that is congruent with an ever widening range of hypothetical circumstances of analytical interest.

Activity-Based Models

The most common form of activity-based PEV models make use of travel diaries from surveys or GPS data logging which are then provided as input to energy and charging simulations that estimate the energy consumption and state of charge of a PEV batteries and therefore the necessity or propensity to recharge at the conclusion of trips [237] [238] [239] [240].

Agent-Based Models

Agent-based models are a subset of activity-based models, in so far as they treat travelers individually and require a representation of each individual's activity schedule in order to model the travel necessary to engage in those activities. What distinguishes agent-based models are two key features: 1) wrapping the individuals in a virtual environment (e.g. the transportation system) with detailed representation of transportation supply and 2) dynamically simulating the agents' interactions with the virtual environment and with each other. These interactions open the opportunity to model the choices of the agents based on empirical studies of human behavior as well as to make agent behavior contingent on the time-evolving state of their environment and other agents.

In [180], the authors conclude that behavior is often missing from models of PEV mobility and charging. They also conclude that agent-based models offer the best promise to fill the gap of neglected traveler behaviors. In [41] and [178], the authors take a random utility choice modeling approach to characterize charging choices. These choice models, coupled with an agent-based framework to simulate the situational experience of PEV drivers, can combine to answer questions about PEVs, infrastructure, and charging that endogenizes the responses of travelers to changes in the system.

Some of the most prominent work in analyzing the promise of electrified autonomous ride hailing fleets come from [208], [210], and [247], where they employ an agent-based model of the fleet and design a heuristic process to size the fleet and dispatch the vehicles to serve demand that is derived from trip data or stochastically created.

Vehicle Grid Integration

Numerous studies have investigated the impacts of managed PEV charging on power systems with RE [172, 2, 3, 163, 171, 4], but most existing literature on PEV-grid interaction (also known as Vehicle Grid Integration (VGI)) either simplifies PEV charging behavior and charging infrastructure or the dispatch of the power system. These simplifications could lead studies to overestimate the availability and willingness of PEV drivers to provide grid services as well as the value that PEV grid services can add to the grid. The travel demands of drivers, the location and availability of chargers, and the user acceptance of managed charging programs are important in modeling a realistic estimate of value of PEV grid services, [1, 179, 5]. In addition, some studies only include PHEVs [195], whose hybrid gasoline-electric powertrains diminish the mobility-charging tradeoff and which have a much smaller grid footprint. Robustly representing both BEV and PHEV drivers' constrained charging choices is critical for assessing the feasibility of managed charging strategies because the ability to fulfill mobility needs without compromise is paramount to drivers and charging infrastructure is constrained [175]. Finally, a complete assessment of the economic potential of VGI would seek to minimize an economic objective and not necessarily an engineering objective such as load flattening [281]. This reflects the reality that the power sector is operated as a market and economic incentives are the appropriate mechanism to alter consumer behavior.

1.3 Contributions and Structure of Dissertation

In this dissertation, I present a body of work that advances our understanding of the technical and economic potential for vehicle grid integration based on a variety of methodological approaches that quantify the opportunity at multiple scales, across multiple geographies, and that cover scenarios with both personally owned PEVs and shared autonomous PEVs. I employ reduced-form models in the context of optimization to solve the charger scheduling and vehicle mobility problems, as well as detailed agent-based models that simulate context-specific traveler behaviors and the dynamics of resource-constrained charging infrastructure.

The following sections describe the work contained in Chapters 2-7 of this dissertation and how they relate to each other.

Siting Electric Vehicle Charging Infrastructure, Chapter 2

PEV chargers are the interface between the transportation and electric power systems. Any comprehensive analysis of vehicle grid integration must therefore account for the format and distribution of chargers in a region of interest. Chapter 2 presents a modeling approach that makes several unique contributions to the problem of siting PEV charging infrastructure and provides a test bed for other highly resolved analyses such as grid impact or vehicle grid integration studies. We have developed an agent-based model that blends transportation demand forecasts and travel survey data to produce realistic, regionally-specific mobility patterns. In addition, we explicitly simulate charging infrastructure as a finite resource, capturing the competition between drivers and forcing some to adapt when PEV charging stations are unavailable. Finally, we model a series of behaviors of the drivers that feature probabilistic discrete choices around charging and adaptation to limited charging access. The model is then used in the context of a robust particle-based optimization scheme called differential evolution to make recommendations on infrastructure siting. We also employ a heuristic optimization scheme to site charging infrastructure for use in comparative analyses.

Economic Value of Charging Flexibility, Chapter 3

Given suitable models of an electrified mobility system, the economics of generation dispatch on the grid, and the charging infrastructure connecting the two systems, we can explore the economic opportunity associated with charging flexibility. Flexibility in charging resides in the fact that vehicles are typically plugged in to the grid for longer than the time needed to actively charge the battery. In an unmanaged scenario, charging commences immediately upon plug-in, but the charging session could be intelligently controlled to minimize the cost of generating or distribution power, then vehicles could be charged at lower cost or with lower environmental externalities.

Chapters 3 and 5 explore the economic value of charging flexibility assuming a fleet of personally owned light-duty vehicles. In both chapters, the ultimate outcome is an estimate of the cost savings if the flexibility inherent in PEV charging was accessible to grid operators. In Chapter 3, we use wholesale locational marginal pricing data from California and New York as the basis for an optimization scheme that charges PEVs at least cost while respecting temporally prioritized mobility constraints.

Agent-Based Modeling of Plug-in Electric Vehicle Mobility and Charging Demand, Chapter 4

In Chapters 4 and 5, we deploy a more comprehensive modeling approach by combining two detailed models, BEAM and PLEXOS. In Chapter 4, we introduce the BEAM model and it's application in simulating PEV charging infrastructure and behavior. This simulation approach is capable of generating charging load profiles at the individual scale which can then be used to quantify load flexibility.

Grid Impacts of Electric Vehicles and Managed Charging in California, Chapter 5

In Chapter 5, we take the individualized charging session estimates as generated by BEAM (in Chapter 4) and then aggregate these for use in PLEXOS, a production cost model of the power sector, which manages the dispatch of generation, storage, and flexible loads to assess the operational impact of PEV charging load in both unmanaged and managed contexts. The value of charging flexibility is therefore assessed as the operational savings realized through smart charging. We analyze both the value of charging flexibility as well as its impact on the curtailment of RE generation sources.

Dispatch of Shared Autonomous Electric Vehicles During Power Outages, Chapter 6

A complete understanding of the benefits and impacts of transportation electrification must account for the dramatic changes underway in urban mobility systems. Shared mobility and vehicle automation have the potential to disrupt incumbent modes of travel and reconfigure both how people move as well as how vehicles are refueled.

Chapters 6 and 7 present two studies which have developed novel methodologies to assess the impact of integrating shared, autonomous, electrified fleets for mobility services with the electric grid. In both approaches, we assume that mobility service providers operating large centrally managed fleets will take every opportunity to minimize costs to remain competitive and profitable. Therefore, we assume the charging of the fleet is always controlled to minimize cost.

In Chapter 6, we solve the economic dispatch of a fleet of autonomous PEVs in two markets simultaneously, the market for mobility and the market for supplying electricity to buildings during power outages. The approach is spatially explicit with exogenous pricing.

National Planning for Shared Automated Electric Vehicles, Chapter 7

The objective of Chapter 7 is to make national scale predictions of the fleet composition and charging infrastructure needs of an electrified mobility on-demand service. In this approach, space is not modeled explicitly in favor of modeling entire regions in an effort to cover the full nation and predict how automated PEV fleets might be dispatched to both serve mobility and charge, in addition to simultaneously sizing the fleets and the charging infrastructure required to support them.

Chapter 2

Siting Electric Vehicle Charging Infrastructure

2.1 Overview

This chapter presents a modeling approach that makes several unique contributions to the problem of siting PEV charging infrastructure and provides a test bed for other highly resolved analyses such as grid impact or vehicle grid integration studies. We have developed an agent-based model that blends transportation demand forecasts and travel survey data to produce realistic, regionally-specific mobility patterns. In addition, we explicitly simulate charging infrastructure as a finite resource, capturing the competition between drivers and forcing some to adapt when PEV charging stations are unavailable. Finally, we model a series of behaviors of the drivers that feature probabilistic discrete choices around charging and adaptation to limited charging access. The model is then used in the context of a robust particle-based optimization scheme called differential evolution to make recommendations on infrastructure siting. We also employ a heuristic optimization scheme to site charging infrastructure – albeit sub-optimally – for use in comparative analyses.

This work originally appeared in the following publication:

Colin J.R. Sheppard, Andrew Harris, and Anand R. Gopal. "Cost-Effective Siting of Electric Vehicle Charging Infrastructure with Agent-Based Modeling". In: *IEEE Transactions on Transportation Electrification* (Mar. 2016)

2.2 Introduction

Plug-in electric vehicles (PEVs) represent a significant opportunity for governments to reduce emissions of both air pollutants and greenhouse gases, in addition to reducing their dependency on foreign sources of energy. Public PEV charging infrastructure is a critical component to accelerate the adoption of PEVs. Installation of infrastructure for PEV charging is typically less expensive than for petroleum fueling but still requires significant capital investment. Comprehensive planning analysis prior to the rollout of electric vehicle charging stations (EVCS) can ensure that charging stations are effectively sited, providing the best returns on investment while also meeting critical service requirements.

Previous attempts to conduct charger siting and PEV/grid impact studies have fallen into three broad categories: cartographic analyses, statistical models based on travel surveys, and spatially-enabled statistical modeling. The following summarizes these approaches and presents an alternative approach, agent-based modeling with explicit representation of EVCS, used by the authors for several regional infrastructure deployment plans.

Cartographic analyses make use of transportation demand estimates, spatially explicit demographic data sets, and expected PEV adoption to develop heat maps that highlight the relative need for EVCS [227] [32] [23] [33] [26]. For example, ICF International [227] completes a suitability analysis through a combination of scoring specific potential locations through site visits and using regional travel demand data to identify areas more likely to be visited by PEV drivers. The Luskin Center for Innovation [32] places more emphasis on identifying different use cases for EVCS and how they align with different land uses and commercial categories. All of the cartographic analyses make aggregated estimates of the number of region-wide chargers that would be appropriate for a given uptake of PEVs. These estimates, combined with the heat maps, provide useful insight into high level planning needs for policymakers. But because they lack any detail at the scale of individual drivers and individual transactions with EVCS, they are incapable of quantitatively assessing spatiotemporal dynamics associated with distributed demand for electricity.

Statistical models based on travel surveys – typically the National Household Travel Survey (NHTS) – are common for investigating the impact of PEVs on bulk power transmission and large-scale resource adequacy, in addition to developing control algorithms for managing the charging of PEVs. Jansen et al. [306] assess the charging demand from simulated PEVs against the marginal generators on the power grid to determine the marginal emissions impacts of PEVs. Zhang et al. [40] [72] use the NHTS to develop control algorithms for coordinated charging schemes to minimize cost to drivers. These efforts have the advantage of simulating charging behavior and other dynamics at the level of individual drivers and are temporally explicit, but they lack the spatial dimension and therefore fail to inform regional planners and policy-makers as to how their results apply within a specific region.

Finally, others have developed spatially explicit models [34] [31] [39], which are capable of producing regionally actionable recommendations for charging infrastructure siting. Nicolous et al. used spatially explicit transportation survey results coupled with a simulation of PEV driving along those routes, to spatially located chargers throughout the California road network. What their analysis did not attempt was to simulate the interactions of PEV drivers competing for limited charging resources. Xu et al.[39] have developed a more formalized optimization scheme for siting centralized EVCS resources. Their analysis is a rigorous approach to spatially explicit infrastructure siting, though it is based on minimizing the travel distance to chargers, rather than focusing on driver experiences and minimizing inconvenience or delay. Kearney [31] expanded on a model [35] which only considers public charging infrastructure insofar as it facilitates or hinders diffusion of PEVs into the auto market. Their analysis is important to consider in a policy context but it does not simulate charging behavior in a manner that is suitable for high resolution EVCS siting recommendations.

One useful tool for planning analysis is the agent-based model (ABM) - a class of computer model designed to explore macro-scale population behavior as a result of micro-scale interactions between the population members and their environment. These models create a virtual environment and populate it with "agents", simulated individuals guided by a set of behavioral algorithms. By monitoring the agents, an ABM can be used to investigate the response of a population to changes in the virtual environment or as a framework for evaluating competing hypotheses of models for decision-making itself.

ABMs have proven useful in a variety of PEV infrastructure studies - the ability to record spatially explicit data unique to each individual driver makes ABMs a powerful tool to determine when, where, and how much each driver will charge [51]. Multiple studies have used driver energy data generated by ABMs to formulate more effective charging schedules given the limits of the existing electrical grid [37] [22]. ABMs also allow agents to affect the behavior of other agents, which has been used to model how the competition between PEVs for limited public charging infrastructure affects long-term PEV adoption rates within a community [219]. Stephens [218] created an ABM to simulate driving behavior of plug-in hybrid electric vehicles (PHEVs) and investigate how their electric miles depend on market penetration, electricity price, and charger availability.

Other models (agent-based or otherwise) simplify charging behavior by assigning chargers on easily quantified criteria, such as physical proximity to residential locations [27], as a function of traffic flow along a given road segment [25], or assuming that drivers can charge in any location [22]. While these simplifications can still produce reasonable results when modeling aggregate grid impacts of charging or PEV adoption rates, spatially explicit driving behavior is essential for determining optimal charger placement. In their simulation of PHEV charging dynamics, Dong and Lin [24] model driver behavior by directly copying GPS travel data (miles traveled and time spent at single locations) for 229 real-world internal combustion engine vehicles. This approach achieves realistic spatial disaggregation for some individual drivers, but the sample size is too limited to produce regional predictions of PEV charging patterns.

A more common approach is to synthesize a schedule for drivers to follow. This approach begins by defining driver activity to be performed on a given day (such as work, school, shopping, etc.) including travel destinations. Departure times are then scheduled based on random distributions [22], through constrained optimization over a metric of utility [37], or based on modeler-defined schedules for work and other travel needs [219]. Though ABMs are best qualified to accommodate individual driving schedules, other models have also used driver schedules to help site charger locations [38].

Despite the advantages of using an ABM to model individual driver-charger behavior, ABMs have been underutilized in charger location optimization studies. Existing charger location optimization studies have been limited by model constraints: lack of realistic driver behavior [27], lack of queuing or competition for chargers [51], and strict limitations on charger power level [25] [38].

Contributions of this Paper

This paper presents a modeling approach that makes several unique contributions to the problem of siting EVCS and provides a test bed for other highly resolved analyses such as grid impact or vehicle grid integration studies. We have developed an ABM that blends transportation demand forecasts and travel survey data to produce realistic, regionally-specific mobility patterns. In addition, we explicitly simulate charging infrastructure as a finite resource, capturing the competition between drivers and forcing some to adapt when EVCS is unavailable. Finally, we model a series of behaviors of the drivers that feature probabilistic discrete choices around charging and adaptation to limited charging access. The model is then used in the context of a robust particle-based optimization scheme called differential evolution to make recommendations on infrastructure siting. We also employ a heuristic optimization scheme to site charging infrastructure – albeit sub-optimally – for use in comparative analyses.

Methodology

This section contains a complete description of the PEVI model, written using the ODD protocol (Overview, Design concepts, and Details), a standard protocol for documenting agent-based models [20] [21].

Purpose

The purpose of this model is to simulate the interaction between a regional fleet of plug-in electric vehicle drivers with public and private charging infrastructure over any time frame. The model accepts as input the location, quantity, and type of electric vehicle charging stations (EVCS) throughout the study region. Drivers and their vehicles are described by inputs that specify driver activity (a departure time and destination for every trip), the distribution of vehicle types, and parameters controlling driver behavior. PEVI then simulates the drivers as they attempt to follow their trip itinerary and interact with the EVCS throughout the region. The experience of drivers (individually or in aggregate) and the usage of the EVCS can be summarized at the end of a model run. The model is intended to be used as tool for analyzing the impacts of alternative EVCS infrastructure scenarios in addition to PEV adoption rates, technology advances, market trends, and driver behaviors.

PEVI is a stochastic model, meaning that a variety of processes and decisions within the model are based on random chance. The primary purpose of including stochastic processes in PEVI is to avoid reaching conclusions that are overly customized to suit one particular set of circumstances. Instead, the model is run many times with the same set of initial conditions and performance metrics are averaged over those runs.

Entities, State Variables, and Scales

Traffic Analysis Zones (TAZs)

TAZs are entities that describe the atomic geographic regions of the environment. All TAZs are interconnected, so a vehicle in one TAZ may travel to any other. While they represent spatially explicit regions, the PEVI model does not store or track spatial data (polygons, lines, etc.) for each TAZ. Instead, the spatial relationships between TAZs are encoded as a table (see Ω in Table 2.2) describing the distances and travel times between all combinations of TAZs. TAZs as an entity are noted in this manuscript by Z and indexed by z and have the state variables listed in Table 2.1.

Table 2.1: TAZ State Variables

Variable	Description
z	Integer identifier (also used as an index over TAZs).
γ	Chargers: a master list of all chargers in the TAZ.
α	Available chargers: a list of available chargers in the TAZ, updated during model as chargers are used.
L	# Levels: a 5-value list containing the number of chargers of each level: 0 (home charging), 1, 2, or 3

Environment

The environment is the entity where all the agents live and interact. In this model it is the geographic region described by the input data. The environment is defined by several global state variables and parameters, which are available to all agents in the model for reference or use, see Table 2.2.

Drivers

Driver agents are used in the model to simulate individual driver and vehicle characteristics combined. These entities are notated by V, are indexed by v, and contain the state variables listed in Table 2.4.

Chargers

Charging agents represent the EVCS installed at a given TAZ. Charging stations can either be Level 1, Level 2, or DC Fast (also referred to as Level 3). In practice, Level 2 chargers may also have a Level 1 capability, in PEVI they are represented as two separate chargers. The charger agents are currently described by the state variables in Table 2.5.

Scales

Scales refer to the spatial and temporal resolution and extent of a model. The spatial resolution and extent of PEVI is defined by the TAZs and therefore is application-specific. To date, the PEVI model has been applied to regions varying in spatial extent from 1,400 km^2 to 34,000 km^2 with spatial resolutions (the average area of each TAZ) ranging from 26

Table 2.2: Global Variables

Variable	Description
t	Time: the decimal number of hours since the beginning of the model run, 0 corresponds to midnight of the first day.
S	Schedule: a compound variable containing the active list of scheduled events (see Section 2.2).
$\Omega_D(Z_O, Z_D)$ $\Omega_T(Z_O, Z_D)$ $\Omega_Z(Z_O, Z_D)$	Origin-Destination Table: stored as a matrix with the following 5 columns but notated as a function taking an origin Z_O, a destination Z_D and returning a distance, a time, or a list of en route TAZs, respectively: 1. Origin TAZ 2. Destination TAZ 3. Distance in miles or km 4. Travel time in decimal hours 5. List of the TAZs along the route between the origin and destination, used for seeking en route chargers.

km^2 to 430 km^2. There is no limit to the number or size of TAZs that can be simulated by PEVI, though there are likely practical limits due to the computational burden of larger or higher resolution systems.

The PEVI model has a continuous temporal resolution because time is modeled using discrete event simulation (see Section 2.2). The temporal extent of the model is also application-specific. To date, the PEVI model has been used to simulate periods ranging from one to four days.

Process Overview and Scheduling

In the PEVI model, time and actions are managed using discrete event simulation. Model processes are maintained as an ordered schedule of events. An event consists of a time, an agent, and an action or block of code. After initialization, the first event on the schedule is dispatched, at which point the specified agent performs the specified action; then the next event on the schedule is dispatched, and so on. Events can be created during initialization or dynamically generated during model execution. In both cases, the dispatch time of the event is used to determine the placement of any new event in the schedule. Events can also be executed immediately as an outcome of some other event; in these cases the discrete event scheduling mechanism is not used in favor of direct code execution.

In PEVI, events are exclusively associated with drivers. Figure 2.1 presents a flow chart

Table 2.3: Driver State Variables

Variable	Description
Y	Vehicle Type: The name of the vehicle model upon which the other variables of this category are based (e.g. "Leaf" or "Volt").
β_{BEV}	Is BEV?: Boolean indicating whether vehicle is a battery electric vehicle (BEV), if not, vehicle is assumed to be a plug-in hybrid electric vehicle (PHEV).
β_u	Unneeded Charge?: Boolean flag indicating whether the driver is seeking a charger because it is actually needed or for some other, less critical reason.
β_r	Willing to Roam?: Boolean indicating whether the driver would consider traveling to a neighboring or en route TAZ to charge.
C	Battery Capacity (kWh): The default energy stored by the battery bank when fully charged. If the vehicle is a PHEV, then the battery capacity indicates the amount of energy available to drive the vehicle in charge depleting mode.
η_e	Electric Fuel Consumption (kWh/unit-distance): The default amount of battery electricity required to travel 1 unit of distance (e.g. miles or kilometers).
η_g	Hybrid Fuel Consumption (gal / mile or liter / km): The default fuel required to travel for a PHEV in charge sustaining mode. (N/A for BEVs).
H_W	Wait Threshold (hours): A duration defining how long the driver will wait to find a charger before giving up (resulting in a "soft-stranding").
Z_H	Home: The home TAZ of the driver.
ϕ	State: A discrete integer value that represents the current state of a driver (*Not Charging*, *Traveling*, *Charging*, *Stranded*).
I	Itinerary: A compound variable containing the intended itinerary of the driver for one day. Each row of the itinerary represents a single trip and includes the following columns: 1) Origin TAZ, 2) Destination TAZ, 3) Departure time (decimal hour of the day), 4) Change flag that defaults to FALSE but is set to TRUE when a trip is due to a change to the driver's itinerary, and 5) Delay amount for tracking delay experienced for each trip in the itinerary.
n	Daily Itinerary End Row: the row in I demarcating the last trip in the present day. n is updated for all drivers at the beginning of each day and can dynamically change if unscheduled trips are added to a driver's itinerary.
r	Current Itinerary Row: used to keep track of the next trip in the driver's itinerary (or the current trip if the driver state is "traveling").
$Z_r = I_{r,1}$	Current TAZ: The TAZ where the driver is currently located.
θ	State of Charge: The fraction of usable energy remaining in the vehicle's battery. A value of 1 indicates a fully charged battery and a value of 0 indicates the battery is effectively empty. Note, if the vehicle is a PHEV, then 0 indicates charge sustaining mode which does not imply the battery is fully depleted.

Table 2.4: Driver State Variables (continued)

Variable	Description
D_X	External Distance (miles or km): The driving distance between a TAZ external to the region of interest to a gateway TAZ within the region of interest. The result of a driver specific random draw from an externally supplied distribution function.
T_X	External Time (hours): The driving time between a TAZ external to the region of interest to a gateway TAZ within the region of interest. The result of a driver specific random draw from an externally supplied distribution function.
M_D	Number of Denials: The number of occurrences when the driver wanted/needed to charge but was unable due to a lack of available chargers.
W_T	Total Itinerary Delay Amount: The total amount of delay the driver has experienced (equivalent to $\sum_{j=1}^{r} I_{j,5}$).

Table 2.5: Charger State Variables

Variable	Description
τ	Charger Type: Integer indicating the station level (0,1,2,3, or 4).
Z	Location: the TAZ where the charger is located.
κ	Charge Rate: The rate at which the charger delivers energy to the vehicle (kW).
U	Energy Price: The price of energy at this charger ($ / kWh).
E	Energy Delivered: The cumulative amount of energy delivered by the charger up to the current moment (kWh).
M_c	Number of Sessions: A count of the number of discrete charging sessions with drivers.

of the driver decision logic. The chart contains a representation of the different states that a driver can have (dark blue rectangles), the event schedulers that determine when a driver executes an event (dark yellow triangles), the events that control process flow (arrows labeled with light yellow rectangles), and the decisions that are evaluated to inform the process flow (light blue diamonds). Detailed specifications for these processes are given in Section 2.2.

In Figure 2.1, event schedulers are depicted as attached to states on the upstream side of the process flow. This placement is intentional and closely tied to the management of PEVI as a discrete event simulation. At any time, drivers have complete knowledge about the state of their vehicle (state of charge, fuel consumption, etc.) and their itinerary. This means that as drivers enter any state, they can determine the time at which they will exit that state and perform an event. For example, when the *Traveling* state is entered, the driver knows where they are going (by virtue of their itinerary) and based on the global origin-destination table, they can determine when they will arrive. The PEVI model takes advantage of this

Table 2.6: Parameter Definitions

Variable	Description (Default Value for Delhi Case Study)
f_s	Charge Safety Factor: multiplier used to approximate the safety factor drivers assume necessary to ensure a trip can be made. (1.1)
d	Charger Search Distance: the distance used to define what TAZs are considered "neighbors" for the purpose of finding a charger. (5 km)
μ_{T_W}	Wait Time Mean: the average amount of time (in hours) that a driver waits before checking again to see if a charger is available. (0.5 hr)
H_R	Willing To Roam Time Threshold: the amount of time (in hours) at which point a driver will consider traveling to neighboring or en route TAZs in order to charge vs. only considering chargers in their current location. (1 hr)
δ	Time Opportunity Cost: the value of a driver's time in units of currency per hour. (3.8 $/hr)
	Probability of Unneeded Charge: the probability that a driver will choose to charge despite not actually needing it. (0.1)
σ_η	Electric Fuel Consumption SD:standard deviation of the truncated normal distribution used to distribute electric fuel consumption among the drivers. (0.2 kWh/km).
μ_η	Electric Fuel Consumption Range: range of the truncated normal distribution used to distribute electric fuel consumption among the drivers. (0.1 kWh/km).
W_S	Soft Strand Penalty: Penalty levied on drivers when they experience a "soft-stranding" or they are unable to access a needed charger after H_W hours. The penalty is in units of hours, which are added to $I_{r,5}$. (4 hr)
W_H	Hard Strand Penalty: Penalty levied on drivers when they experience a "hard-stranding" or there are no chargers within range and the driver cannot execute their next trip. The penalty is in units of hours, which are added to $I_{r,5}$. (6 hr)
F_θ	Starting State of Charge Distribution: user specified cumulative probability distribution used to initialize θ for vehicles at the beginning of the model run.
F_{H_W}	Wait Threshold Distribution: user specified cumulative probability distribution used to initialize each driver's wait threshold variable (H_W).
F_{D_X}, F_{T_X}	External Distance Distribution and External Time Distribution used to initialize the distance and time of travel needed by the driver for an external trip.
C_{ij}	Charger Infrastructure: matrix containing the number of chargers of level j at TAZ i.
A_C	Charger Type Input File: File path to the text file containing the chargers types and their associated state variables.

Table 2.7: Parameter Definitions (continued)

Variable	Description (Default Value for Delhi Case Study)
A_D	Driver Input File: File path to the text file containing the driver itineraries for the model run.
A_O	OD Input File: File path to the text file containing the origin-destination data for the model run. The TAZ numbers in this file must correspond to the TAZ numbers in A_C.
A_V	Vehicle Type Input File: File path to the text file containing vehicle parameters (name, electric fuel consumption rate, hybrid gasoline fuel consumption rate, battery capacity, market fraction).

foresight and model scheduling is structured so that drivers schedule events as they enter a new state.

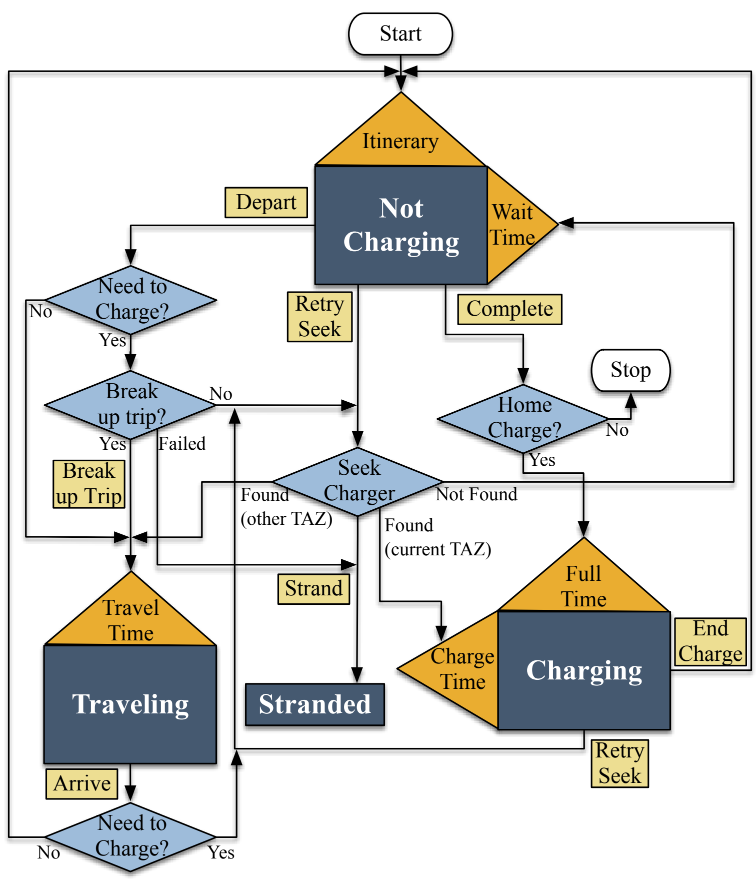

Figure 2.1: This flow chart illustrates the four driver states (dark blue rectangles), the events that control transitions between states (arrows labeled with light yellow rectangles), the decision logic used to inform transitions (light blue diamonds) and the event schedulers that dictate when events are executed (dark yellow triangles).

Design Concepts

Basic Principles

PEVI is designed to address the challenge of developing a plan for the deployment of EVCS throughout a region for varying levels of PEV adoption. PEVI accomplishes this by simulating PEV driving and charging at the individual level and by using best available mobility data for regional transportation networks. This approach endogenizes driver charging behaviors around two key decisions: 1) whether to engage in a charging session, and 2) where and what level charger to use. In addition, PEVI simulates the dynamics of multiple drivers competing for limited charging infrastructure and the adaptations necessary when drivers cannot get the charge they need.

Objective

The objective of each driver in the PEVI model is to complete their itinerary and to do so at minimal cost. Drivers attempt to execute every trip in their itinerary, but with some discretion. Drivers can choose when and which type of charger to use in pursuit of their objective. When drivers make this choice, they select the charger that provides the needed energy at the least cost to the driver. This economic decision accounts for the opportunity cost of delays in the driver's itinerary by valuing the driver's time at rate defined by the parameter δ.

Drivers also elect to use chargers during the day even when they don't strictly need the energy, this behavior is based on empirical evidence that PEV drivers charge their vehicle for reasons beyond strict execution of their itinerary (e.g. for convenience or to maximize electric distance driven).

Adaptation

The general form of a driver's experience consists of the following:

- Depart according to the next trip in the itinerary
- Arrive at the destination
- Decide whether to attempt a charging session
- Seek the charger that provides the energy desired at the least cost
- Engage in the charging session
- End the charging session
- Make the next departure

Drivers also adapt to circumstances that do not fit the above narrative. This includes retrying the *Seek Charger* decision when they are unable to access a charger or when the current session is at a power level too low to charge their vehicle in time (Sections 2.2 and 2.2). In addition, drivers can add new trips to their itinerary to make use of chargers in neighboring TAZs or en route to their destination (Sections 2.2 and 2.2).

Sensing

Modern PEV charging infrastructure is capable of reporting the state of the charger (available vs. in-use) to online services. At the same time, most modern PEVs are equipped with cellular connections (or through equivalent services on smart phones) allowing drivers to instantaneously know the locations of all chargers in their vicinity and whether or not the charger is available. PEVI therefore assumes that drivers can sense the location, type, price, and availability of all chargers in the model. Some chargers on the market allow drivers to make a reservation in order guarantee availability at a future time. This capability is not implemented in PEVI.

Stochasticity

Several pseudorandom processes are used to introduce variability in the model:

- Several state variables of drivers are initialized to the result of a random draw (Section 2.2).
- The *Wait Time* event scheduler uses a random draw from an exponential distribution to vary the time that drivers wait before seeking available chargers after an unsuccessful search (Section 2.2).
- The *Need to Charge* decision employs a random draw to simulate drivers who occasionally elect to charge their vehicle when they do not strictly need the energy (Section 2.2).
- The *Home Charge* decision employs a random draw to simulate drivers who occasionally elect not to charge their vehicle when they arrive at home (Section 2.2).

Initialization

Model initialization involves the following steps:

- Model parameters (Table 2.7) and various input data are read from input files and initialized (e.g. TAZs, time and distance matrices, vehicle and charger properties, and driver itineraries).
- Drivers are assigned a vehicle type based on the market fractions of the vehicle types and the total number of drivers.

- Driver state variables are initialized including random draws for η_e, θ, T_X, D_X, and H_W.
- Finally, the first *Depart* event of each driver's itinerary is added to the schedule S for dispatch.

Emergence

At the conclusion of a model run, all of the following metrics of service to PEV drivers from the charging infrastructure can be quantified in aggregate form or disaggregated in time, space, by charger type, by vehicle type, or by individual driver:

- Delay and stranding experienced by drivers
- Instantaneous power drawn by chargers
- Duty factor of the chargers and energy dispensed to vehicles
- Electric energy and petroleum consumed by vehicles
- Total and electric-only distance driven
- Number of failed attempts to access a charger at the time of seeking

Submodel Details

The following sections provide detailed descriptions of the PEVI submodels.

Itinerary Generation

The set of driver itineraries used by PEVI are exogenous to the model and are therefore application-specific. But because they are so critical to the realism of model results, this section will present the general approach to developing itineraries that has been used to date.

Ultimately, an activity-based model is necessary to produce driver itineraries which reflect where and when drivers travel as well as how long they spend at their destinations and how many chained trips they execute in a day. Depending on the region of study, an established activity-based travel demand model may be available and therefore could be directly employed to generate driver itineraries for PEVI. In most of the regions for which PEVI has been applied (Delhi, India and several California counties), there was no activity model available. Therefore an activity model was developed using the non-parametric resampling technique described below.

This approach was designed to reproduce the statistical properties of two key datasets: outputs from a travel demand model and a transportation survey relevant to the study region.

- Travel Demand: The most critical component to building a set of realistic driver itineraries for PEVI is determining where drivers go when they travel. Fortunately, most metropolitan regions (and many rural regions as well) use regional travel demand models to project regional growth or changes in mobility for transportation infrastructure planning purposes. The traditional form of a travel demand model is the "four step" model. These models use current and projected land-use, demographics, and local traffic counts to forecast future traffic trends. Regions are divided into travel analysis zones (TAZs) and their output includes an estimate of the daily trip count between every pair of zones, usually disaggregated by travel mode (automobile, walking, bus, etc.), trip purpose (home-based, work-based, etc.), and time of day (hourly or AM/PM peaks).

- Transportation Surveys: While regional travel demand data is necessary to build realistic driver itineraries, there are some critical missing components to the outputs of a four-step model. They often provide no information about exactly when trips are made, how long drivers spend at their destinations, where the drivers live, or what trips drivers chain together into a daily tour. Transportation survey data can fill in many of these missing components. Most regional and national transportation agencies worldwide conduct periodic surveys to assess a wide variety of transportation-related trends and behaviors. Typical surveys involve an intake form where respondent demographic data are collected. Surveys also ask the respondent to record a detailed log of their travel over some period of time. Each log entry typically details the time of departure, time of arrival, time spent at the destination (dwell time), distance traveled, and trip type (home to work, work to other, etc.).

- Travel Activity Through Non-Parametric Resampling: Driver itineraries can be synthesized by strategically blending the outputs of a four-step travel demand model with transportation survey data. Respondents are drawn randomly from the survey pool and their tour is fit into the road network of the region in a manner consistent with the demand for trips as specified by the travel demand outputs. A complete description of this algorithm is available in [64].

Itinerary Event Scheduler

The itinerary submodel is an event scheduler. Drivers schedule the *Depart* event to occur at the departure time of the next trip in their itinerary $I_{r,3}$. If $I_{r,3} < t$, the driver executes the *Depart* event immediately. If the driver's itinerary has no more trips, then the driver executes the *Complete* event.

Depart Event

The driver executes the *Need to Charge* decision. If no charge is needed, then the driver transitions to *Traveling*. If a charge is needed, the driver executes the *Break Up Trip* decision and either executes the *Break Up Trip* event and transitions to the *Traveling* state or executes the *Seek Charger* decision.

Need to Charge Decision

To make this decision, β_u is initialized to FALSE and four values are estimated:

- $R_R \equiv$ Remaining Range: the distance remaining (set to positive infinity if β_{BEV} is false)
$$R_R = (\theta * C)/(\eta_e f_s) \tag{2.1}$$
- $D_T \equiv$ Trip Distance: the distance to complete the next trip in the driver's itinerary
$$D_T = \Omega_D(I_{r,1}, I_{r,2}) \tag{2.2}$$
- $D_J \equiv$ Journey Distance: the distance to complete all of the remaining trips in the driver's itinerary for the current day
$$D_J = \sum_{i=r}^{n} \Omega_D(I_{i,1}, I_{i,2}) \tag{2.3}$$
- $T_D \equiv$ Time Until Departure: the time in hours remaining before the vehicle is due to depart
$$T_D = I_{r,3} - t \tag{2.4}$$

Table 2.8 mathematically details the decision, which is also explained here. If the driver has just arrived to a destination (the calling event is *Arrive*) and the remaining range R_R is less than is needed for the rest of the driver's trips D_J, then return TRUE. If the driver is departing, return TRUE if the remaining range R_R is less than the next trip distance D_T. Otherwise, return TRUE only if the driver just arrived and the state of charge θ is less than one and the time until departure T_D is greater than the willing to roam time threshold H_R and a random draw is less than a logistic function of the state of charge.

Travel Time Event Scheduler

The travel time submodel is an event scheduler. The *Arrival* event is scheduled for $\Omega_T(I_{r,1}, I_{r,2})$ hours from the present moment.

During PEVI model execution, travel time and distance between all internal pairs of TAZs is determined (via the Ω function) by looking up the value in the appropriate row of the origin destination table indexed by the source and destination TAZ. Travel times are determined using appropriate data sources for the application (e.g. a mapping API or through GIS analysis of a road network shapefile).

PEVI also has the capability of representing "external" TAZs, which are typically defined at the gateways to the region on major arterials. Travel distances and times to/from external TAZs are determined stochastically during model initialization once per driver according to the Distribution submodel (Section 2.2) and F_{D_X}, F_{T_X}.

Table 2.8: Need to Charge Scheduler

If	**Then**
(Calling event is *Arrive*) $\cap$ $R_R < D_J$	Return TRUE
(Calling event is *Depart*) $\cap$ $R_R < D_T$	Return TRUE
(Calling event is *Arrive*) $\cap$ $(\theta < 1) \cap$ $(T_D \geq H_R) \cap \left(x < \frac{P_U}{1+e^{-5+10\theta}}\right)$ where x is drawn from $X \sim uniform(0,1)$	Return TRUE and set β_u to TRUE.
Otherwise	Return FALSE

Arrive Event

The driver executes the *Need to Charge* decision, after which the driver transitions to the *Not Charging* state or executes the *Seek Charger* decision.

Seek Charger Decision

This submodel is based on an economic model that compares the total cost of charging (including the opportunity cost of a driver's time) from all relevant charging alternatives, selecting the least cost option. The submodel relies on use of a nearest neighbor function defined as:

$$\Gamma(Z_z) = \{Z_i \ \forall i \neq z \mid \Omega_D(Z_z, Z_i) < d\} \tag{2.5}$$

The submodel consists of the following actions:

(a) Set β_r to $TRUE$ if $\beta_{BEV} \cap (T_D < H_R) \cap \neg\beta_u$, otherwise set to $FALSE$.

(b) Assemble the set of TAZs and charger type combinations available to the driver. This set of charger alternatives is denoted by $\mathbb{Z}_{z,l}$ and is found according to the following expression:

$$\mathbb{Z}_{z,l} = \begin{cases} \left\{ \frac{(Z, Z_\alpha) \forall Z \epsilon}{\{\Gamma(Z_r) \cup \Omega_Z(Z_{r,1}, Z_{r,2})\}} \right\} & \text{for } \beta_r \\ \{(Z_r, Z_{r,\alpha})\} & \text{otherwise} \end{cases} \tag{2.6}$$

The index i will be used below to reference each combination of TAZ and charger type (z and l) with at least one available charger. Note that some of the variables with the subscript x for "extra" will be zero for chargers in Z_r or en route as they only apply to travel that's additional to the driver's itinerary. The one exception to this is

$T_{C,x}$, which will be non-zero for en route TAZs because the time spent charging is an opportunity cost to the driver.

(c) If no available chargers are found, then increment the driver variable M_D and check to see if the driver has been delayed for a total time W_T greater than H_W. If the driver has been delayed longer than the threshold, they are soft-stranded, execute the *Strand* event. Otherwise, transition to the state *Not Charging* and stop this action.

(d) Calculate the following values:

(i) $\beta_{3f} \equiv$ Level 3 And Too Full: This boolean value is $TRUE$ if the charger under consideration has $\tau = 3$ and $\theta >= 0.8$. If β_{3f} for alternative i, then i is not considered.

(ii) $W_3 \equiv$ Level 3 Time Penalty: Set this to ∞ if $D_T > 0.8C\eta_e f_s$ (i.e. the distance to the destination is greater than how far the vehicle can go on a full level 3 charge). Otherwise set to 0. This penalizes level 3 charging when a level 1 or 2 charge can accommodate the driver's trip without an additional stop or another charging session.

(iii) $N_E \equiv$ Trip Or Journey Energy Need: This value depends on the amount of time before the next departure in the driver's itinerary as well as the current state of charge and the charger type. If $T_D < H_R$, then only the energy needed for the next trip is considered, otherwise the energy needed for the journey is used. If the energy needed for the trip or journey is greater than the energy needed to fill the battery (or in the case of level 3, to achieve 80% state of charge) then N_E is set to the battery limiting value.

As a formula, the value is calculated as follows. First, if $T_D < H_W$, set D to D_T, else set D to D_J.

$$N_E = \begin{cases} min\begin{pmatrix} max[0, Df_s\eta_e - \theta C], \\ max[0, (0.8-\theta)C] \end{pmatrix} & \tau = 3 \\ min\begin{pmatrix} max[0, Df_s\eta_e - \theta C], \\ max[0, (1-\theta)C] \end{pmatrix} & \text{otherwise} \end{cases} \tag{2.7}$$

(iv) $T'_{T,i}, D'_{T,i}, E'_{T,i} \equiv$ Extra Time, Distance, and Energy For Travel: The additional travel time and distance needed to accommodate the detour, equal to the difference between first traveling to the intermediate TAZ, then to the destination TAZ vs. traveling straight to the destination TAZ. the energy needed to accommodate the extra travel is calculated as $E'_{T,i} = D'_{T,i}\eta_e f_s$.

(v) $T'_{C,i} \equiv$ Extra Time Until End Charge: If β_{COD}, then this value is set to the amount of delay in the driver's itinerary that would be necessary to use the charging alternative, calculated as $max(0, N_T T_D)$ if the charger is in the origin and 0 if the charger is in the destination TAZ. If $\neg\beta_{COD}$, then the value is an estimate of the extra time a driver would spend charging, equal to the value of

T_E as calculated by the *Charge Time* submodel (Section 2.2) with the following modifications:

(i) T_D is decreased by $\Omega_T(I_{r,1}, Z_i)$

(ii) θ is decreased by $\left(\frac{\Omega_D(I_{r,1}, Z_i)\eta_e}{C}\right)$

(iii) D_T and D_J are assumed to begin at Z_i

(e) Estimate the cost of the alternative:

$$W_i = \delta(T'_{C,i} + T'_{T,i} + W_3) + U_i(N_E + E'_{T,i}) \tag{2.8}$$

(f) Chose the alternative i^* with the minimum cost. If $Z_{i^*} = Z_r$, execute the *Charge Time* event scheduler. If $Z_{i^*} = I_{r,2}$, then update the departure time of the next trip in the driver's itinerary to be the present moment and call the *Travel Time* event scheduler.

If $Z_i \neq Z_r \cap Z_i \neq I_{r,2}$, then test to ensure that the driver is not caught in an endless loop between two TAZs by testing if $\sum_{j=1}^{r} I_{j,4} \geq 10$ (i.e. has the driver changed their itinerary 10 or more times). If the driver is caught in an endless loop, consider it a soft-stranding and execute the *Strand* event. Otherwise update the driver's itinerary to include the new destination TAZ (unless $Z_{i^*} = I_{r,2}$) with a depart time equal to t and call the *Travel Time* event scheduler.

If no alternatives are found, determine whether chargers exist but are just unavailable or if no chargers exist. If no chargers exist and $\neg\beta_u$, then the driver is hard-stranded. Execute the *Strand* event.

Charge Time Event Scheduler

The *Charge Time* event scheduler is executed after a driver has performed the *Seek Charger* decision, selected an available charger, and optionally traveled to that charger. The submodel decides whether the driver will attempt to retry finding a charger later in the day (necessary to allow drivers to make temporary use of lower level chargers when higher levels are currently unavailable) or to schedule the *End Charge* event.

To make this determination, the following values are estimated:

- $\beta_{COD} \equiv$ Charger In Origin Or Destination: this Boolean describes whether the charger is located in a TAZ that is a part of the driver's itinerary vs. a neighboring TAZ or an en route TAZ.

- T_D: see Equation 2.4

- D_T: see Equation 2.2

- $N_T \equiv$ Trip Charge Time Need: the amount of charging time needed to complete the next trip in the itinerary, if β_{BEV} is FALSE then set N_T to 0 to indicate that there is no need for charge to complete the trip, otherwise use the following formula:

$$N_T = max\left[0, \frac{D_T f_s \eta_e - \theta C}{\kappa}\right] \tag{2.9}$$

- D_J: see Equation 2.3
- $N_J \equiv$ Journey Charge Time Need: the amount of charging time needed to complete the remaining trips in the itinerary

$$N_J = max\left[0, \frac{D_J f_s \eta_e - \theta C}{\kappa}\right] \tag{2.10}$$

- $N_F \equiv$ Full Charge Time Need: the amount of charging time to complete a full charge

$$N_F = \begin{cases} max\left[0, \frac{(0.8-\theta)C}{\kappa}\right] & \text{if } \tau = 3 \\ \frac{(1-\theta)C}{\kappa} & \text{otherwise} \end{cases} \tag{2.11}$$

- $T_R \equiv$ Time Until End Charge: the anticipated time in hours remaining before the driver chooses to end charging or the vehicle is fully charged. Table 2.9 mathematically details how this value is calculated; the logic is also explained here. If the next trip is too far to make on a full battery ($N_F < N_T$), then T_R is set so as to fill the battery. If the time until departure T_D is less than the trip charge time need N_T, T_R is set to N_T to ensure the driver can make the next trip, but this will incur delay. If the charger is in the origin or destination TAZ, then T_R is set so the battery will be filled or the driver departs, whichever comes first. If the charger level is 3, T_R is set so the battery is filled (to 80% SOC), the driver departs, or enough range has been acquired to complete the driver's journey, whichever comes first. Otherwise T_R is set so the battery has enough range to make their next trip or the driver departs, whichever comes first.

Table 2.10 mathematically details how the *Charge Time* event scheduler decision is made and at what time the corresponding event is to be scheduled; the logic is also explained here. The driver schedules *Retry Seek* with the objective of finding a higher level charger if all of the following conditions are TRUE: 1) the charge is needed (β_u is FALSE); 2) the charger level is less than 3 ($\tau < 3$); 3) the time before the charge session will end T_R is less than enough to get a full charge N_F; 4) either the time until end charge T_R is greater than the time until departure T_D or less than the time needed to acquire enough range for the journey mobility $T_R < N_J$; and 5) the time until departure T_D is greater than the willing to roam threshold H_R. Otherwise, the driver schedules the *End Charge* event.

Table 2.9: Time Until End Charge

If	**Then set T_R to**	**Other Actions**
$N_F <= N_T$	N_F	
$T_D < N_T$	N_T	Delay itinerary with next trip occurring N_T hours from the present moment.
β_{COD}	$min(T_D, N_F)$	
$\tau = 3$	$min(T_D, N_F, N_J)$	
otherwise	$min(T_D, N_T)$	

Table 2.10: Charge Time Scheduler

If	**Then**
$\neg\beta_u \cap (0 < T_R < N_F) \cap (\tau < 3) \cap [(T_R > T_D) \cup (T_R < N_J)] \cap (T_D > H_R)$	Schedule *Retry Seek* event to occur after t_W hours where $t_W = max\,[T_D - H_R, x]$ and x is drawn from $X \sim exp(\mu = \mu_{T_W})$
otherwise	Schedule *End Charge* event to occur after T_R hours.

Wait Time Event Scheduler

The wait time submodel is an event scheduler. It is executed after a driver has performed the *Seek Charger* decision and found none that are available. The submodel decides whether the driver will attempt to retry finding a charger or, if sufficient charge is available, abandon the charging attempt and schedule a departure.

To make this determination, first estimate R_R, D_T, D_J, and T_D, based on Equations 2.1, 2.2, 2.3, and 2.4. Table 2.11 mathematically details how the decision is made and at what time the corresponding event is to be scheduled; the logic is also explained here. If the driver has experienced more delay W_T than the wait time threshold H_W, the driver is considered soft-stranded and schedules no further action. If the remaining range R_R of the vehicle is less than the trip distance T_D, the driver schedules *Retry Seek* to occur a randomly distributed amount of time in the future. This behavior is designed to model the fact that a driver conducting activity at a destination will not be capable of continuously monitoring a charger until it becomes free, rather, the monitoring would happen at discrete moments in time when the driver checks on the status of the charger (either physically or over the internet). If, on the other hand, the remaining range is sufficient to complete the next trip but not sufficient to complete all of the remaining trips in the driver's itinerary, the driver schedules *Retry Seek* if the time until departure T_D is greater than the willing to roam time threshold H_R, otherwise the driver schedules the *Depart* event. This structure is intended to account for the fact that the driver has compelling motivation to use a charger and therefore would be willing to interrupt their activity to initiate a session, but as the time until departure draws near, there are diminishing returns on starting a new charging session and therefore the driver eventually opts to depart, postponing the charge event for a different destination. Finally, if the remaining range is greater than the journey distance D_J, the *Depart* event is scheduled and no further action is taken.

Table 2.11: Wait Time Scheduler

If	**Then**
$W_T \geq H_W$	Add W_S to $I_{r,5}$ and do not schedule any additional actions
$R_R < T_D$	Schedule *Retry Seek* to occur after t_W hours where t_W is drawn from $X \sim exp(\mu = \mu_{T_W})$
$D_T <= R_R < D_J$	If $T_D > H_R$, schedule *Retry Seek* event to occur after t_W hours where $t_W = max[T_D - H_R, x]$ and x is drawn from $X \sim exp(\mu = \mu_{T_W})$, otherwise schedule *Depart* event to occur after T_D hours.
$R_R >= D_J$	Schedule *Depart* event to occur after T_D hours.

Break Up Trip Decision

This decision is performed after a driver attempts to depart but first determines that a charge is needed. One option available to the driver is to break their trip into sub-trips in order to find an available charger at a neighboring TAZ or en route to their destination. If the battery is full ($\theta = 1$) or no chargers exist in the current TAZ, then this decision returns

$TRUE$ and the *Break Up Trip* event is executed. Otherwise, the decision returns $FALSE$ and the *Seek Charger* decision is executed.

Break Up Trip Event

Break Up Trip is an event which uses a scoring system to choose an intermediate destination between the driver's current TAZ and destination.

- If $(\theta = 1) \cap \left(\frac{\theta C}{\eta_e} < f_S I_{r,2}\right)$ (i.e. the driver has a full battery and cannot make the next trip) or if $\theta >= 0.8$ and Z_r only has level 3 chargers available, then the driver attempts to break the trip into smaller trips with intermediate stops for charging.

- The driver only considers reachable en route TAZs $\mathbb{Z} = \{Z \epsilon \Omega_Z(I_{r,1}, I_{r,2}) | \Omega_D(I_{r,1}, Z) <= R_R\}$

- The search is first restricted to the elements of $\mathbb{Z}$ that would allow the driver to reach the ultimate destination in one trip after recharging (note that this must be based on $\theta = 0.8$ if only level 3 chargers are available in the candidate TAZ). If no such TAZs can be found, or all of these TAZs have a score of 0, then all reachable en route TAZs are considered.

- Each reachable en route TAZ is assigned a score equal to the number of available chargers or a certain level times the level number (E.g. if two level 3 and one level 2 chargers are available then the score would be 2 * 3 + 1 * 2 = 8). If the TAZ is the driver's home, then 8 is added to the score for that TAZ (in other words, a home charger is as valuable as 4 level 2 chargers but not as valuable as 3 level 3 chargers).

- The TAZ with the highest score is selected (ties are broken by selecting the furthest TAZ from the current location). The TAZ is added to the driver's itinerary with t as the departure time and the *Travel Time* event scheduler is executed. If no en route TAZs have any available chargers (i.e. if they all have a score of 0), then the driver selects the most distant reachable TAZ. If no TAZs are reachable, the driver is hard-stranded and executes the *Strand* event.

Home Charge Decision

The *Home Charge* decision is executed when the driver has completed their itinerary. The decision involves a random Bernoulli trial with a probability that increases with decreasing state of charge. The result of the decision is β_h where:

$$\beta_h = \begin{cases} TRUE & \text{for} (Z_r = Z_H) \cap (\theta < 1) \cap x < \frac{1}{1+e^{-5+6\theta}} \\ FALSE & \text{otherwise} \end{cases} \tag{2.12}$$

Full Charge Time Event Scheduler

This event scheduler schedules the *End Charge* event to occur after N_F hours, where:

$$N_F = \frac{(1-\theta)C}{\kappa} \tag{2.13}$$

Strand Event

Drivers are either soft-stranded or hard-stranded. In both cases no further actions are scheduled for the driver. A delay penalty is levied to the driver by adding to $I_{r,5}$ the value of W_S or W_H for soft or hard stranding, respectively.

Distribution

PEVI allows the modeler to define probability distributions for certain entity state variables (e.g. $F_{D_X}, F_{T_X}, F_\theta$). Distributions are provided to PEVI in the form of a text file containing cumulative probabilities and the corresponding quantiles. During model execution, random values are drawn from a uniform distribution on the interval [0,1) and then the appropriate quantile is determined by linear interpolation between the two bracketing values in the table.

Heuristic Optimization of EVCS

The charging infrastructure siting problem is an integer programming problem that treats the simulation model as a block box and seeks to minimize the present value of the per driver delay experienced over a 10 year time horizon subject to the placement of EVCS of alternative levels throughout the TAZs. The problem is formulated as follows:

$$\min_K E(W) = E\left\{\sum_{y=0}^{10}\left[\frac{\sum_v s\delta W_{T,v}(K)}{(1+r)^y}\right]\right\}\frac{1}{s'} \tag{2.14}$$

Subject to:

$$\sum_{z,l} U_l k_{z,l} \leq B \tag{2.15}$$

Where K is the matrix of chargers with elements $k_{z,l}$ for each charger level l and TAZ z, $W_{T,v}$ is the total delay experienced by driver v during the model as a function of K, s is a scaling factor to convert the delay from one day (or several days) to an annual value, r is the discount rate, U_l is the installed cost of a charger of level l, and s' scales the final value into units of \$/driver/day.

This is a stochastic heuristic optimization, so the expected value of the objective foundation is approximated by running the model with replication and averaging the results. The heuristic algorithm builds out the infrastructure from some base scenario (typically from the existing portfolio of EVCS). The algorithm uses a one-at-a-time approach, testing individually the impact of increasing each element of the K matrix by a single charger (or for larger problems, small banks of chargers). The TAZ/level combination that yields the largest reduction in total delay per dollar spent on infrastructure is selected according to the following expression.

$$\underset{z,l}{\operatorname{argmin}} \frac{\partial W / \partial k_{z,l}}{U_l} \tag{2.16}$$

This optimization scheme is heuristic because it cannot be guaranteed to produce a globally optimal solution. We examine the approximate optimality of this scheme by comparing the results to another algorithm, differential evolution, which is well known as a robust "global" optimization technique.

Differential Evolution Optimization Scheme

Differential evolution is also a heuristic optimization scheme, but it has been shown to exhibit substantial robustness in the face of highly non-linear objective functions with correlated regressors and prevalent local minima [217] [226] [225] [224]. The algorithm itself is relatively simple. A set of candidate particles (each a vector representing values of the decision variables which are randomly initialized throughout the decision space) are potentially updated with each generation through mutation and evaluation of the objective function. For each particle, a mutant is created by uniformly sampling three other particles, and adding the vector difference between two of those particles to the third. This step tends to create mutants that align in the search space, promoting faster exploration of regions with high gradients and more extensive exploration of low-gradient regions. After the mutation step, there is a crossover step, where only a randomly sampled subset of the decision variables are actually replaced in the original candidate particle by the mutant. Finally, greedy selection is employed where the candidate particle is only replaced by the new particle if it yields a lower value of the objective function.

Discussion

The PEVI model has to date been applied to the metropolitan region of Delhi, India as well as six Californian counties (Humboldt, Shasta, Siskiyou, Tehama, Glenn, Colusa). We focus on the Delhi case study here because it reflects the most extensive and largest scale application of the model. In the following discussion, we describe the application of PEVI to Delhi, the results of the driver activity generation process, the comparison between our heuristic optimization scheme and differential evolution, the sensitivity of the model to several critical modeling assumptions, and finally we feature some selected sensitivity results which showcase the ability of PEVI to explore uncertainties surrounding the future of technology and regulatory trends that could impact PEV adoption and charging infrastructure availability.

Model Application

The region of application of the EVSE siting analysis was the National Capitol Territory (NCT) of Delhi, India. The metropolitan area covers 1400 square kilometers containing over 2300 kilometers of paved road surfaces. In 2008, 52% of households owned a motorized vehicle and 19% owned a car. Residents traveled approximately 22 million kilometers per day in cars and taxis, about 19% of total daily travel [223].

Several general-purpose transportation planning studies have been commissioned by the NCT of Delhi. These studies, performed by RITES Ltd., provided the travel demand projections and travel survey data needed to apply the non-parametric resampling technique described in Section 2.2. In addition, these studies provided the road network and link performance data necessary to characterize travel times during average and congested conditions. The travel demand estimates were for mobility in the year 2021 and the household travel survey was from 2008, containing over 45,000 responses by Delhi residents [223] [222].

As PEVs come to market in India, there will be a variety of form factors with a variety of battery capacities and fuel consumption rates. The relative market share of these various options will be important from the perspective of deploying charging infrastructure. This analysis did not involve a detailed forecast of EV market evolution, but we did assume three vehicle classes: low, medium, and high, referring to the power capacity of the electric motor and not necessarily to the range of the vehicles (Table 2.12).

Table 2.12: Three vehicle classes included simultaneously in the base scenario for the PEVI application to Delhi.

Class	**Effective Battery Capacity (kWh)**	**Electric Consumption Rate (Wh/km)**	**Range (km)**	**Market Penetration**
Low	6.5	11.4	57	33.3%
Med	14.3	14.5	99	33.3%
High	20.9	21.7	96	33.3%

The region was split into 53 TAZs and EV owner homes where assumed to be distributed in proportion to the population. In each TAZ, it is possible to site three types of chargers as described in Table 2.13. Other default parameter values are noted in Table 2.7.

Driver Activity

The driver itineraries used in PEVI are critical to the realism of the simulation and the utility of the results. We therefore present results from the Delhi case study of applying the non-parametric resampling technique described in Section 2.2. In Figure 2.2, the spatial distribution of travel demand (as quantified by departure trips) is compared between the

Table 2.13: Characteristics of charging infrastructure assumed in the Delhi application of the PEVI model.

Level	Capacity (kW)	Installed Cost ($)	Charging Price ($/kWh)
1	1.5	500	0.20
2	6.6	5,000	0.34
3	50	25,000	0.55

origin-destination data used by the technique and the output of the resampling process. Analogously, the temporal distribution (segregated by trip purpose) is compared in Figure 2.3 between the survey data used by the technique and the outputs of the process. There is clearly a high degree of similarity between the distributions, an expected result given that the input distributions were directly used to synthesize driver activity. But there is not perfect correlation between input and output. This is due to the constraint-relaxation necessary for the driver trips from the survey data to be reconciled with the origin destination matrices of the travel demand model.

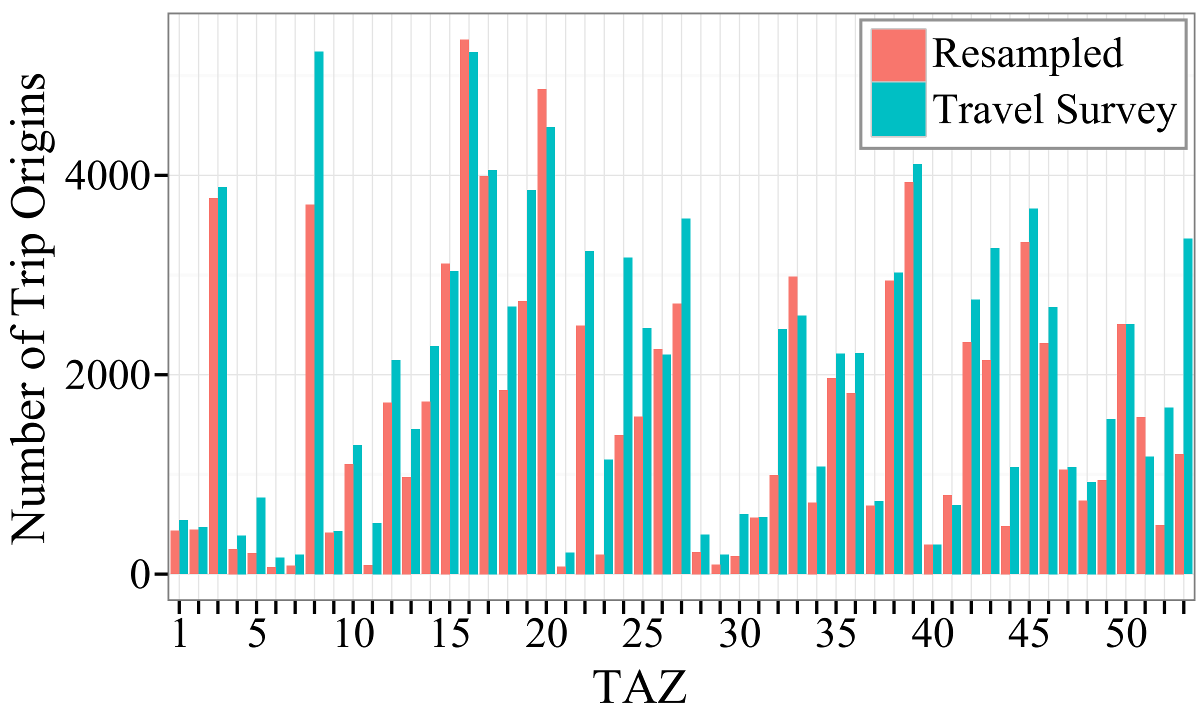

Figure 2.2: A comparison of the spatial distribution of travel demand (trip departures by TAZ) between the travel demand model used as input to the non-parametric resampling algorithm and the resulting activity for the Delhi case study.

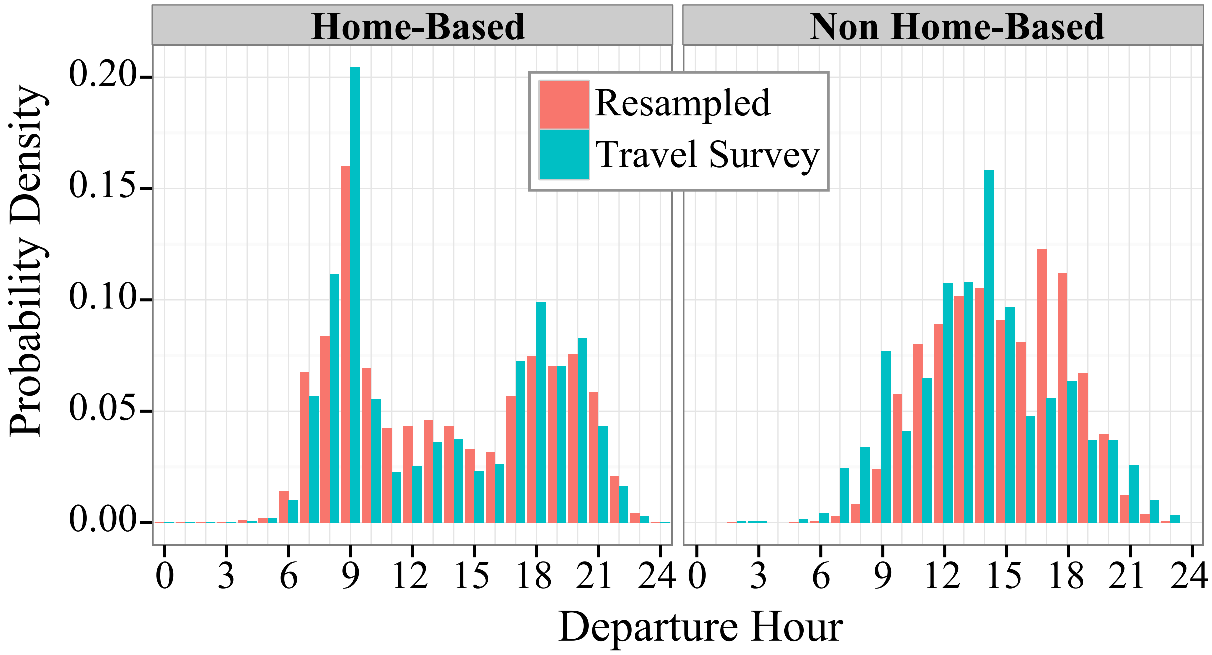

Figure 2.3: A comparison of the temporal distribution of travel demand (trip departures by hour and trip purpose) between the travel demand model used as input to the non-parametric resampling algorithm and the resulting activity for the Delhi case study.

Heuristic Optimization vs. Differential Evolution

There is a dramatic difference in computational burden between the application of heuristic optimization (HO) vs. differential evolution (DE). When we apply HO to the base scenario at 0.5% penetration of EVs into the Delhi 2020 vehicle fleet, we reach convergence after approximately 300 iterations, taking 30 hours on a 12-core personal computer. In this case, an entire pseudo Pareto optimality curve is generated, showing not just the final EVCS portfolio but a prioritized ordering of how the infrastructure should be deployed. The DE scheme has much slower convergence properties with the parameters we attempted (48 particles, scaling factor $F = 1$, crossover ratio of 0.96), taking over 1000 iterations and 120 hours on the same 12-core machine. DE only yields a single point on the Pareto optimality curve, making the exploration of Pareto optimality fronts across a wide variety of sensitivity analyses extremely time consuming. DE is approximately 400 times more time-intensive than HO.

Ideally, we could accept the results of HO as sufficiently close to DE and use the faster technique as a proxy for the more robust scheme. We have found that the two schemes produce results that share some commonalities, making HO useful for sensitivity analysis. But there are non-trivial differences in the results, such that we do not recommend HO for reporting final recommendations on infrastructure deployment, particularly with respect to the distribution of charging level.

In Table 2.14 we report aggregated results of applying both HO and DE to the base scenario with two cost constraints (i.e. in both cases we attempt to minimize the present value of driver delay subject to a maximum investment of $1.5M and $2.25M of charging infrastructure). For the two constraints the total power capacity of EVCS sited is similar between the two schemes (1% and 11% difference, respectively). However, DE outperforms HO with respect to the objective function by $0.18 and $0.37 per driver per day, primarily by siting fewer level 3 chargers in favor of more level 1 and 2 chargers.

Table 2.14: Results of differential evolution (DE) and heuristic optimization (HE) at two cost constraints.

Cost Constraint ($M)	**Method**	**Total Capacity (kW)**	**PV of Delay ($/ driver/day)**	**L1, L2, L3 Capacity (kW)**
1.5	HE	1920	$0.72	134, 363, 1650
	DE	2150	$0.54	318, 525, 1090
	Difference	-11%	$0.18	-58%, -31%, 51%
2.25	HE	2820	$0.57	176, 548, 2100
	DE	2840	$0.20	412, 903, 1530
	Difference	-1%	$0.37	-57%, -39%, 37%

We also investigated the difference in the spatial distribution of EVCS between the two sets of solutions. As shown in Figure 2.4, when the results are paired in terms of the power capacity of EVCS sited in each TAZ, the outcomes are correlated (with a correlation coefficient of 0.87), but not in perfect agreement. We note, however, that when HO is applied multiple times under the same set of assumptions, but with random seed replication, we find that the resulting capacity of EVCS by TAZ is correlated between replicates with an average correlation coefficient of 0.93. So some of the unexplained variation between the HO and DE results are due to random variation and not necessarily the performance of HO.

Ultimately, we can conclude that HO cannot be trusted to produce an optimal distribution of charging infrastructure in terms of charger type and – to a lesser extent – spatial distribution. We do, however, believe that the results from HO are still useful insofar as they can be produced more readily and they show promising agreement in terms of total capacity of EVCS sited. Moreover, while the results are biased in favor of higher level chargers, we consider this error to be in a conservative direction, as there are ancillary benefits to deploying higher level charging. In particular, higher level chargers align with the attitudinal preference of potential adopters of EVs [221] [220], an effect not yet quantified in PEVI.

We therefore cautiously present a series of sensitivity investigations based on the results of HO. We believe they reveal important insights into the *relative* impact of various assumptions and scenarios on infrastructure deployment. But we make it clear that the results

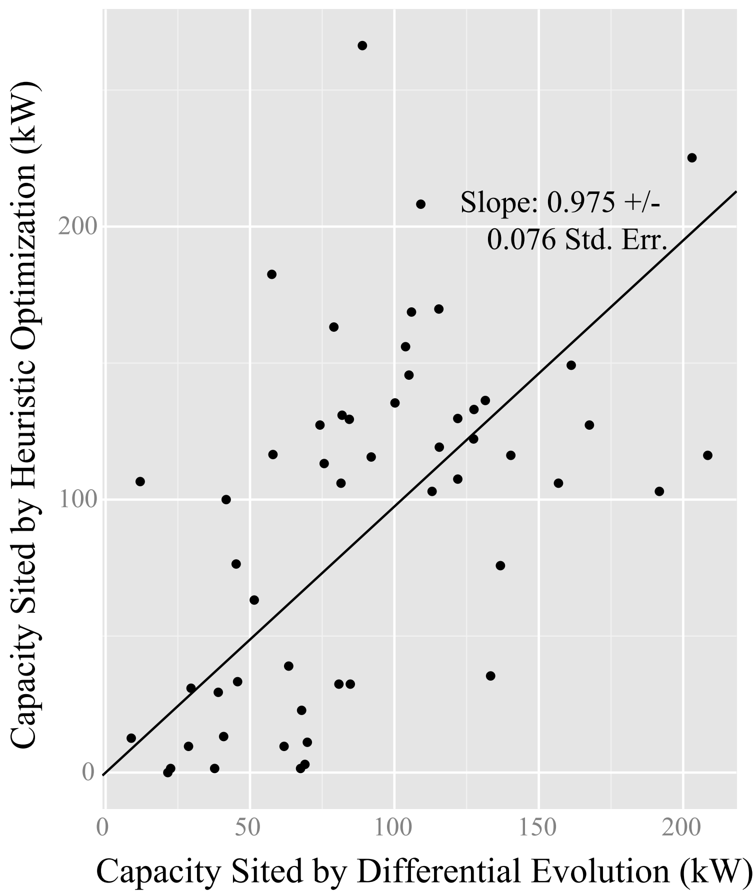

Figure 2.4: Charger capacity (aggregated across charger level) sited in each TAZ by the heuristic optimization and differential evolution schemes. The linear trend line has a correlation coefficient of 0.87.

are only approximations of an optimal distribution of chargers and should not be taken as prescriptive of a truly cost-effective deployment of infrastructure.

Sensitivity to Key Assumptions

We investigate the impact on model results of three key assumptions about driver behavior that we make in the PEVI model. The first is the assumption of cost minimization during charger selection, which assumes complete driver rationality. The second is our default value for H_R, the willing to roam time threshold, which was not based on an empirical study. The third assumption is the scoring system used in the *Break Up Trip* submodel (Section 2.2), which somewhat arbitrarily assigns scores to alternative.

Our analysis examines the impact if these assumptions are varied or implemented in an entirely arbitrary manner. All of the results were based on running the PEVI with the charging infrastructure identified by the heuristic optimization scheme for our base scenario at 1% fleet penetration. The key metric of interest is the present value of driver delay, i.e., same metric used as the objective of the EVCS siting process.

Driver Rationality

The first assumption is complete driver rationality during the Seek Charger Decision. As expressed in Section 2.2, we assume drivers choose a charger so as to minimize their costs. In reality, the choice of where to charge and at what level is unlikely to be perfectly rational. To test the impact of this assumption, we developed an alternative algorithm for charger selection which simply identifies all available chargers and chooses one at random.

The result of making this change is a 17% increase in driver delay when chargers are selected randomly instead of according to a cost minimizing approach. This is a substantial difference in delay and represents an upper bound on the potential impact of non-rationality in driver behavior. That acknowledged, it is certain that true driver behavior will not be either completely rational or completely irrational, but somewhere in between. Even if behavior is at the midpoint between these two extremes (suggesting that half of drivers do not take cost or the value of their time into account at all), then the impact would be less than a 10% difference in driver delay. Ultimately, this would require more charging infrastructure to mitigate, so we suggest further research to properly characterize the discrete choice behavior of drivers in order to produce more reliable results.

Willing to Roam Threshold

Our default assumption for H_R is 1 hour. This assumption was not based on an empirical analysis, so we investigated the impact on driver delay when this parameter is varied between 0.5 and 2 hours. The result is that delay is decreased by 10% when the threshold is 2 hours and increased by 4% when the threshold is 0.5 hours. The direction of these changes is due to the fact that more flexibility in the driver's schedule allows more opportunities to take advantage of available chargers in a nearby or en route TAZs. The rationale for having a smaller value for H_R is the disutility that drivers experience when they have to cut short their planned activity in order to ensure their vehicle is properly charged. In future revisions of this model, we plan to approach this tradeoff more systematically, accounting for the utility of engaging in activities and balancing this against the disutility of engaging in travel or charging.

Willing to Roam Threshold

Finally, we investigate the impact of the scoring system defined in the $Break\ Up\ Trip$ submodel. We do this again by implementing an alternative version of the submodel that randomly chooses a TAZ as the destination, instead of using the scoring system. The impact on driver delay is minor, about a 0.1% increase in delay due to drivers making ill-advised choices. This lack of sensitivity is primarily due to the fact that the $Break\ Up\ Trip$ decision is rarely executed.

Charger Siting

The result of applying the heuristic optimization scheme is illustrated in Figures 2.5 and 2.6. As shown by the pseudo Pareto optimality curves in Figure 2.5, as chargers are sited for a given penetration level, there is a decreasing return on investment in terms of driving down the objective function (i.e. the present value of driver delay). The spatial distribution of EVCS (Figure 2.6) exhibits patterns consistent with common sense, public chargers tend to be sited in higher numbers in higher density regions of the city and along higher traffic corridors.

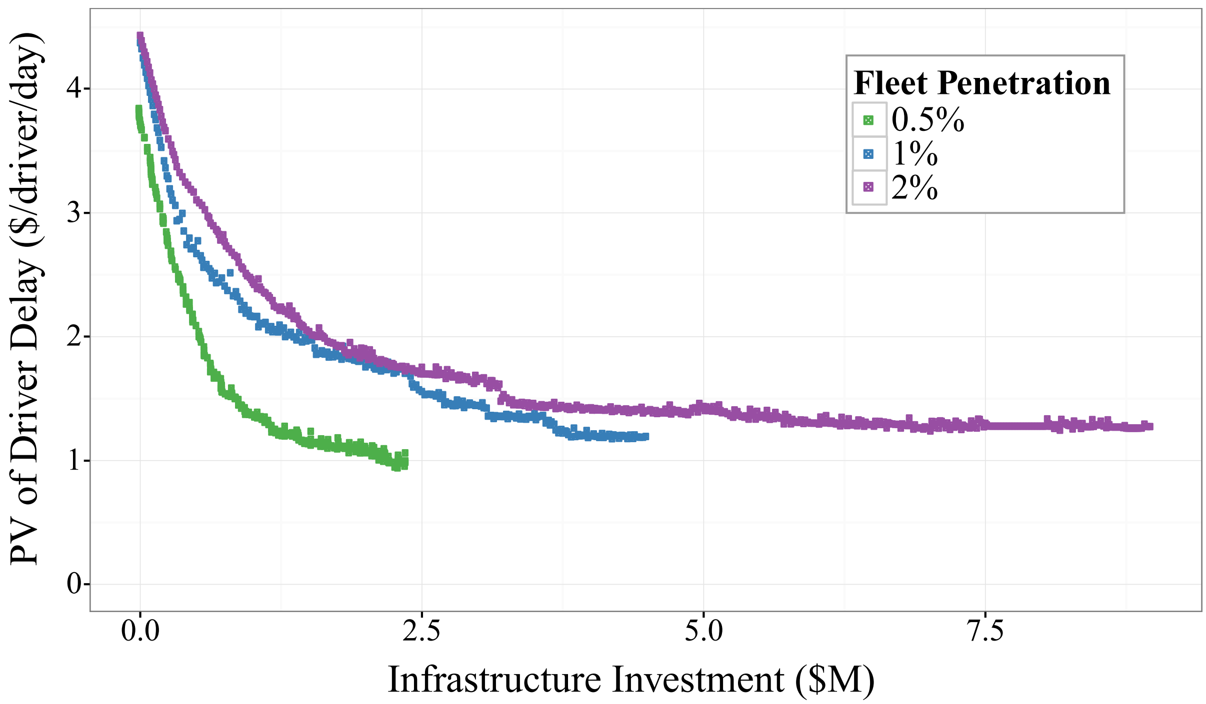

Figure 2.5: Pseudo Pareto optimality curves for 0.5%, 1%, and 2% fleet penetrations (5000, 10,000, and 20,000 PEVs, respectively) from the Delhi case study in charging infrastructure siting.

Simulating Multi-Unit Housing Challenges

One key challenge faced by EVCS planners is how to support PEV adoption by people residing in multi-unit housing. For the Delhi case study, we were able to bound this issue by selectively adding or removing the ability of simulated drivers to charge in their home TAZ. The results (Figure 2.7) are based on siting chargers so as to reach an equivalent level of service (i.e. to achieve the same value of the objective function: $2.50/driver/day). More public charging infrastructure is needed when drivers cannot charge at home, but the need is not one-for-one. Indeed, between the 100% Home Charging scenario and the 0% Home

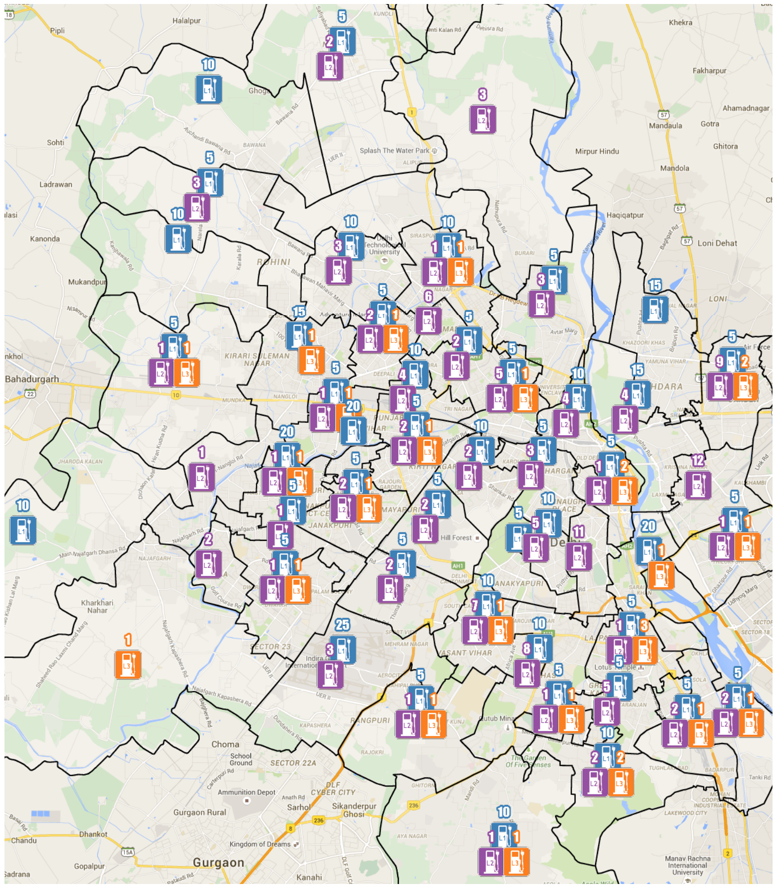

Figure 2.6: Spatial distribution of charging infrastructure based on differential evolution scheme at 0.5% penetration, or 5,000 PEVs, and a cost constraint of $2.25.

Charging scenario presented in Figure 2.7, approximately 10,000 residential chargers are effectively removed from the simulation, but the increase in sited EVCS is only about 700 in order to achieve the same level of service.

Impact of Vehicle Class on EVCS

Market trends in PEV adoption are also uncertain and difficult to forecast. The heuristic optimization process was therefore repeated for the Delhi case study under different assumptions about the class of vehicles on the road. The base scenario assumes that there is an even split between vehicles of low, medium, and high capacity. Two additional scenarios were conducted assuming that all vehicles are either of low or high capacity. Here "capacity" refers to the power of the electric motor but the scenarios also correspond to increasing aggregate range of the vehicles from low to high. Like the Multi-Unit scenarios above, the results presented in Figure 2.8 correspond to the infrastructure required to achieve an equivalent level of service (delay valued at $2.65/driver/day). While providing the same level of service, vehicle class has a substantial impact on the overall number of chargers sited. A

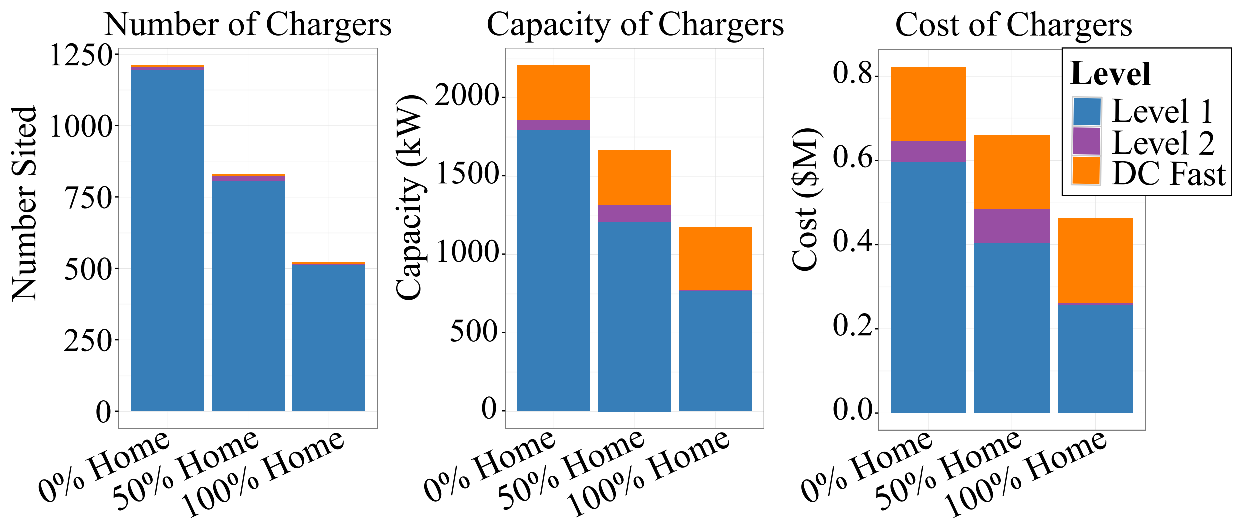

Figure 2.7: The number, capacity, and cost of public chargers needed to achieve an equivalent level of service (delay costing $2.5/driver/day) for varying levels of access to chargers at home at 1% fleet penetration for Delhi. Increasing the number of residential chargers decreases – but does not eliminate – the need for public chargers.

fleet of low capacity PEVs requires roughly 60% more charging infrastructure (in terms of capacity and cost) as a fleet of high capacity PEVs.

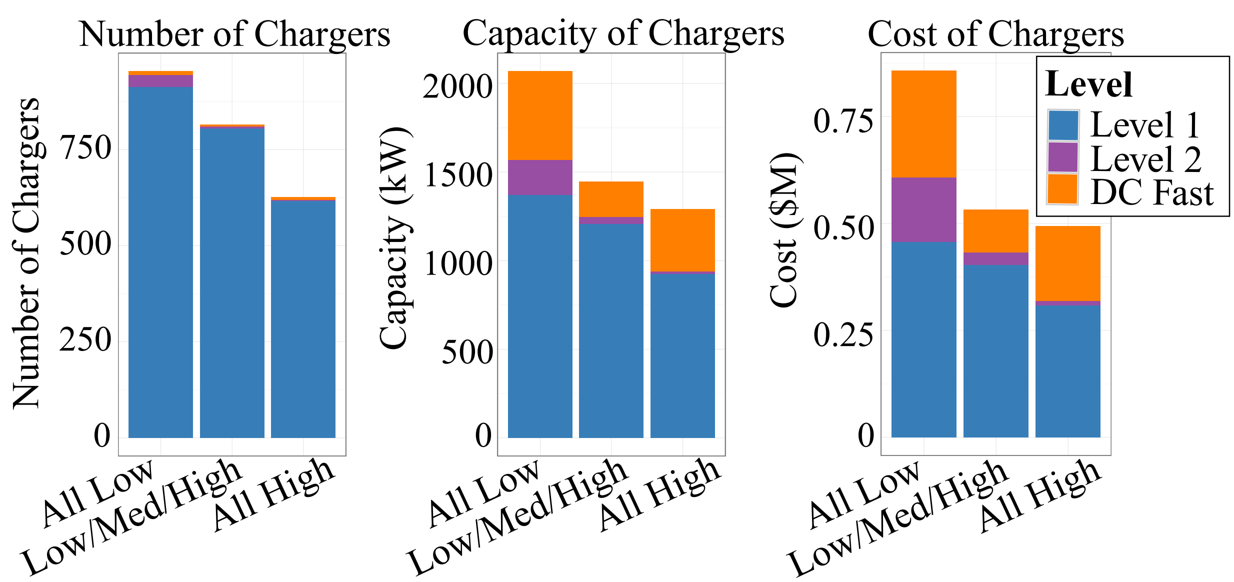

Figure 2.8: The number, capacity, and cost of chargers sited for three vehicle class scenarios at 1% fleet penetration in Delhi. All scenarios represent the infrastructure required to maintain the same level of service systemwide (delay costing $2.65/driver/day). Increasing the capacity of the vehicle fleet leads to a reduction in need for charging infrastructure.

Impact of Range Anxiety on EVCS

Because range anxiety is such a critical barrier to PEV uptake, an additional heuristic optimization was performed after tripling the value placed on drivers' time. The extra value is used as a proxy for the higher priority drivers may place on minimizing delay. When the value placed on driver's time was tripled, the number of chargers sited by the heuristic optimization process was predictably higher (Figure 2.9). Notably, the emphasis was mostly on Level 1 and DC Fast chargers. The total infrastructure cost increased by \$1.2M.

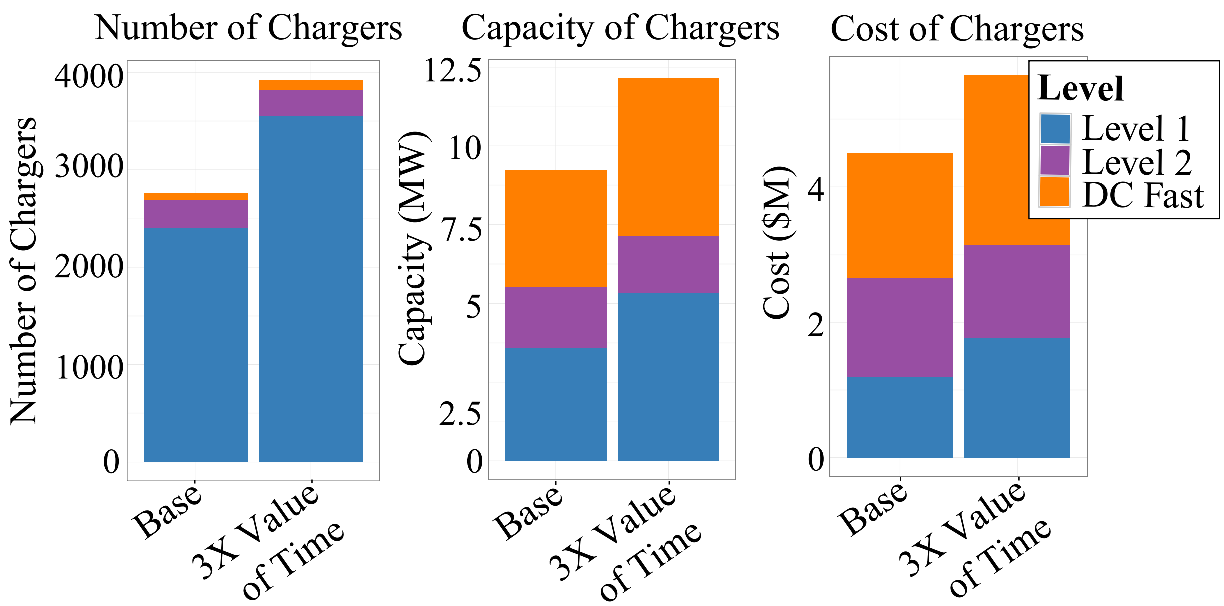

Figure 2.9: The number, capacity, and cost of chargers sited in the base scenario and with simulated high range anxiety at 1% fleet penetration in Delhi. Increasing the value of drivers' time places a greater emphasis on Level 1 and fast-charging infrastructure.

Impact of Congestion on EVCS

We also simulated the impact of heavy congestion and climate control on simulation results. A worst case scenario was developed, assuming that congestion occurred during the entirety of the model run and that the outdoor temperature was 35°C, resulting in constant air-conditioning use. The extra energy to keep the vehicles air-conditioned was based on the work of Barnitt [69]. We again compare the charging infrastructure necessary to achieve an equivalent level of service between the two scenarios (delay cost in \$2.65/driver/day). In the worst-case scenario, congestion has a substantial impact on driver delay and the number of stranded drivers. Achieving the same level of service requires 1500 more chargers, 6000kW more capacity, and \$3M more investment in the congested scenario (Figure 2.10).

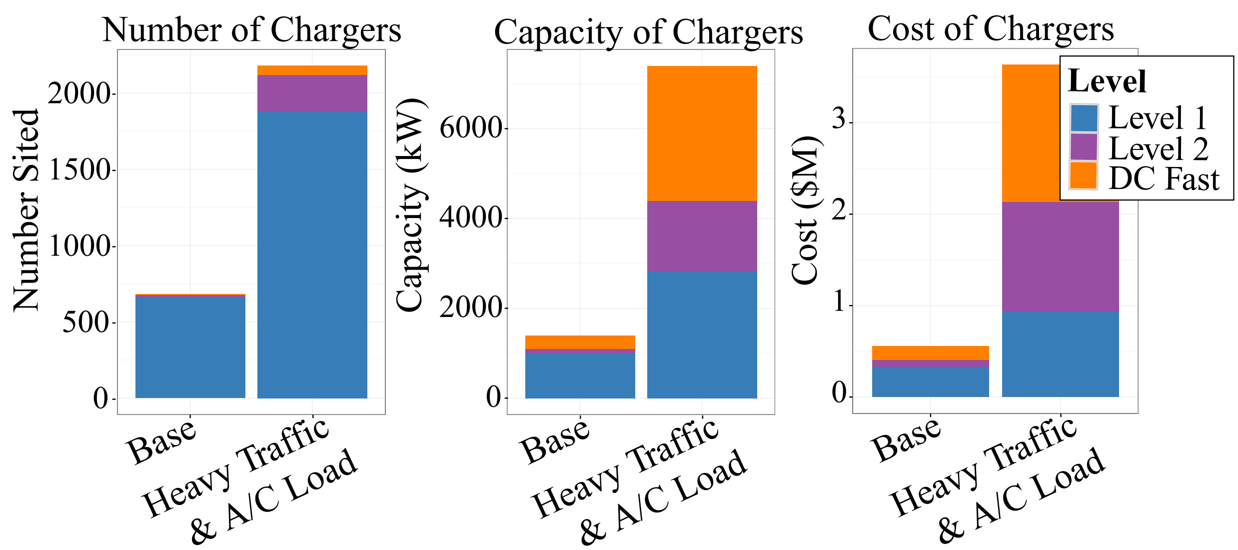

Figure 2.10: The number, capacity, and cost of chargers needed to achieve an equivalent level of service (delay costing $2.65/driver/day) between the base scenario and with heavy congestion at 1% fleet penetration.

Assessing Grid Impacts of PEV Adoption

The outputs of PEVI include spatially explicit PEV charging profiles by driver and charger type that can be aggregated to any spatial unit. Figure 2.11 shows an example of aggregated load curves from Delhi across groups of 20 TAZs for the a simulation of 0.5% fleet penetration. It is clear that there is spatial variation in charging demand and that DC Fast chargers will make a substantial impact on distribution circuits even at this minimal penetration of EVs.

PEV Demand Response Potential Analysis

Because PEVI simulates individual drivers and the mobility needs of drivers are known, it can be used to assess the flexibility of charging demand. For the Delhi case study, there was a high degree of flexibility in the demand if we assume that all charging not immediately needed for mobility can be deferred to later hours of the day (Figure 2.12). This result represents the technical potential of smart charging. Key to our upcoming research efforts will be to use PEVI to estimate the economic and market potential of smart charging, where the risk of impacting driver mobility is quantitatively analyzed in the context of aggregated demand response from PEVs.

Conclusion

We present a detailed description of the Plug-in Electric Vehicle Infrastructure (PEVI) Model. PEVI is a spatially explicit agent-based microsimulation model that represents charg-

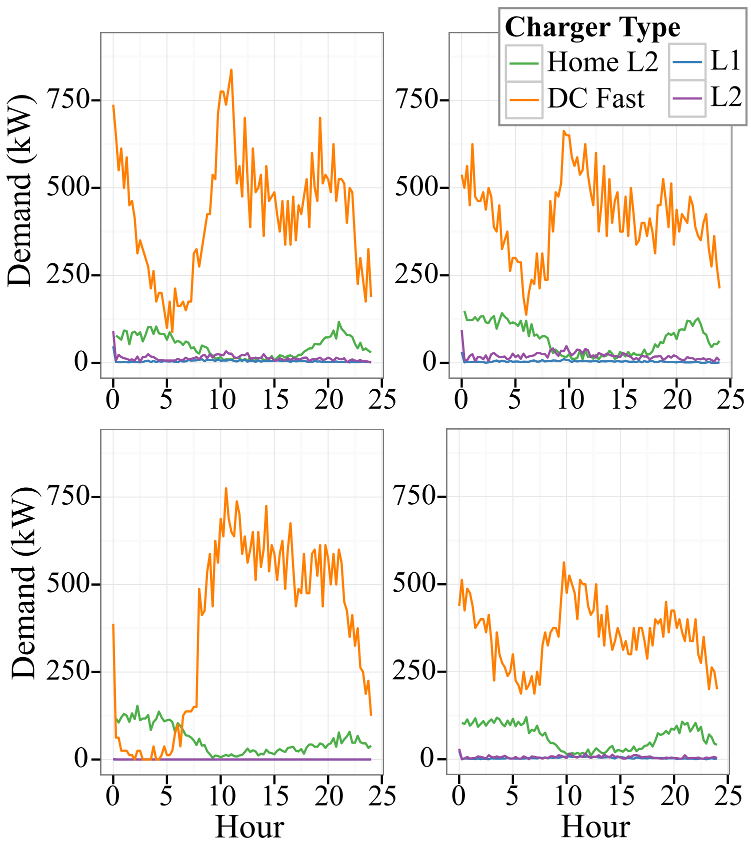

Figure 2.11: Charging demand by PEV drivers at example spatial aggregations based on results from the Humboldt case study.

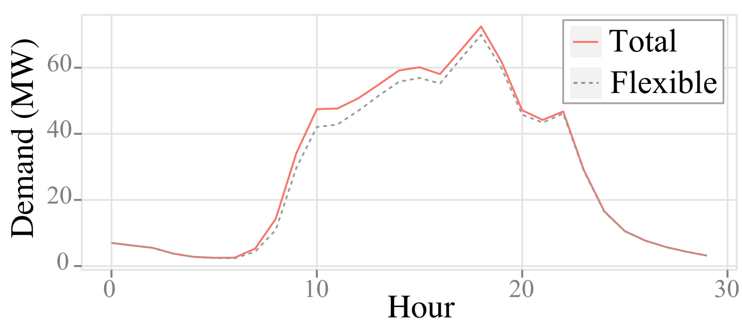

Figure 2.12: Total load and flexible load from PEV drivers in the Delhi case study where flexible load is defined as all charging that can be deferred to later hours without sacrificing driver mobility.

ing infrastructure, charging behavior, and competition for scarce EVCS. By leveraging the best available transportation demand data from a region, PEVI provides high resolution insight into emergent outcomes of PEV drivers interacting with EVCS throughout a transportation network. We highlight results from case studies to illustrate how PEVI is used in a heuristic optimization scheme to site regional EVCS and to explore the impact of adoption trends on the need for EVCS and on the electricity grid.

Chapter 3

Economic Value of Charging Flexibility

3.1 Overview

This Chapter explores the economic value of charging flexibility assuming a fleet of personally owned light-duty vehicles. We use wholesale locational marginal pricing data from California and New York as the basis for an optimization scheme that charges PEVs at least cost while respecting temporally prioritized mobility constraints. The pricing arbitrage between high and low times of day becomes the assumed value of charging flexibility.

This work originally appeared in the following working paper (reprinted with permission from Sanjae Bae):

Colin Sheppard and Sangjae Bae. "Techno-Economic Potential of Mobility-Informed Smart Charging". In: *Working Paper* (June 2016). DOI: DOI10.13140/RG.2.1.1338.3289

3.2 Introduction

Background

Currently, the global response to the threat of climate change is producing two dramatic transformations in how we use energy. The first is the substitution of high carbon generators with low or zero carbon generators on the electric grid, which will require corresponding increases in dispatchable generation and flexible loads. The other transformation is the adoption of plug-in electric vehicles (PEVs), which could play a critical role both in reducing greenhouse gas emissions (GHG) and potentially contributing to grid reliability.

In August 2015, the U.S. Environmental Protection Agency released the Clean Power Plan (CPP), mandating that stationary electric generators meet carbon dioxide performance rate targets by 2030. Individual States are empowered to decide how best to achieve these targets, which can be done at the scale of individual power plants or across a state as a whole through a combination of measures [103]. A natural consequence of these aggressive targets will be a reduction in fossil-fueled generators (particularly coal-fired plants) and an accelerated deployment of intermittent renewable resources (wind and solar). According to the North American Electric Reliability Corporation, the CPP will hasten a "fundamental change in electricity generation mix in the United States and transform grid-level reliability services, diversity, and flexibility"[100]. ERCOT estimates that the CPP will force 4.2GW of coal capacity in its grid to retire by 2030 which – without 329 miles of transmission upgrades or other measures – would lead to 47 transmission circuits and 11 transformers exceeding thermal capacity limits [104].

In California, studies of the new Renewable Portfolio Standard (50% renewables by 2030) have shown that online combustion turbine generators will be needed to provide intra-hour load following down capability to the grid, which will result in the curtailment of wind and solar generation [102]. Nelson and Wisland (2015) identified non-generation flexibility (including demand response, storage, and net electricity exports) as key solutions to the projected problem of renewable curtailment [67].

PEVs could reduce U.S. greenhouse gas emissions (GHG) by more than 60% and oil dependence by more than 80% [42], but demand growth from PEVs could be substantial. Based on one forecast, aggregate U.S. peak load from PEVs could be 18.6GW by 2050 [98]. Emerging economies represent particularly high impact opportunities for reducing future emissions due to dramatic vehicle ownership growth rates, e.g. 6% and 12.5% in China and India, respectively [74]. Indeed, governments worldwide see PEVs as integral to achieving climate goals. By 2020, China is targeting 2 million PEVs and India seeks 6-7 million hybrid and electric vehicles[61][28].

These two transformations are merging to form a novel transportation-electricity nexus. PEVs could be used as an energy storage asset or as flexible demand to accommodate a cleaner, more intermittent grid portfolio. But can PEVs reliably support the grid without compromising their primary purpose, mobility? This and related questions are under active study. For example, to what extent do managing charging sessions enable GHG reductions [56][149]? What protocols and algorithms should be used to optimize the dispatch of PEV charging [96, 73, 75, 72]? To the knowledge of the authors, what remains unanswered is the question of whether PEVs will be inframarginal in electricity markets as a controllable load. That is, given there will be competition among distributed energy resources (DERs) that can offer flexibility services (both in the form of load shaping and supplying ancillary services), will PEVs be capable of offering such services at a low enough cost to stay competitive in these markets?

Answering this question requires a holistic analytical approach that captures real world dynamics and practical constraints in both the transportation and electric systems. The following analysis takes an initial step in this direction by developing a methodology for valuation of flexibility services from PEVs given an assumed ability to defer load into the future and to provide ancillary services.

Approach

If PEVs are to provide flexibility services to the power grid, systems of control must be designed to modulate the timing and rate at which PEVs charge their batteries as well as discharge back to the grid in the case of vehicle-to-grid (V2G) technologies. One complicating factor to this problem is how to manage charging without impacting driver mobility. There are a variety of approaches that account for this issue. Ma et al. (2010), Finn et al. (2012), and others have developed techniques to control charging power within a single charging session constrained such that the final state of charge of the vehicle be the same as an unmanaged session [96, 73]. In [75] they assume charging can be managed over the course of a day, but they implement a scheme that makes no attempt to quantify mobility constraints [75]. Zhang et al. only constrain charging to meet aggregated daily mobility needs without consideration for future mobility or the sub-daily distribution of driving events [72].

Our approach is to assume that PEV demand response aggregators will be able to manage charging across charging sessions. We also assume that aggregators will have access to sufficient mobility data from the drivers and/or schedules of future mobility events that reliable driver-specific forecasts of future mobility can be generated at the level of individual drivers. Further, we assume that the technology and regulatory framework exist such that aggregators can expose drivers to wholesale power markets allowing them to optimize over energy prices and ancillary service opportunities. We do not assume that drivers will actually pay the wholesale price of electricity, but rather that the value of PEV flexibility will be dictated by the marginal cost of electricity and the wholesale cost of providing ancillary services.

We therefore propose a scheme for optimizing the charging profiles of individual drivers based an objective that simultaneously considers the costs of charging and the benefits associated with providing ancillary services. Our constraints are structured to ensure that future mobility is achievable, but with a decaying weighting scheme that discounts the importance of future mobility as a function of time until that future event. In other words, we attempt to quantitatively account for the fact that mobility one hour into the future is much more important to the decision to charge in the current hour than mobility 48 hours into the future.

3.3 Methodology

Data

The mobility data we used for this analysis is based on the 2011 Atlanta Regional Travel Survey [251]. The survey involved 10,278 households completing travel diaries over the course of multiple days (up to 7 days). The advantage to working with a multi-day survey (as opposed to a single-day survey like the National Household Transportation Survey) is that it can be used to develop autoregressive time series models of driver mobility which could then inform the constraints of an operational dispatch algorithm.

The survey data were formatted as input to the Plug-in Electric Vehicle Infrastructure (PEVI) model. PEVI is an agent-based microsimulation model [60] that simulates drivers as they attempt to execute trip plans in an EV. Drivers attempt to access public charging infrastructure as their EV batteries become depleted. In addition, drivers charge in public venues even if they are able to complete their future trips based on a random process whose probability increases with a decreasing state of charge in the battery.

For the Atlanta simulation, public charging infrastructure was assumed to be effectively unlimited. Drivers could access a level 2 charger (with a maximum charging rate of 7kW) at home and either a level 2 or a DC Fast charger (50kW) in public locations. In public, the cost of charging is $0.34/kWh for a Level 2 and $0.55/kWh for a DC Fast Charger (drivers attempt to minimize their cost by choosing cheaper charging while avoiding delays). Drivers were all assumed to be in a battery electric vehicle with a battery capacity of 24kWh or 68 miles of range. Drivers use a 10% factor of safety in their range estimations.

The charging profiles from the PEVI simulation were integrated with the original Atlanta mobility data to produce a set of mobility/charging events which include features such as the state of charge of the battery, energy charged by charging sessions and discharged by taking trips. The resulting mobility and charging profiles were then randomly shuffled and appended together, producing a total sequence of 20 years of activity. For the remainder of this analysis, we refer to the 20 different years as 20 separate "drivers" despite each year being composed of over 80 drivers from the original Atlanta survey.

Locational marginal price (LMP) and ancillary services pricing data were obtained from CAISO and NYISO for the year 2014. There are over 2000 nodes in the CAISO system, due to time/computational constraints, we randomly sampled 10% of the 1500 load nodes to run the optimization on a total of 150 nodes. In addition, we used LMP data from all 15 of the NYISO pricing zones. For simplicity, we chose only one ancillary service from each ISO, regulation up (from regulation up/down) from CAISO and (unified) regulation from NYISO, we refer to these as "reg" or "regulation" below. Finally, we used Pacific Gas & Electric rate schedules to compare the result of optimizing over wholesale prices to four retail scenarios. For the residential sector we used the TOU E7 schedule along with the EV-A and EV-B schedules; for the commercial sector we used the energy portion of the E19S schedule (our optimization scheme is not designed to minimize demand charges).

Optimization problem

We model the optimization problem as a cost minimizing linear program with a moving 24-hour decision horizon. Because the market clearing price data were from day ahead markets, our decisions are at the hourly time scale. In each hour, there are two decisions to be made, the power to be delivered to the PEV charger and the power to be sold into the ancillary services market for regulation (modeled as a negative cost). When a PEV sells regulation capacity, we do not distinguish between up or down regulation, but rather we constrain the rate of charging to be sufficient to allow the charger to modulate in either direction by the committed amount. We assume that providing regulation results in zero net energy imbalance from what would otherwise be delivered through charging. Table 1 presents the notation and assumptions for key variables and parameters and the mathematical formulation is presented below.

Objective

Table 3.1: Parameters, variables, and assumptions of the linear program.

Notation	Description	Notes
N	Number of time steps in the moving horizon period	Assumed 24 hours
M	Number of time steps over which to consider future mobility in constraint on deferrable charge	Assumed 48 hours
k_t	Rate of charge of the charger during period t (kW)	Decision variable
c_t	Capacity used to provide ancillary service at time period t ($/MWh)	Decision variable
x_t	Energy delivered to the PEV by the charger (kWh)	$x_t = k_t \Delta t$
		Upstream of conversion losses associated with charging
y_t	Energy expended by the battery to achieve mobility (kWh)	Inclusive of efficiency losses
$p_{e,t}$	Price of energy at time period t ($/kWh)	
pc, t	Capacity payment for ancillary service at time t ($/kW)	
u_t	Fraction of time period t the PEV is plugged in and able to charge	Assumed 0 for hours with mobility events and 1 for all other hours.
λ	Charging rate of station (kW)	Assumed 7 kW for L2 charger
Δ_t	Length of time step (hours)	1 hour
SOC_t	Effective state of charge of the battery at the beginning of time period t.	$SOC_{t+1} = SOC_t + \Delta SOC_{x,t} + \Delta SOC_{y,t}$
η	Conservation efficiency of charging the battery	Assumed 0.92 %
C	Capacity of the battery (kWh)	Assumed 24 kWh
$\Delta SOC_{x,t}$	Change in state of charge from the beginning to end of period t due to charging	$\Delta SOC_{x,t} = x_t \eta / C, Always >= 0$
$\Delta SOC_{y,t}$	Change in state of charge from the beginning to end of period t due to driving	$\Delta SOC_{y,t} = y_t / C, Always <= 0$
w_j	Weighting factor at time j relevant to present time t to discount future changes in SOC	$w_j = \alpha e^{-\beta(t_j - t_i)^2}$
α, β	Parameters to the weighting function	Assumed $\alpha = 1.5, \beta = 0.001$

$$min\ z(k_t, c_t) = \sum_{t=1}^{N} p_{e,t}x_t - p_{c,t}c_t \tag{3.1}$$

Constraints

As described above, the capacity committed as an ancillary service contributes to a lower and upper bound on the power at which the battery is charged within the same hour. This allows the fully committed capacity to be used during regulation:

$$c_t \leq k_t \leq (\lambda u_t - c_t) \tag{3.2}$$

The mobility constraints represent a minimum bound on the charge delivered in time t such that the SOC cannot become negative over the mobility time horizon (from time t to M) while accounting for the time value of changes in SOC. For each charging decision at time t, there is a separate mobility constraint for every subsequent time step from t to time M. The resulting constraints ranging from t = 1 to N are as follows:

$$\begin{aligned}
-\left[SOC_t + \Delta SOC_{t,y}\right] &\leq \Delta SOC_{t,x} && (3.3)\\
-\left[SOC_t + \Delta SOC_{t,y} + \sum_{j=t+1}^{t+1} w_j(\Delta SOC_{j,x} + \Delta SOC_{j,y})\right] &\leq \Delta SOC_{t,x} && (3.4)\\
-\left[SOC_t + \Delta SOC_{t,y} + \sum_{j=t+1}^{t+2} w_j(\Delta SOC_{j,x} + \Delta SOC_{j,y})\right] &\leq \Delta SOC_{t,x} && (3.5)\\
\vdots \quad &\vdots \quad \vdots && (3.6)\\
-\left[SOC_t + \Delta SOC_{t,y} + \sum_{j=t+1}^{M} w_j(\Delta SOC_{j,x} + \Delta SOC_{j,y})\right] &\leq \Delta SOC_{t,x} && (3.7)
\end{aligned}$$

For $j = N$ the $SOC_{j,x}$ value includes the decision variable; for $j > N$, we assume charging profiles based on the simulated charging from the PEVI model. Finally, while the mobility constraints prevent SOC from going negative, the SOC must also be constrained from exceeding 100%:

$$SOC_{t,x} \leq 1 - SOC_t \tag{3.8}$$

The objective function and constraints above are all linear in the decision variables and therefore we deployed linear programming (LP) solvers implemented in both the R and Python programming languages (the dual implementation was used to verify results and debug). Based on pricing and mobility data for 365 days, we run the solver 364 times to optimize the charging schedule and ancillary service participation for each day. At the end of each daily solution, we use the value of SOC_{25} to seed the value of SOC_1 for the next day.

After each annual optimization is complete, the year is summarized by the following metrics of performance:

- Cost Savings ($/year) - The difference between the cost of charging the vehicle without managed charging and the net cost (energy cost minus ancillary service benefit) of the optimized charging schedule.
- Average Annual SOC - A rough measure of where the driver maintains the battery SOC under the cost minimized charging schedule.

3.4 Results & Discussion

When the optimization scheme is applied to a single driver for a single year at a single node in CAISO, we find that the charging profile changes from predominantly daytime to predominantly night time charging (Figure 3.1). The shift is expected given the energy prices are lower during off-peak hours. We hypothesize that the remaining charging during the day is due both to mobility and to opportunity charging related to selling capacity to the ancillary services market. As shown in Figure 3.2, the majority of charge events also include a commitment of capacity for regulation in an equivalent amount to the power drawn by the charger (89% of charge events) or if the charger operates above 3.5kW (half of the 7kW maximum) then the capacity sold is the difference between charging and 7kW (7.4% of charge events). In only 3.6% of charge events do ancillary services appear to go under utilized; these correspond to events where the price for regulation is 0 (33% of the 3.6% of total charging events) and where plug time is less than 100%, in which case the capacity sold is equal to the difference between charging and u*7kW.

In Figure 3.3, the results of running the optimization for all 20 drivers against all 150 CAISO nodes and all 15 NYISO nodes are presented as box and whisker plots. Cost savings are 58% higher on average in NYISO than in CAISO. The baseline cost for charging a vehicle using the wholesale LMP is $305/year on average (across nodes) for NYISO and $272/year on average for CAISO. But the relatively higher energy prices in NYISO only explain about 40% of the difference in cost savings between the ISO's. As seen in Figure 3.4, when costs are disaggregated by energy (blue positive bars) and ancillary services (orange bars), it is clear that the ancillary benefits make up a substantial portion of both the cost savings (17-55%) and the difference between the ISO's (60%).

While we see in Figure 3.3 that driver mobility causes some variability in the resulting cost savings, we chose to complete the remainder of the analysis below based on one driver for time/computational purposes. We use driver 1 for this purpose whose cost savings are near the center for both the NYISO and CAISO LMP nodes across all 20 drivers.

We explored the spatio-seasonal distribution of cost savings in California based on the CAISO results for driver 1. We see that savings peak in quarters 2 and 3 which correlates to the LMP of energy more strongly than the seasonal variations in regulation pricing. Spatially

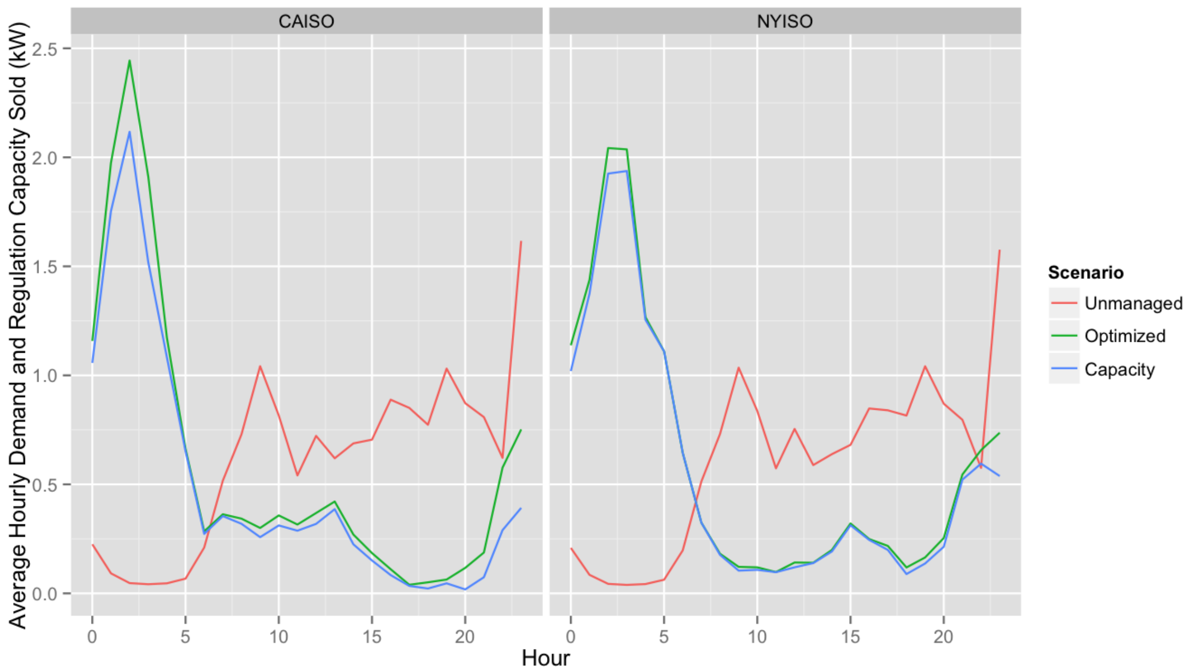

Figure 3.1: Hourly energy charged to the battery and capacity sold as ancillary service across all drivers and nodes in each ISO.

there tend to be higher prices near the population centers and in certain regions of the central valley.

We explored the impact of different rate schedules on the cost savings of managed charging. In Figure 3.6, the "ENERGY-AND-REG" scenario is compared to an "ENERGY-ONLY" scenario for the CAISO nodes. The figure also presents savings associated with optimal charging against four retail rate schedules. The wholesale comparison reveals that adding ancillary services to the scheme increases cost savings by 10%. For the retail rate comparisons, it is important to concede that it is unrealistic to assume that drivers only face a single rate schedule when charging. But it is nevertheless instructive to see that the EV rate schedules offer dramatically higher savings than the standard TOU schedule. This is by design, the EV schedules are intended to strongly incentivize off-peak charging and a managed charging schedule can easily take advantage of this incentive while meeting mobility constraints. Finally, while the commercial rate schedule offers the least cost savings of the four retail scenarios, it is critical to note that demand charges typically represent a substantial portion of electricity billings and therefore excluding them from this analysis fails to capture the true potential for smart charging to save costs in public venues and places of work.

For the sensitivity analysis below, we present only results from the NYISO nodes. We chose NYISO because there was greater variation in prices across NYISO nodes which we felt might be more revealing than the CAISO data set.

Under unmanaged conditions, the average SOC for drivers over the course of a year is

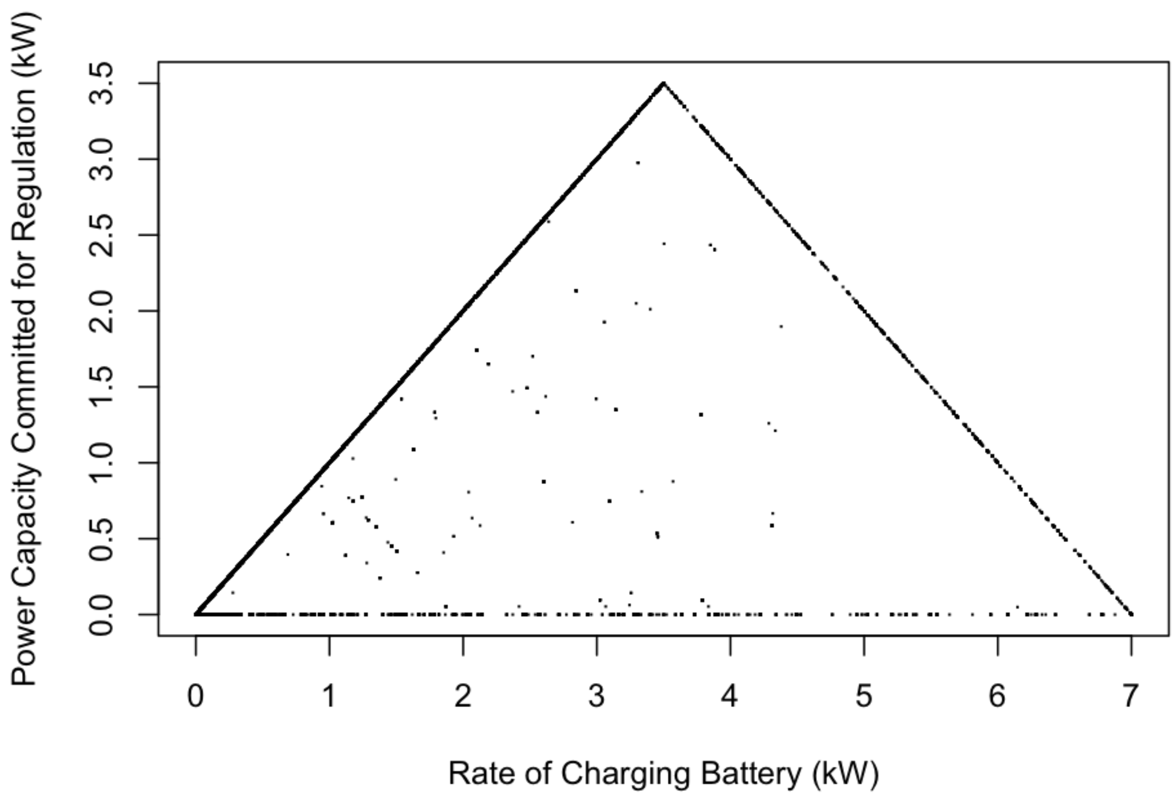

Figure 3.2: Power capacity sold as ancillary service versus power used to charge the battery for one driver over all CAISO and NYISO nodes.

˜73%. In NYISO under optimal scheduling, the average SOC is ˜45%. Because energy LMP prices are almost always higher than ancillary service prices (this is true 99.7% of the year), drivers are effectively charging their batteries to achieve their mobility only and not to fill the battery. In order to explore the impact of ancillary service price on this dynamic, we ran the optimization again for the NYISO nodes with proportional increases in regulation price signal. The results in Figure 3.7 show that cost savings go up roughly proportionally to the increase in regulation prices and that some nodes exhibit an increase in average SOC with regulation prices at the highest price explored. Under very high regulation prices, selling capacity can become more lucrative than deferring charing which incentivizes drivers to charge more frequently. Ultimately, the optimization scheme could be revised to disincentivize low SOC or incomplete charging sessions.

Figure 3.8 presents the results of varying the assumed battery capacity (left plot) and charger capacity (right plot) of the vehicles and chargers, respectively, for the NYISO nodes. As battery capacity increases, mobility becomes less of a constraint and the driver can take greater advantage of low energy pricing and/or high regulation pricing. Likewise, at higher

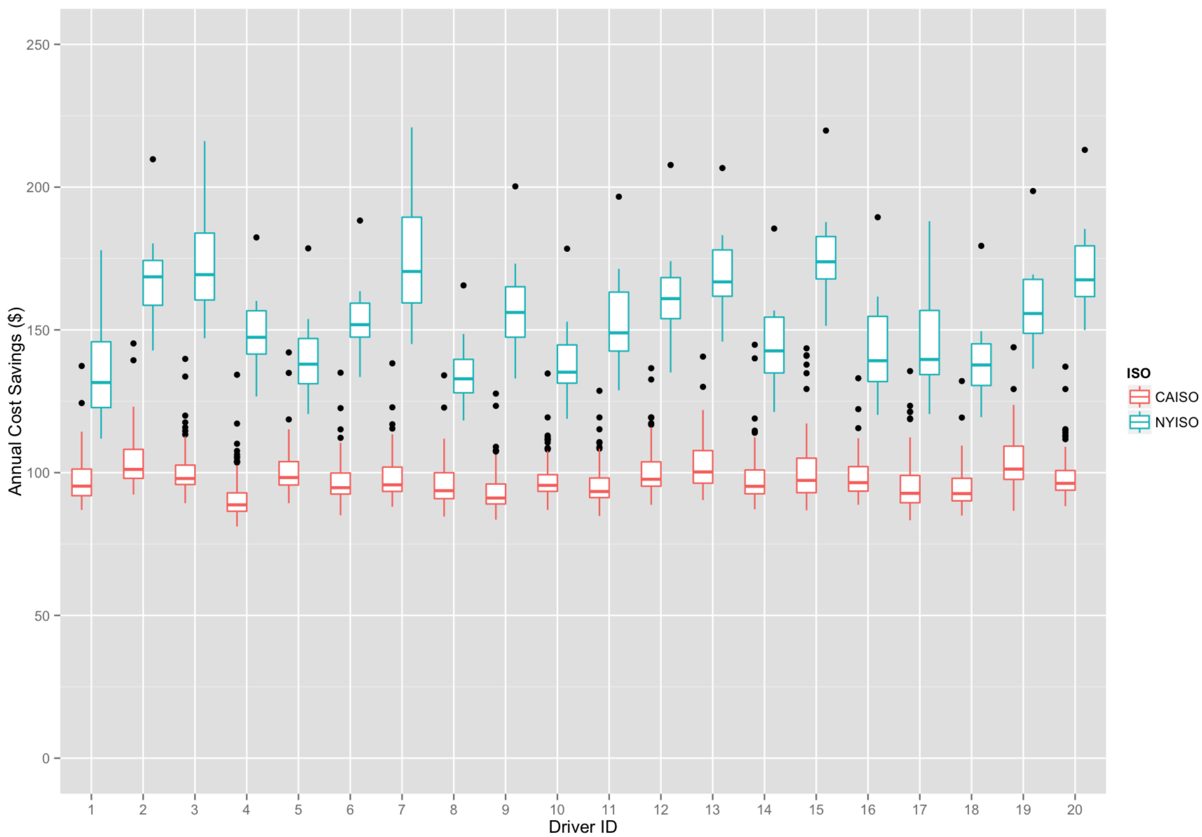

Figure 3.3: Annual cost savings by driver for all CAISO and NYISO nodes.

capacities, charging can be more easily concentrated into the highest opportunity hours of the day. There is very little increase in cost savings from 20kW to 100kW, which is due to the fact that a 24kWh battery can be fully charged within a single hour at a 26kW level or higher (the difference being conversion losses). Over the range of charging levels explored, cost savings max out at $31/year. For the range of battery capacities explored, the savings increases at some node are as high as $18/year. With combinations of higher batteries and higher charging levels, the savings would presumably be greater than what we explored.

Finally, in Figure 3.9, we explore the assumed risk tolerance of drivers by varying the parameters of the weighting function on future changes in SOC. A weighting function that is constant at 1 represents the most conservative profile and a function that drops rapidly is the most aggressive. The cost savings increase as the weighting function becomes more aggressive, but across the NYISO nodes, these additional savings are all less than $11 per year. Further study is necessary to quantify the risk of impacting driver mobility associated with adopting more aggressive weighting strategies.

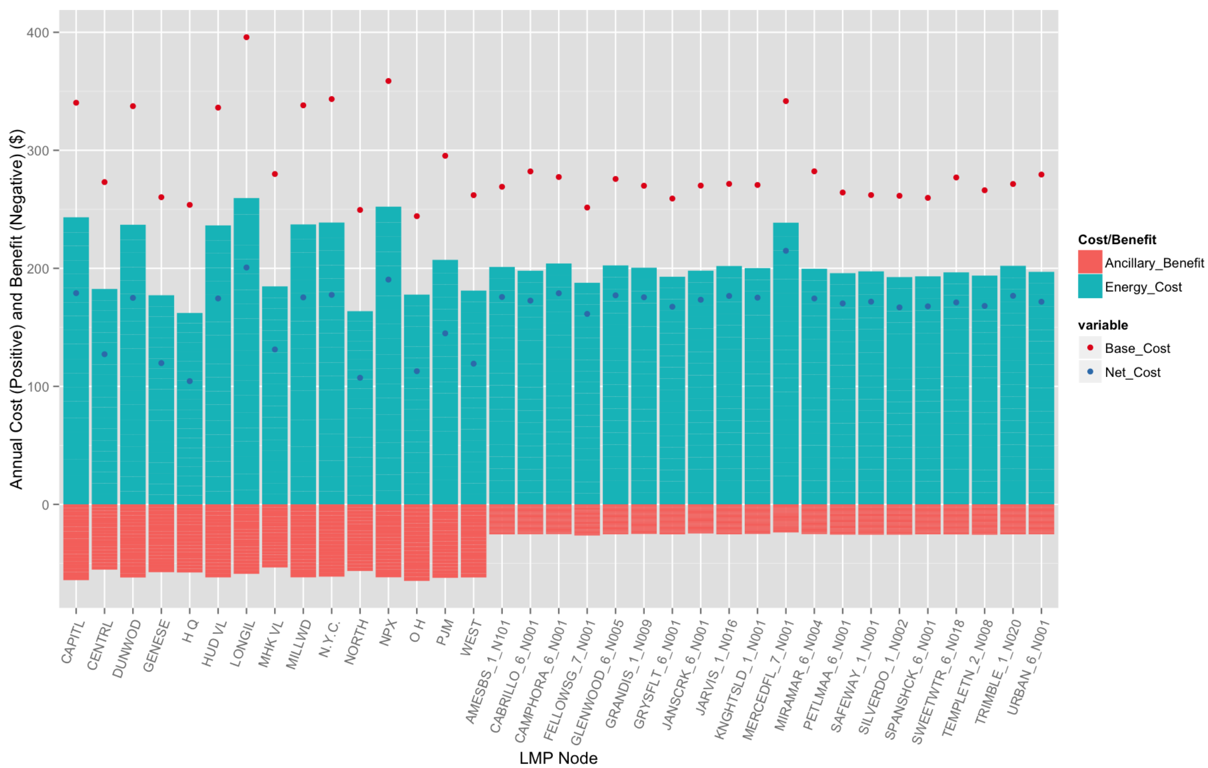

Figure 3.4: Annual costs by LMP node for NYISO (15 leftmost bars) and CAISO (20 rightmost bars), averaged across 20 drivers. The baseline cost of charging (red dot) and net cost after optimization (blue dot) are also plotted.

3.5 Conclusions

We developed an approach to quantify the value of PEV flexibility services that consider the potential for PEVs to both load shift and provide ancillary services. We found that the annual cost savings due to optimizing dispatch come primarily from savings on the price of energy but that providing ancillary services contributes non-negligible value to the solution. The cost savings are sensitive to location, the pricing scheme (retail vs. wholesale) and – to a limited extent – the capacity of the battery and charging level of the charger. We found the cost savings to be somewhat insensitive to the shape of the weighting function applied to future changes in SOC.

We make the following recommendations for future research:

- Diagnose and fix SOC anomalies
- Use more realistic constraints around access to charging infrastructure in the charging simulation phase
- Use forecasts of future mobility and charging instead of simulated or known data
- Add an anxiety penalty (penalize lower SOC) or a penalty on incomplete charging sessions

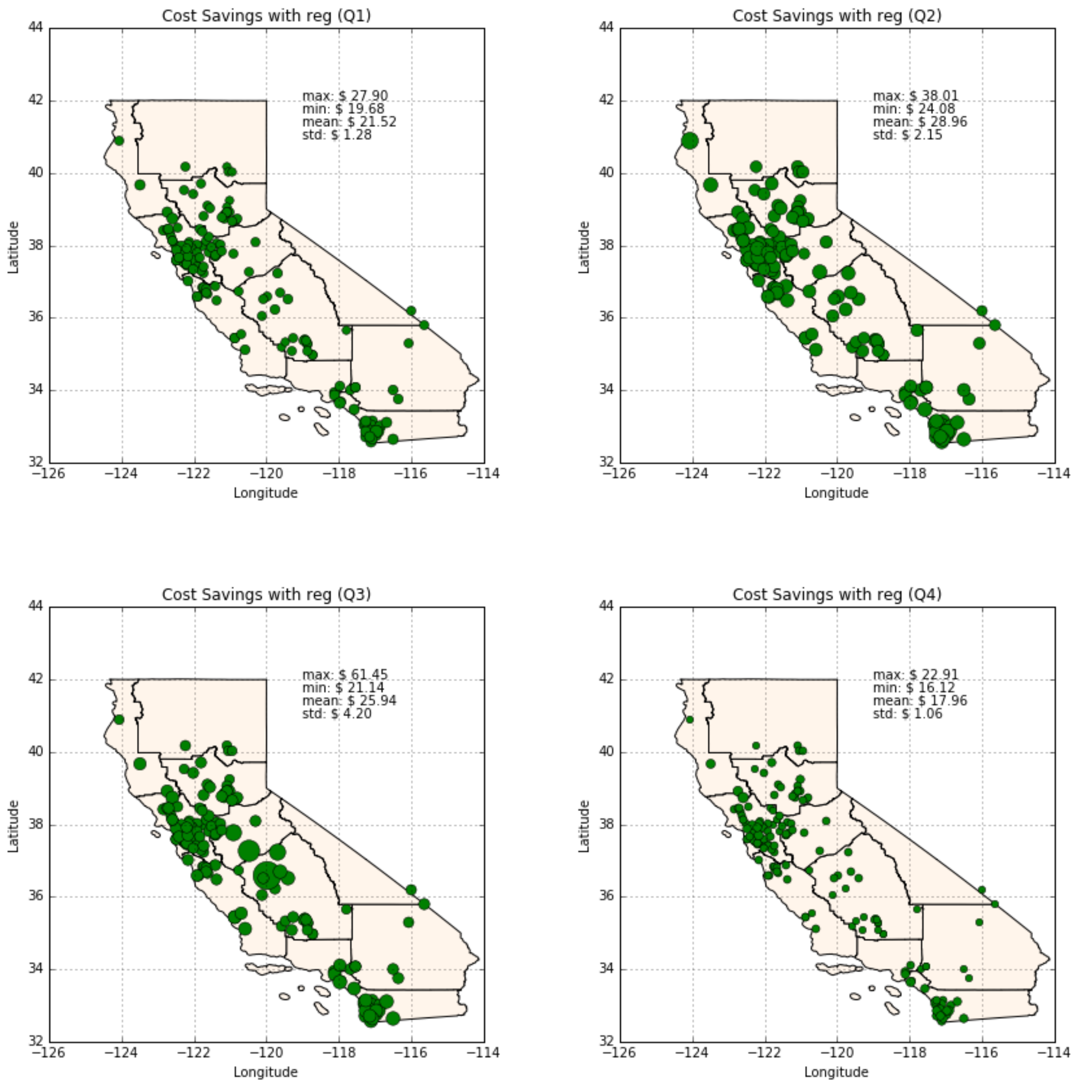

Figure 3.5: Quarterly cost savings by CAISO LMP node.

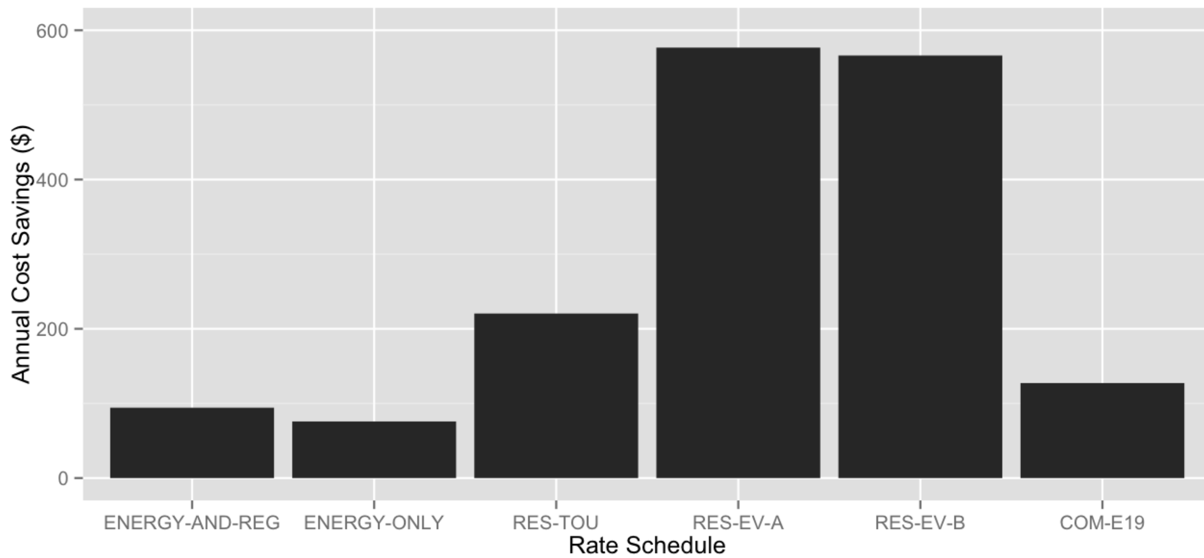

Figure 3.6: Annual cost savings by rate schedule for NYISO nodes (BASE and ENERGY-ONLY) and PG&E retail rate schedules.

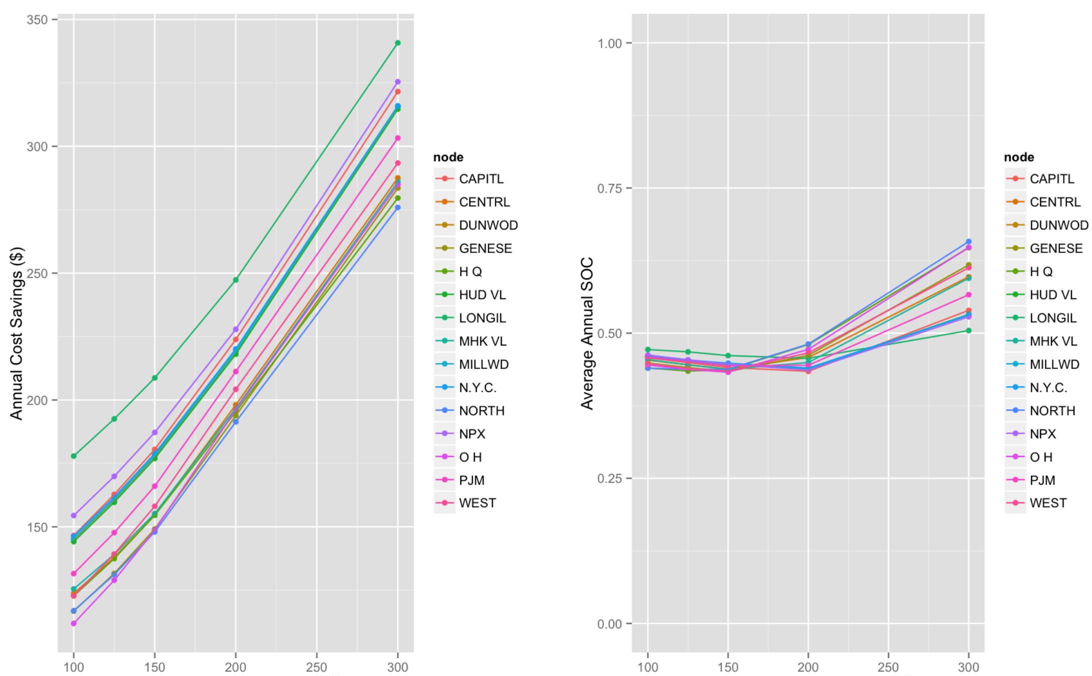

Figure 3.7: Annual savings and average SOC after increasing regulation prices in NYISO.

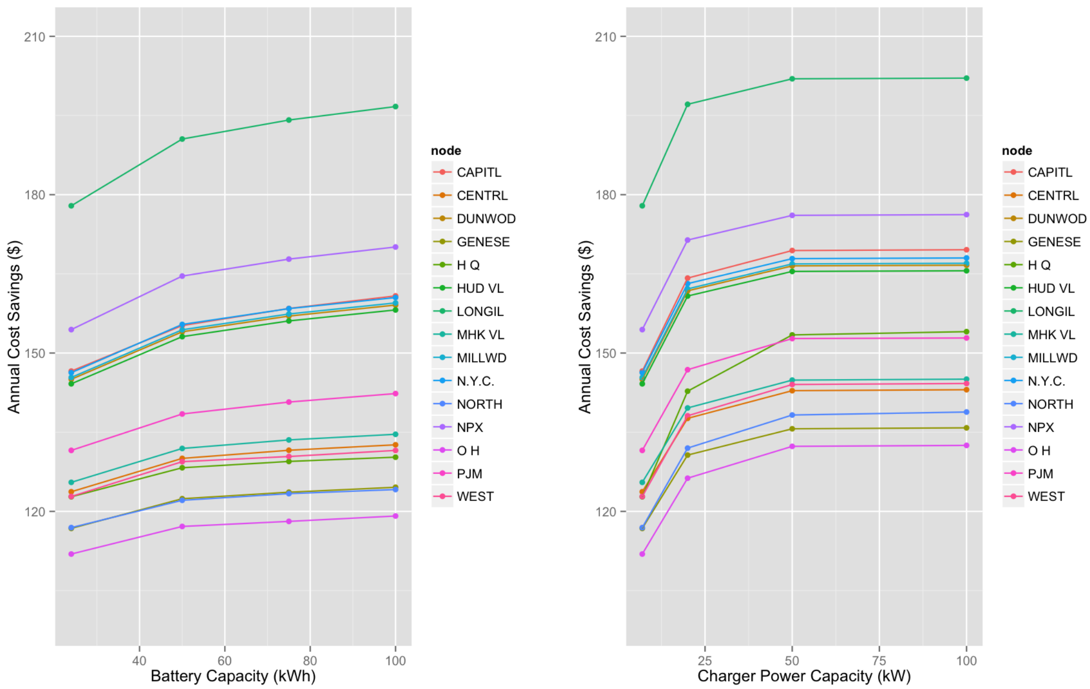

Figure 3.8: Annual savings by battery capacity and charger capacity at ten NYISO nodes.

- Penalized battery degradation (as measured by number of battery cycles over the year)
- Use other pricing data from other regions
- Use pricing data from prospective capacity expansion and production cost models of the future electric grid
- Add demand charge avoidance or minimization to the optimization scheme for use with retail commercial rate schedules
- Simulate a retail / wholesale scheme that takes advantage of TOU retail rate minimization and sells demand response or regulation in the wholesale market
- Aggregate PEVs of different battery capacities and different mobility profiles to assess the aggregate impact of PEV flexibility services on the bulk electric grid
- Bidding into a regulation market adds a risk of mobility impingement that we haven't accounted for. On average, we would expect the energy used during these charging sessions to be equal to the energy planned by the optimization scheme. But real-time grid imbalances would result in net deviations from the scheduled energy delivered to the battery. Further research would analyze the frequency of occurrence of this imbalance and amend the dispatch algorithm to remain robust in the face of this uncertainty.

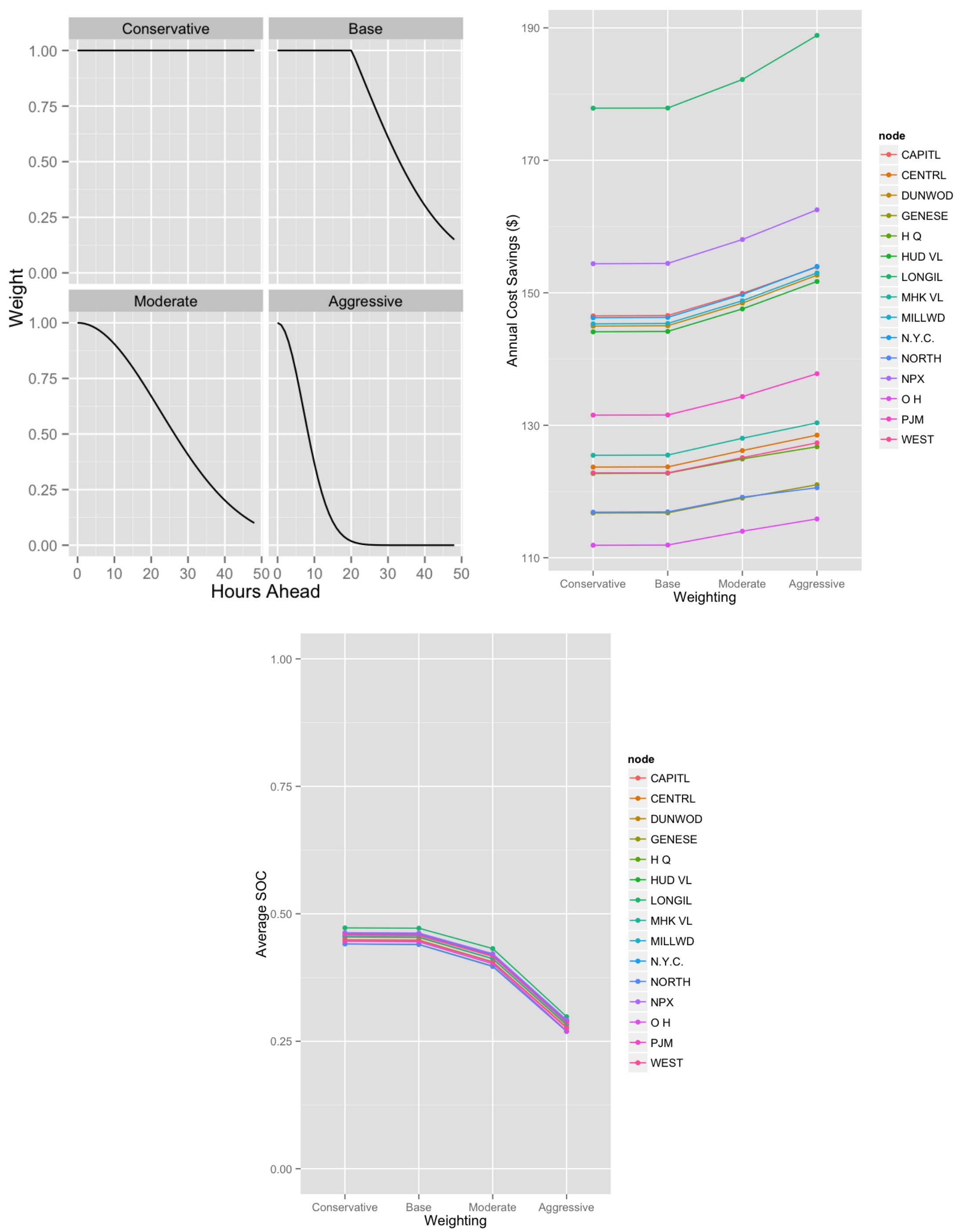

Figure 3.9: Weighting functions, annual cost savings, and average SOC by weighting strategy at in NYISO.

Chapter 4

Agent-Based Modeling of Plug-in Electric Vehicle Mobility and Charging Demand

4.1 Overview

This Chapter summarizes the BEAM modeling framework (Behavior, Energy, Mobility, and Autonomy) and its application to simulating plug-in electric vehicle (PEV) mobility, energy consumption, and spatiotemporal charging demand. BEAM is an agent-based model of PEV mobility and charging behavior designed as an extension to MATSim (the Multi-Agent Transportation Simulation model). We apply BEAM to the San Francisco Bay Area and conduct a calibration and validation of its prediction of charging load based on observed charging infrastructure utilization for the region in 2016. We then explore the impact of a variety of common modeling assumptions in the literature regarding charging infrastructure availability and driver behavior. We find that accurately reproducing observed charging patterns requires an explicit representation of spatially disaggregated charging infrastructure as well as a more nuanced model of the decision to charge that balances tradeoffs people make with regards to time, cost, convenience, and range anxiety.

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4.2 Introduction

The benefits that accrue from the various programs of the U.S. Department of Energy's Vehicle Technologies Office (VTO) are estimated on a biannual basis in the BaSce (Baseline & Scenarios) analysis. To date, the BaSce analysis has estimated the benefits and costs of plug-in electric vehicles (PEV). This analysis assumes that large-scale deployment will not significantly alter the electric power system or change the benefits and costs associated with fueling infrastructure (both for electricity and petroleum). This assumption is unlikely to be true in the case of large-scale electrification of transport, which would be the result of any VTO success scenario. Hence, Lawrence Berkeley National Laboratory (LBNL), in collaboration with Argonne National Laboratory (ANL), is improving the BaSce analysis to better estimate the benefits and costs of PEV deployment by including the impacts on the power system, smart charging, and changes in fueling and charging infrastructure.

LBNL is updating, calibrating and validating the Behavior Energy Autonomy Mobility (BEAM) model in order to improve the PEV benefits analysis as described above. As a first step, BEAM has been calibrated and validated with mobility and charging data from the nine-county San Francisco Bay Area. This progress report describes these efforts in detail. Possible research next steps are to link BEAM to the electricity sector production cost model, PLEXOS, to estimate power sector benefits and costs and extend to a national level using either a reduced form approach or a transferability approach.

4.3 Methodology

Agent-Based Integrated Systems Modeling

Urban systems are multilayered, interconnected networks of physical and cyber infrastructure designed entirely around human beings. The preferences, behaviors, and experiences of people are essential to understanding and predicting the impacts of emerging technologies and urban development. We therefore center our methodological approach on humans and represent their preference and behavior endogenously in our modeling framework. At the heart of our model are behaviorally rich and modular agents, which live in an artificially created urban environment. This can be used for a wide variety of retrospective and prospective analyses.

Agent-based models are conceptually simple. The isolated actions of agents and their interactions with the environment and other agents can be defined with a combination of technical familiarity and common sense. The emergent outcomes of agent-based models are complex. As agent-based modelers, we should spend as much time exploring and interpreting outcomes as we do specifying models and simulation experiments. Through this process of interpretation, agent-based models can inspire insight into system dynamics that challenge intuition and preconceived notions.

The BEAM Framework

The BEAM Framework (Behavior, Energy, Autonomy, and Mobility) is the collection of software tools that we have developed and integrated to enable robust simulation of the transportation-electric system. To date, our work has been focused on PEV mobility and charging behavior, which we have approached by creating a new extension to the MATSim model (Multi-Agent Transportation Simulation [1]). Expanding the scope of BEAM by coupling the MATSim model with PLEXOS to resolve grid operations and production costs in BEAM can provide further analysis insights. The following provides an overview of the key features of the BEAM Framework that are implemented to date.

MATSim

BEAM is an extension of MATSim, an open source transportation systems modeling framework. MATSim – Multi-Agent Transportation Simulation – takes a unique and powerful approach to modeling transportation systems. In addition to simulating systems with extremely high fidelity (i.e., by explicitly representing individuals and their interactions with detailed models of infrastructure), MATSim captures the emergent outcomes of self-interested participants in a market.

In the case of traffic modeling, the market is the transportation system itself, within which participants have a choice in what goods to procure (e.g., what mode of transport to use, what route to take, what time to depart). All participants attempt to maximize their individual utility, but their choices have externalities (i.e., congestion), which impact the utility of other market participants. MATSim provides a reinforcement learning-based framework for resolving the aggregated impact of all agents operating in this market.

Specifically, MATSim allows the modeler to simulate the outcome of agents acting in a greedy manner (referred to as "execution" in Figure 4.1) then observes the outcome of that set of actions in terms of the utility of each agent's experience ("scoring"), then adapt the actions of the agents based on the combined service of the system including the externalities imposed by the entire population ("replanning"). The simulation is iteratively adjusted in this way until it has converged to a state of Nash equilibrium, where agents can no longer improve their individual utility by taking adaptive measures (also known as "user equilibrium").

MATSim is a well-documented, thriving open source software project. More can be learned about the approach and the key modeling assumptions in [37].

BEAM Extension of MATSim

BEAM leverages MATSim and extends some of its existing contributions related to plug-in electric vehicles (PEVs) [37, 149]. Agent behavior associated with PEV charging and corresponding infrastructure interactions have been redesigned in substantial detail to allow for more realistic and sophisticated PEV scenario modeling which was not possible with the existing models. The utility provided to PEV agent drivers during the simulation are combined with the MATSim utility functions associated with mobility. In this way, the tradeoffs associated with PEVs and charging are integrated with overall tradeoffs associated with mobility. BEAM allows the modeler to therefore simulate PEV charging in a manner that is much more realistic given the fact that charging is inextricably linked to mobility.

In BEAM, PEVs are explicitly modeled due to practical differences from conventional vehicles. Because charging is slow relative to gasoline/diesel refueling, BEAM focuses on enabling accurate modeling of energy consumption, charging infrastructure, charging behavior, and charge/discharge control. These elements are further described in the following sections.

Before simulating PEV drivers in BEAM, a final set of travel plans and network performance estimates are first determined by using MATSim alone and thus assuming first that

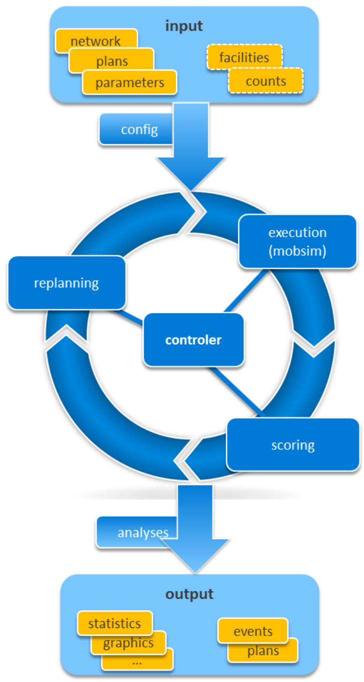

Figure 4.1: Process flow of the MATSim iterative simulation loop.

all vehicles are conventional vehicles. This is achieved by iteratively allowing the agents in MATSim to adapt their routes and departure times to relax the congestion in the network to a degree that individual utility cannot be increased further through travel plan adaptation.

Once the user equilibrium network assignment is achieved, the flows and travel times on the network are saved to file and used in subsequent BEAM runs as input. The PEVs are therefore assumed to be "congestion takers," not "congestion makers." That is, the routing choices made by PEVs are assumed to not influence travel times. For larger scale simulations, this assumption can be relaxed by iteratively rerunning the MATSim core to reestablish user network equilibrium after PEVs have modified their mobility in light of constraints around charging and PEV range.

Finally, MATSim is a highly modular simulation tool that has been used extensively for planning and analysis of multi-modal urban transportation systems. By using MATSim for the BEAM framework, we intend to leverage this capability in the future to conduct analysis of PEVs in the context of a multi-modal system. For example, when agents can choose their mode, the presence or absence of charging infrastructure will influence whether they drive the PEV at all. This capability will also form the basis for future analysis of the impacts of mobility-as-a-service and fully autonomous vehicles on the dynamics of the transportation-electric system.

Plug-in Electric Vehicles In BEAM, the vehicle is modeled as a separate entity from the agent. Vehicles can be battery electric (BEVs) or plug-in hybrid electric (PHEVs). The key attributes of the vehicle can be defined to match existing or future vehicle technologies are listed in Table 4.1.

Table 4.1: Vehicle attributes in BEAM.

Attribute	**Description**
Vehicle Name	E.g. the make/model or generic vehicle class.
Electric Energy Consumption Model	See Section 4.3.
Petroleum Energy Consumption Model	For PHEVs. See Section 4.3.
Battery Capacity	Useable capacity of the battery.
Max Level 2 Charging Power	Vehicle imposed limit on Level 2 charging.
Max DC Fast Charging Power	Vehicle imposed limit on DC Fast charging.
Max Discharging Power	Vehicle imposed limit on discharging if V2G capable.
Compatible Plug Types	List of plug interfaces compatible with vehicle.

Energy Consumption Models Energy consumption is evaluated at the spatial scale of the network link and can be modeled as a function of a variety of characteristics including average speed of travel, link class (e.g., arterial, feeder, local), link inclination, and link congestion. An example of an electric energy consumption model from [124] is shown in Figure 4.2. When a vehicle is driven along a route in BEAM, the total energy consumed is the sum of the energy consumed along each link of the route.

Each vehicle class can have its own energy model. PHEVs have two consumption models, the electric consumption model for charge depletion mode and petroleum consumption model for charge sustaining mode.

Charging Infrastructure Charging infrastructure is defined and organized in a hierarchical fashion in BEAM. There is a physical dimension and a management dimension to the representation of chargers.

The physical chargers are organized as illustrated in Figure 4.3. Each charging site represents a collection of infrastructure in one geographic location (e.g., a parking lot or a home). Within a site there can be one or more charging points. A charging point has a finite number of parking spaces nearby which allow physical access to the point. Each charging point supports one or more charging plugs. Each charging plug is of a particular plug type (i.e., this is where port interfaces like J1772 vs CHAdeMO vs Tesla are specified).

The management of chargers is organized as follows. Each charging site is associated with a charging policy and a charging network operator. The charging policy defines the pricing and parking policy associated with the site. The charging network operator is the entity that controls the charge/discharge rate of the vehicle during a charging session, which can be subject to constraints imposed by the physical infrastructure and the vehicle.

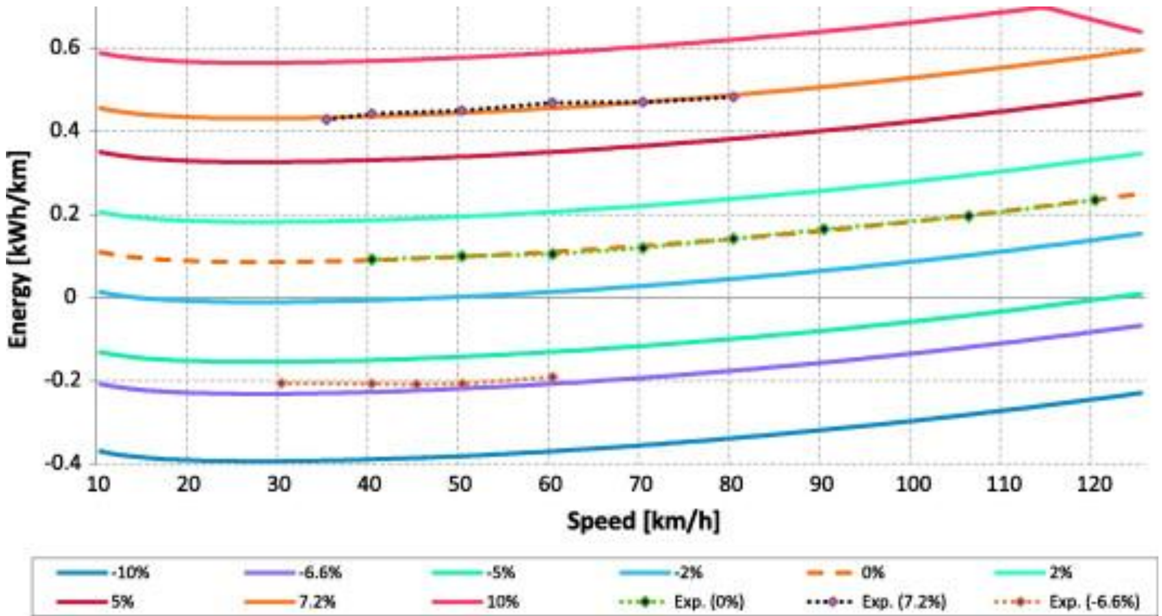

Figure 4.2: Figure reprinted from [124]: "Energy consumption per unit of distance required to maintain a constant speed for several degrees of inclination and experimental runs (Exp.) for 0%, 7.2% and −6.6%."

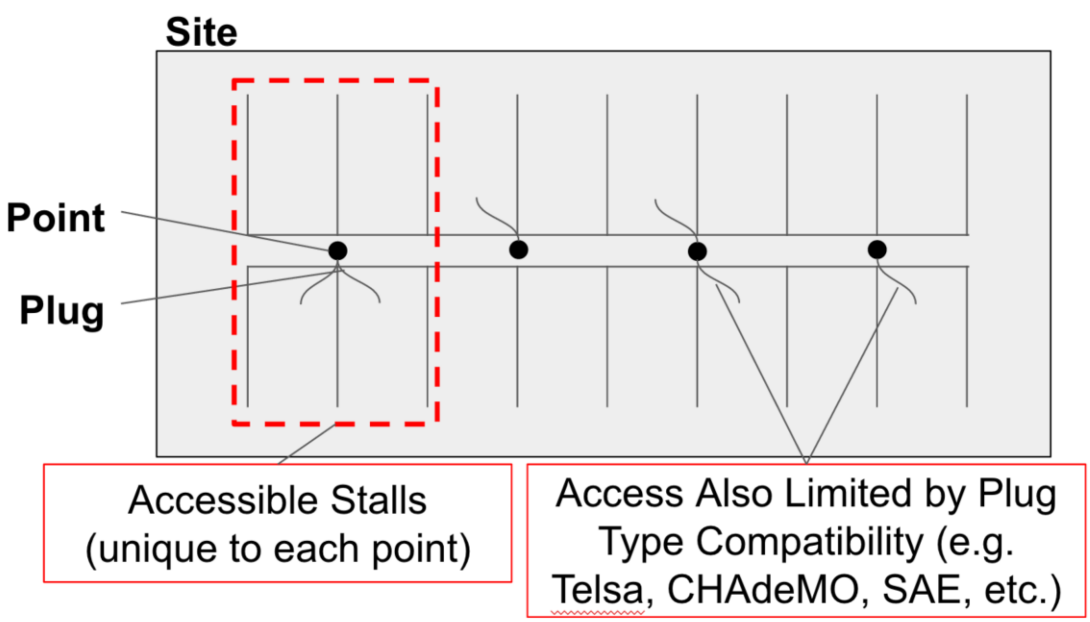

Figure 4.3: In BEAM, charging sites have multiple charging points which are accessible to limited parking spaces and can have multiple charging plugs of various types.

Heterogeneous policies and/or network operators at a single parking lot can be accommodated in BEAM by defining multiple sites with the same geographic coordinates; i.e., the specific location of a site need not be unique.

Charging Queues In BEAM, PEVs that attempt to charge at a single charging point are assumed to enter a charging queue. There are two types of charging queues, fast queues (which apply only to DC Fast chargers) and slow queues (Level 1 and 2 chargers).

Fast queues are defined at the site level. They assume that drivers attend their vehicles (or stay close by) during fast charging. Drivers are assumed to therefore be close enough to unplug and remove their vehicle immediately at the conclusion of the charging session so that the next vehicle in the fast queue can start its charging session immediately. A single fast queue can be served by multiple charging points. This is predicated on the idea that vehicles are attended by the drivers and turnover occurs rapidly, so that immediate physical access to chargers on arrival is not a concern. The maximum length of the charging queue should be based on some realistic estimates for the number of vehicles that are expected to wait in line for a fast charge. For the analysis in this report, we assume three times the number of DC Fast charging plugs at a site. In other words, we assume no more than three drivers wait in line for any single plug.

Slow charging queues are defined for each charging point and are constrained by the number of physical spaces that can access the point. Slow charging queues are assumed to have a delay between the conclusion of one charging session and the beginning of the next. The length of the delay is configurable and can vary depending on whether the charger is assumed to have a notification system in place to alert the next driver or whether the next session is somehow started automatically. Charging points are assumed to be accessible from 2, 4 or 6 parking spaces with an average of 2.4 spaces.

Model Events and Processes During a BEAM simulation, events occur in chronological order according to a dynamic schedule that manages what actions specific agents or infrastructure should take at what time. Typically agents schedule themselves to perform specific actions based on the process flow diagram in Figure 4.4. Some actions (such as "dequeue" and "end session") are scheduled by the charging infrastructure though they ultimately lead to actions by the agents. Table 4.2 provides a brief description of the logical flow associated with the actions and decisions in Figure 4.4.

A typical path through the states in diagram in Figure 4.4 might be the following:

- A driver begins the day at home, their activity ends, and they execute the "Departure Decision." Because their battery is full, they choose to Depart and enter the Traveling state.

- Upon arrival to their place of work, they execute the "Arrival Decision." Because there were no chargers within their initial search distance, they choose to Expand Search and re-execute the "Arrival Decision." They find chargers in their new search radius and select one of them for a charging session, executing the "Selected Charger" action.

- The charger is unoccupied, so the driver changes state to Pre-Charge and then the "Dequeue" action is immediately executed, changing their state to Charging. When the batter is full the "End Session" action is executed and the driver state is changed to Post-Charge.
- When the driver's work activity ends, they execute the "Departure Decision" and again elect to execute the Depart action since their battery is full.

Charging Behavior Agents in BEAM are assumed to have the following foresight and sensing capabilities with respect to mobility, traffic, and charging infrastructure:

- They have a pre-determined plan for their day's activities, including the ending time of each activity, the type of activity, and the location (latitude/longitude coordinates).
- They choose routes through the road network that minimizes travel time (see Section 4.3 for further information on how routing and traffic is modeled in BEAM).
- They are aware of the state and attributes of their vehicle (i.e., the state of charge, remaining range, charging/discharging power capabilities, etc.).
- They are aware of the current state of the charging infrastructure at all times, including: what chargers are located within a given search radius, whether charging plugs are available (not in use and with open parking spaces), accessible (in use but with open parking spaces), or inaccessible (no ability to park within reach of a plug), and all attributes of the charger (i.e. price, power capacity, distance to their activity).

Based on some or all of the above factors, drivers make two key decisions during a BEAM simulation (see "Arrival Decision" and "Departure Decision" in Figure 4.4 and Table 4.2 above). BEAM provides a flexible framework for the modeler to define the form of these decisions. Each decision model is designed to be capable of making a choice for both decision points in Figure 4.4. To date, three decision models have been implemented in BEAM, which are described in Table 4.3.

Nested Logit Charging Decision Model A nested logit decision model is a hierarchical discrete choice model that is composed of a series of nested multinomial logit choice models. An example of how this model is structured for charging decisions in BEAM is presented in Figure 4.5. Ultimately, the specific alternatives of the overall choice are the leaves of the nested tree. But the nested structure allows the model to more appropriately capture the correlation among alternatives within a nest. For example, if a new charger is added as an alternative to the "yes" nest, then the probability of selecting all other alternatives will

Table 4.2: Description of agent actions and decisions in BEAM.

Name	Description
Arrival Decision	Agent senses charging infrastructure around their activity and decides whether to a) engage in a charging session (triggering the "Selected Charger" action) b) expand the search area for nearby chargers ("Expand Search" action) c) abort the search for chargers (transition of Parked state and then execute the "Abort" action) d) search for chargers at a later time (transition to Parked state then execute the "Try Again" action).
Abort	In this action, the agent has chosen not to charge during their current activity, in which case they schedule the "Departure Decision" to occur at the time of departure defined by the agent's mobility plan.
Try Again	The agent has chosen not to charge at the present moment, but rather to schedule themselves to perform the "Arrival Decision" again at a configurable amount of time later (assumed 30 minutes for this analysis).
Expand Search	In this action, the agent immediately repeats the "Arrival Decision" but with a search radius twice as large as the previous search. This search radius is initialized to 200m and is limited to a maximum of 2 miles.
Selected Charger	The agent has selected a charger and transitioned to the Pre-Charge state which puts the agent in the queue to charge (see Charging Queues in Section 4.3). The charger schedules the "Dequeue" action to occur immediately or at some point in the future when the queue has dissipated.
Dequeue	The agent is discharged from the charging queue and changes state to Charging, thereby beginning the charging session. The "End Session" action is scheduled by the charging network operator.
End Session	The charging session is completed, the agent state transitions to Post Charge, and the vehicle is assumed to remain plugged in to the charger until either the agent departs or another vehicle dequeues from the charging queue.
Departure Decision	The agent senses charging infrastructure around their current and next activities in addition to along the route connecting the two activities. The agent decides whether to engage in an en-route charging session. If yes, the agent executes the "Selected En Route" action. Otherwise, the "Depart" action is executed immediately.
Selected En Route	The agent transitions to the En Route to Charge state and schedules the "Reassess" decision to occur at the moment of arrival to the en-route charger.
Reassess	Once the agent arrives to the en-route charging site, they sense the state of the charging infrastructure at that site and make a final decision on whether to engage in a session. Charging will only occur if at least one charger at the site is accessible. If a charger is found, the "Engage" action is executed; otherwise the "Abort" action is executed.
Engage	The agent has selected a charger; they transition to the Pre-Charge state, which puts them in the queue to charge (see Charging Queues in Section 4.3). The charger schedules the "Dequeue" action to occur immediately or at some point in the future when the queue has dissipated.
Abort En Route	The agent has chosen not to charge, transitions to the Traveling state, and schedules itself to execute the "Arrival" decision upon arrival at its next destination.
Depart	The agent transitions to the Traveling state and schedules itself to execute the "Arrival" decision upon arrival at its next destination.

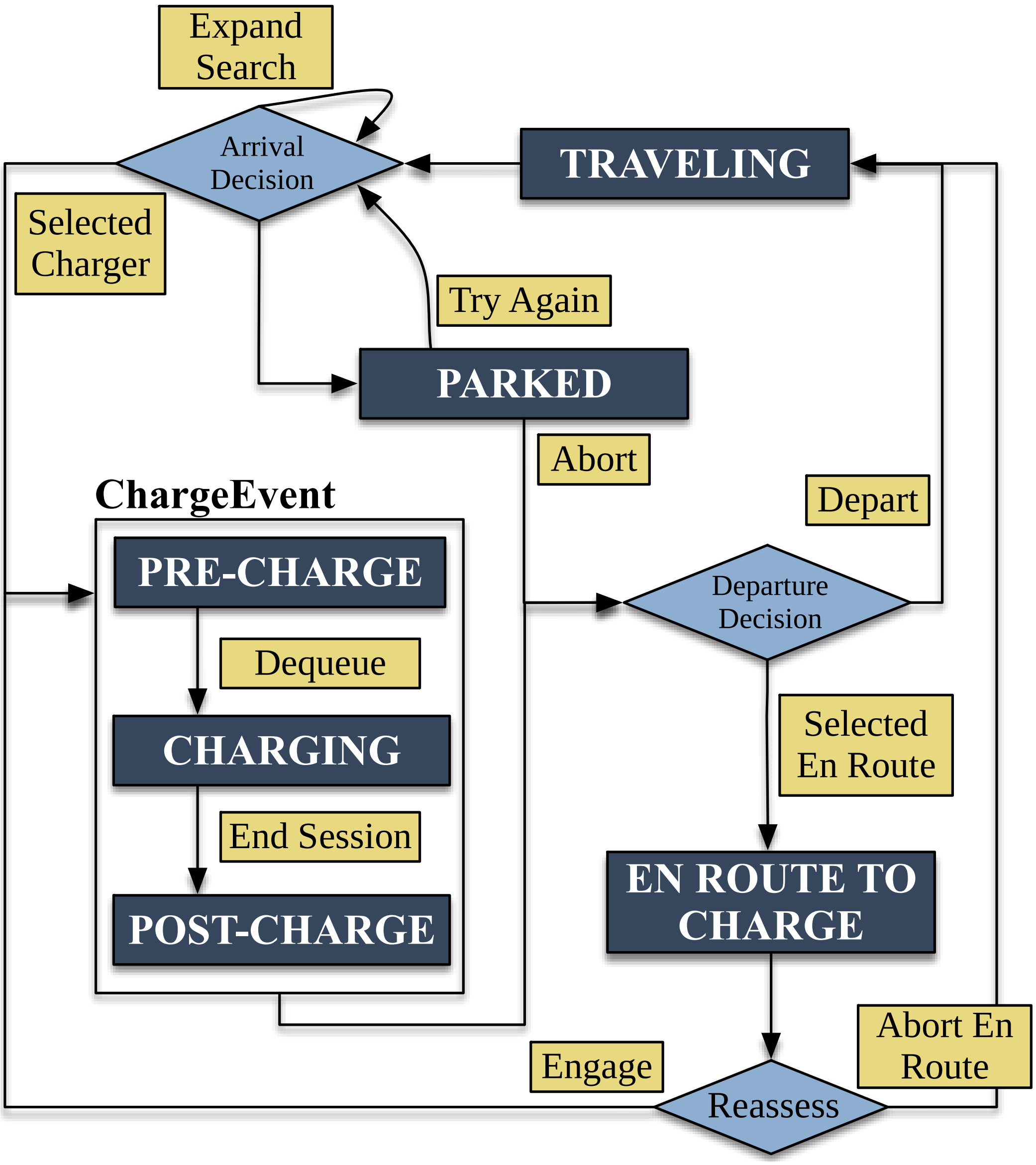

Figure 4.4: States (dark blue), actions (yellow), and decisions (light blue) of agents in BEAM.

decrease to "make room" for the new entrant. But most of the change in probability should come from the other charger alternatives in the "yes" nest, rather than equally from all alternatives including those in the "no" nest. Employing a nested logit specification rather than a flat multinomial specification makes it possible to capture this correlation.

The nested logit model specification from [144] is used in BEAM, but in the special case where all mixture coefficients are given a value of one. Given some nest m is certain to be chosen, the probability of choosing one of the alternatives n from all possible alternatives

Table 4.3: Decision models currently implemented in BEAM. The agent population can be programmed to use any or all of these models during any simulation.

Decision Model	Description
Always Charge On Arrival	The agent always chooses to charge during the "Arrival Decision" unless there are no accessible chargers within the search radius. If no charger is found, the "Expand Search" action is scheduled until the maximum search distance is exceeded. If multiple chargers of different levels are found, the agent prioritizes level 2 followed by DC Fast followed by Level 1. On departure, the agent always chooses to "Depart" rather than "Selected En Route."
Uniform Random	The agent chooses to charge with 50% probability during the "Arrival Decision" unless there are no accessible chargers within the search radius. In no charger is found, the "Expand Search" action is scheduled until the maximum search distance is exceeded. If multiple chargers of different levels are found, the agent prioritizes Level 2 followed by DC Fast followed by Level 1.
On departure, the agent always chooses to "Depart" rather than "Selected En Route."	
Nested Logit	The agent uses a nested logit discrete choice model to make separate "Arrival Decision" and "Departure Decision". The models are described in detail in Section 4.3.

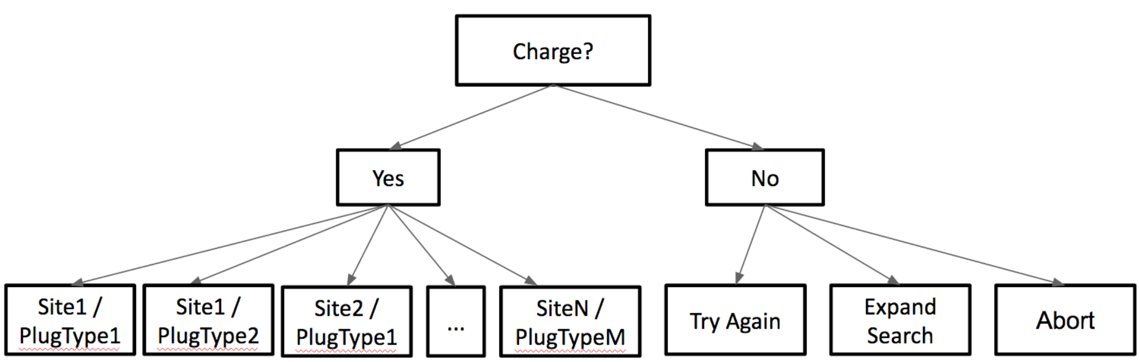

Figure 4.5: Structure of the arrival decision model in BEAM for deciding what site/level charger to select or – if charging is not chosen – what adaptation strategy to elect.

N_m within that nest, is expressed as a multinomial logit formulation, i.e.:

$$P(n|m) = \frac{(e^{V_n})^{1/\mu_m}}{\sum_{n' \in N_m} (e^{V_{n'}})^{1/\mu_m}}$$

Where V_n is the utility of alterative n (the utility functions used in BEAM are described below) and μ_m is the nest elasticity (a value between zero and 1), which is a measure of the relative correlation between the nest and all alternatives or nests at higher levels of the nested logit tree. Once we relax the assumption that nest m will be chosen, then to find the marginal probability of alternative n among all alternatives requires an application of the chain rule:

$$P(n) = \sum_m P(n|m)P(m)$$

Where $P(m)$ is based on the expected maximum utility of the alternatives within that nest:

$$P(m) = \frac{(\sum_{n' \in N_m} (e^{V_{n'}})^{1/\mu_m})^{\mu_m}}{\sum_m (\sum_{n' \in N_m} (e^{V_{n'}})^{1/\mu_m})^{\mu_m}}$$

This structure can be adopted for any number of nests and alternatives. In BEAM, the choice model consists of one parent nest and two sub nests: “yes” and “no” (Figure 4.5).

To execute the decision, a search of all accessible chargers within the search radius is performed. For each unique combination of charging site and plug type, an alternative to the “yes” nest is created. The utility of that alternative is calculated by gathering the required data needed to evaluate the utility function described below. Once the utilities of all alternatives are determined, the marginal probability of each alternative is calculated and a choice is randomly sampled from the resulting discrete probability distribution.

The utility of the charging alternatives are expressed as linear functions of the attributes of the agent and alternative, according to the following model:

$$V_n = \beta x + \gamma y$$

Where β and γ are vectors of coefficients and x and y are vectors of agent and charger attributes, respectively, as listed in Table 4.4. The coefficient values in Table 4.4 are the result of the calibration process described below in Section 5.2 (DOUBT).

Charge/Discharge Control As described in Section 4.3, the charging network operator is the entity that controls the duration and speed of the charging session. For the analysis in this report, there is only one network operator defined, called “Unmanaged.” In this case the rate and timing of charging represents how chargers behave when no management occurs, namely, the battery in the vehicle is charged at the maximum rate permitted by the charger and vehicle (each has its own limit, the lesser of the two is used by the “unmanaged” network operator). The time of the charging session as determined by the “unmanaged” operator is therefore the energy needed to fill the battery divided by the rate of charge.

Control of the charging rate and duration of charging sessions are managed by the network operator to allow the modeler to create other types of operators that manage charging sessions in order to achieve objectives associated with supporting the electric grid or exploiting economic opportunities in the electric system. BEAM is designed to support these alternative scheduling and charging capabilities and to do so in a manner that simulates a system with heterogeneity in how charging sessions are managed. For example, there could be a variety of network operators with competing shares of the market and competing interests managing separate charging sessions in one model run.

Table 4.4: Utility function attributes and coefficients in the calibrated nested logit model in BEAM.

Utility Function	**Attribute Type**	**Name**	**Units**	**Calibrated Coefficient**
Charging Site/Level	Agent	Remaining Range	mi	−0.025
	Agent	Remaining Travel Distance in Day	mi	0.005
	Agent	Next Trip Travel Distance	mi	0.05
	Agent	Planned Dwell Time	hr	0.25
	Agent	Is BEV	dummy	2.5
	Charger	Cost	$	−4.5
	Charger	Capacity	kW	0.001
	Charger	Distance to Activity	mi	−1
	Charger	At Home and Is Home Charger	dummy	2.5
	Charger	Is Available	dummy	2.5
	N/A	Intercept	dummy	5
Try Later	Agent	Remaining Range	mi	−0.05
	Agent	Remaining Travel Distance in Day	mi	0.025
	Agent	Next Trip Travel Distance	mi	0.05
	Agent	Planned Dwell Time	hr	0.35
	Agent	Is BEV	dummy	−2.5
	Agent	At Home	dummy	0
	Agent	Search Radius	mi	1.5
	N/A	Intercept	dummy	−2.5
Expand Search	Agent	Remaining Range	mi	−0.05
	Agent	Remaining Travel Distance in Day	mi	0.025
	Agent	Next Trip Travel Distance	mi	0.05
	Agent	Planned Dwell Time	hr	0.35
	Agent Is BEV	dummy	2.5	
	Agent	At Home	dummy	−5
	Agent	Search Radius	mi	−3
	N/A	Intercept	dummy	−0.5
Abort	Agent	Remaining Range	mi	0.05
	Agent	Remaining Travel Distance in Day	mi	−0.025
	Agent	Next Trip Travel Distance	mi	−0.05
	Agent	Planned Dwell Time	hr	−0.35
	Agent	Is BEV	dummy	−2.5
	Agent	At Home	dummy	2
	Agent	Search Radius	mi	1
	N/A	Intercept	dummy	5

4.4 Model Application

The purpose of our initial application of BEAM is to simulate PEV mobility and charging patterns in the San Francisco Bay Area based on current (mid 2016) estimates of personal mobility, vehicle ownership, and charging infrastructure. We then compare the simulated charging demand profiles to observed profiles, which were obtained by systematically polling the availability of charging infrastructure on public station locator tools. This comparison serves as a means to calibrate the charging decision models in BEAM, such that observed patterns of charger utilization can be reproduced more accurately.

San Francisco Bay Area

The focus of the analysis in this report is on the nine San Francisco Bay Area counties, which are San Francisco, San Mateo, Santa Clara, Alameda, Contra Costa, Solano, Napa, Sonoma, and Marin. The reason for limiting the scope to the Bay Area is a matter of data availability and the fact that the Bay Area is one of the highest metropolitan regions nationwide for PEV adoption and charging infrastructure deployment.

Urban Mobility

Based on work by [145] and [123], BEAM leverages the mobility plans of the canonical Smart Bay model. Smart Bay features agent plans derived from the San Francisco Bay Area Metropolitan Transportation Commission's (MTC) activity-based travel demand model. In addition to being spatially and temporally explicit, the activities are further disaggregated by purpose (one of: home, work, shopping, dining out, university, school, social, escort, and other).

While the full Bay Area population consists of $\sim$2.6M households, for computational tractability, a down-sampled population of 463,000 agents was used as the basis for a calibration of Smart Bay to traffic data from the Caltrans Performance Measurement System. The calibration process involves running MATSim until user equilibrium is achieved and then comparing simulated versus observed traffic counts on screen lines throughout the Bay Area road network. By iteratively adjusting model parameters associated with queuing on links and flow capacities, the Smart Bay model was calibrated to reproduce observed traffic flows with the virtual population.

The MTC activity plans can be replaced by state-of-the-art mobility plans produced by [140] through sampling from an Input-Output Hidden Markov Model (IO-HMM) that was fit to anonymized cellular-derived locational data in the San Francisco Bay Area. The process of sampling activities from the IO-HMM yields individual daily plans for an arbitrary number of hypothetical residents of the Bay Area.

PEV Ownership

For the analysis presented in this report, we assumed vehicle ownership to be captured spatially and by vehicle type from the database of claimed PEV rebates available through the California Clean Vehicle Rebate Project [142] (CVRP). The data from CVRP includes the make and model of each rebate in addition to the zip code of the applicant. Based on these data, we show the uptake of PEVs in the Bay Area by make and vintage in Figure 4.6.

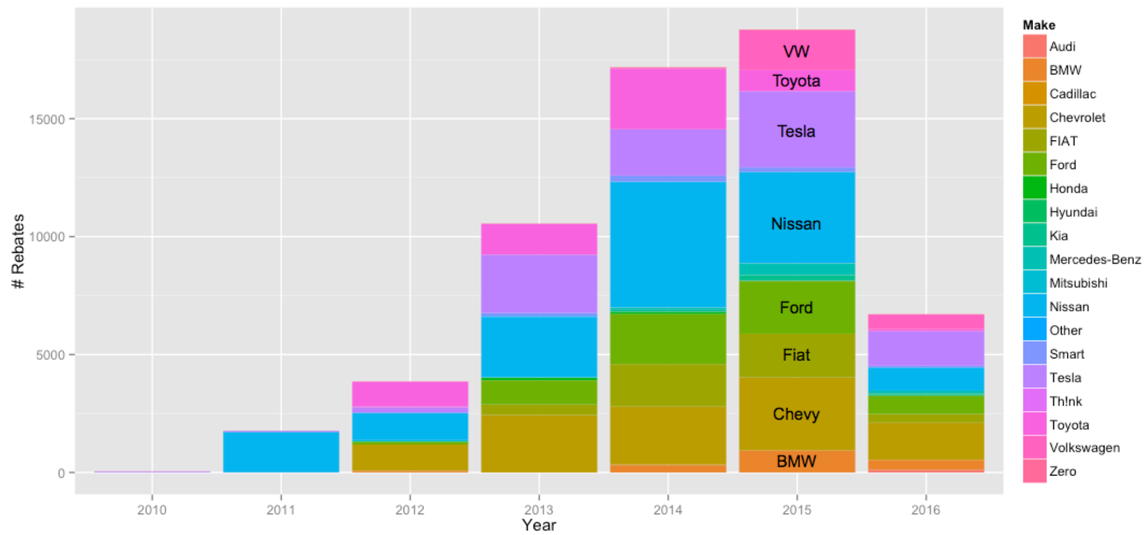

Figure 4.6: Rebates claimed in the San Francisco Bay Area as mid-2016 by vehicle make and year (data from California Clean Vehicle Rebate Project).

In total, there were ∼59,000 rebate claims in the Bay Area by mid-2016. We use the spatial and vehicle type distributions from the CVRP database directly as inputs to the BEAM model with 59,000 agents. These agents are then assigned daily mobility plans by sampling from the original set of 463,000 Smart Bay model plans. During this sampling process it was made sure that agent home locations are in line with the spatial distribution present in the CVRP data.

While the CVRP data is highly specific and useful for calibrating BEAM, we recognize that rebates only mark the location of a PEV owner at the time of purchase. More ideal would be to use DMV records, which are renewed every year. We have an agreement with NREL to make use of statistically representative DMV data from the SERA (Scenarios, Evaluation, Regionalization, and Analysis) model [151], which can be used with BEAM.

The vehicle attributes are summarized in Table 4.5. The source for these data were a combination of resources from OEM model specifications and the U.S. DOE fuel economy website [357]. The electric energy consumption models for all PEVS are based on the work of [124]. The PHEVs use a petroleum consumption model corresponding to a constant rate of consumption per mile traveled that varies by make/model of vehicle as presented in Table 4.5.

Table 4.5: Vehicle attributes assumed in BEAM.

Make	Class	Battery Capacity (kWh)	Level 2 Charging Limit (kW)	DC Fast Charging Limit (kW)	Gas Fuel Economy (MPG)
Nissan	BEV	21	7	50	
Chevrolet	PHEV	11.78	7	50	42
Tesla	BEV	68.64	20	125	
Ford	PHEV	7.35	7	125	38
Toyota	PHEV	3.19	7	50	52
FIAT	BEV	24.36	7	50	
Volkswagen	PHEV	24.07	7.2	50	30
BMW	BEV	21.87	7.4	50	
Mercedes-Benz	BEV	34.8	10	50	
Smart	BEV	21.76	3.3	50	
Kia	BEV	29.76	6.6	50	
Honda	BEV	23.78	6.6	50	
Zero	BEV	2.15	3.3	50	
Audi	PHEV	6.08	3.3	50	35
Mitsubishi	BEV	17.7	3.3	50	
Cadillac	PHEV	16.4	3.3	50	25
Hyundai	PHEV	9.18	6.6	50	40
Th!nk	BEV	7.83	6.6	50	
Other	BEV	22.4	6.6	50	

Charging Infrastructure

The Bay Area application of BEAM uses charging infrastructure data from the U.S. DOE Alternative Fuels Data Center, a public nationwide repository of PEV charging station and other alternative fueling station locations and attributes. Table 4.6 and Table 4.7 list attributes and market penetration of charger types and network operators. Figure 4.7 depicts the composition of public chargers in the Bay Area by network operator.

In addition to public charging infrastructure, BEAM explicitly represents residential chargers that are exclusively accessible to each agent when at home. Based on results from a California survey of PEV owners [141], we assume 90% of drivers have a Level 2 charger installed at home. The remaining 10% are assumed to only have a Level 1 charger available. See Section 4.3 for details on how drivers are assigned to home locations in the Bay Area application of BEAM.

Table 4.6: Power capacity and the market penetration of charger types in the Bay Area application of BEAM.

Name	Power Capacity (kW)	# in SF Bay Area
CHAdeMO	50	113
J-1772-1	1.92	180
J-1772-2	19.2	1127
SAE-Combo-3	240	34
Tesla-2	20	89
Tesla-3	120	8

Table 4.7: The assumed price of charging and market penetration of network operators in the Bay Area application of BEAM.

Network Operator	Price for L1/L2/DC Fast ($/kWh)	# in SF Bay Area
ChargePoint	0.3/0.4/0.5	785
Blink	NA/0.5/0.6	117
EvGo	NA/0.4/0.5	94
Tesla	NA/0.4/0.5	97
Other	0.3/0.4/0.5	458
Home	0.15/0.15/NA	59000

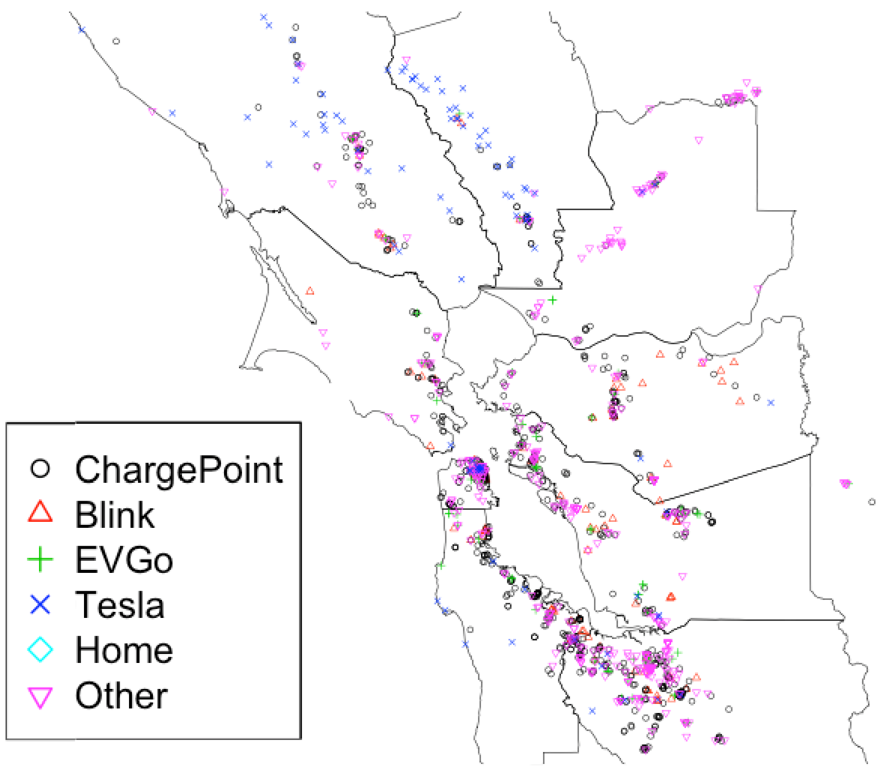

Figure 4.7: Charging Infrastructure in the San Francisco Bay Area as of mid-2016 according to data from the Alternative Fuels Data Center.

Charging Utilization

Charging network operators (e.g. ChargePoint, EVGo, and Blink) publish station locators online to assist PEV drivers in finding nearby chargers. These locators also feature real-time availability information on a subset of charging stations (specifically, those chargers that are connected to the internet through a LAN or cellular connection). By systematically polling these publicly available APIs, we have developed a database of instantaneous charger availability throughout the United States. Temporally, the data are relatively low-resolution (samples are taken approximately twice per hour) but when analyzing patterns at sufficient levels of aggregation (e.g., at the scale of a county or metropolitan region) and average over a sufficiently large number of observed days, the data set is a valuable resource for validating the aggregated emergent outcomes of a simulation model like BEAM.

In Figure 4.8 and Figure 4.9, we present observed average hourly utilization of public charging infrastructure for the whole Bay Area and by county, respectively. These data were produced by averaging the hourly counts of chargers in use for all non-holiday weekdays over a period of three months from June through August 2016. In Section 5.2 (DOUBT) below, we use these data directly in the process of calibrating the decision model used in BEAM.

These utilization data are not the most ideal data source for analyzing charging patterns and grid impacts of PEV adoption. Namely, they don't distinguish between a vehicle that is drawing power and one whose battery is full but is still plugged in and engaged in a charging session (most chargers meter by the hour). BEAM is capable of producing spatiotemporal patterns of both charger utilization in this sense as well as profiles of power consumption. For calibration, the former is used to enable an apples-to-apples comparison of infrastructure utilization, while the latter is used for analysis of the impact of model assumptions on charging profiles. In future work, we plan to obtain data directly from a charging network operator to allow additional calibration that considers both utilization and instantaneous power consumption.

4.5 Results and Analysis

PEV Trip Demand

The PEV trip demand for our Bay Area BEAM application comes directly from the mobility inputs described in Section 4.2. In Figure 4.10 and Figure 4.11, we show the temporal distribution of trip departures in the mobility data disaggregated by activity type. In Figure 4.10, the activity types refer to the activity being completed at the time of departure while in Figure 4.11 the types refer to the destination activity. In Figure 4.12 we show the distribution of travel distances in the Bay Area application, both by individual trip and by total travel distance each day.

Preliminary Model Calibration and Validation

The calibration exercise was designed to do a preliminary calibration of the parameters of the nested logit choice model before engaging in further analysis. The ideal method of parameterization would be a combination of discrete choice analysis from revealed and stated preference data sets. To date, there has been some stated preference survey and

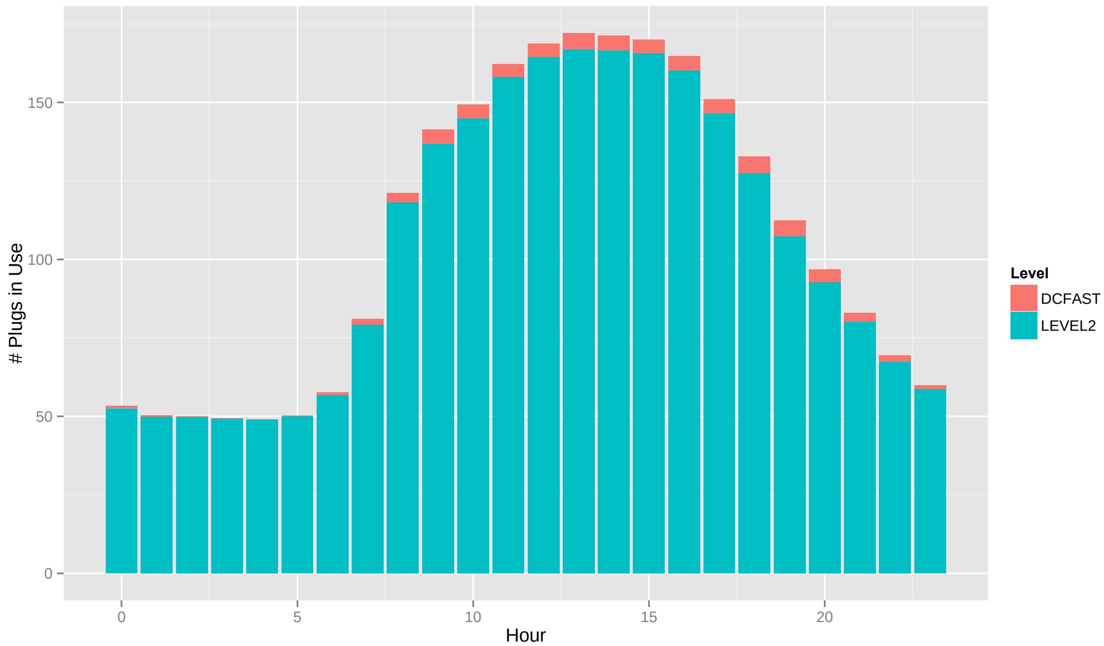

Figure 4.8: Observed utilization of chargers on a weekday aggregated across San Francisco Bay Area.

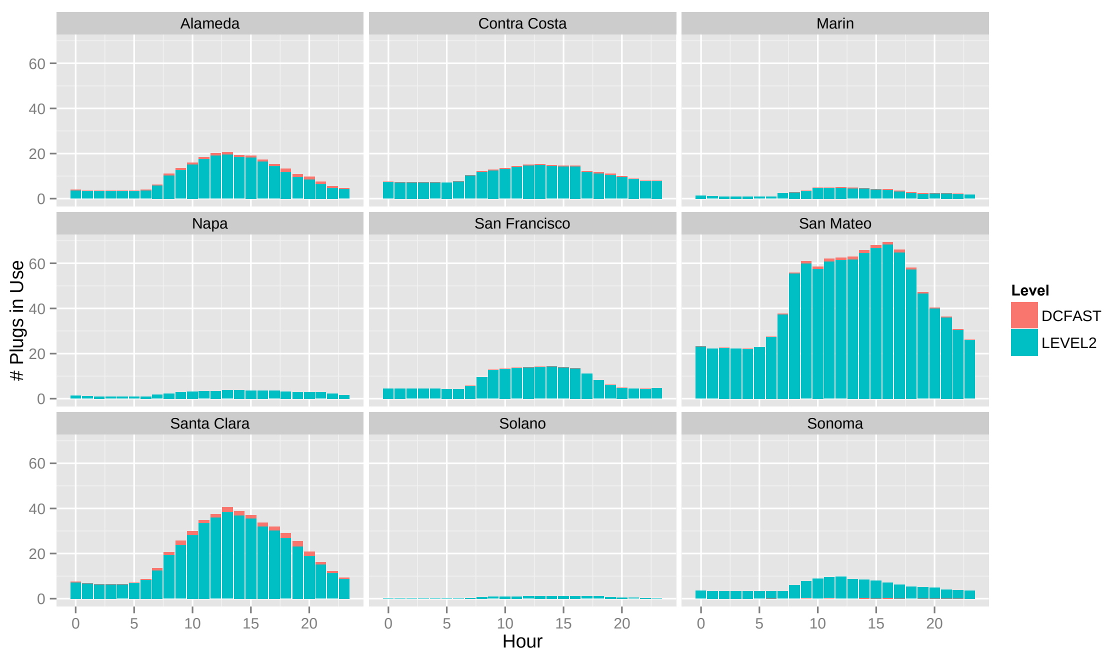

Figure 4.9: Observed utilization of chargers on a weekday by county across San Francisco Bay Area.

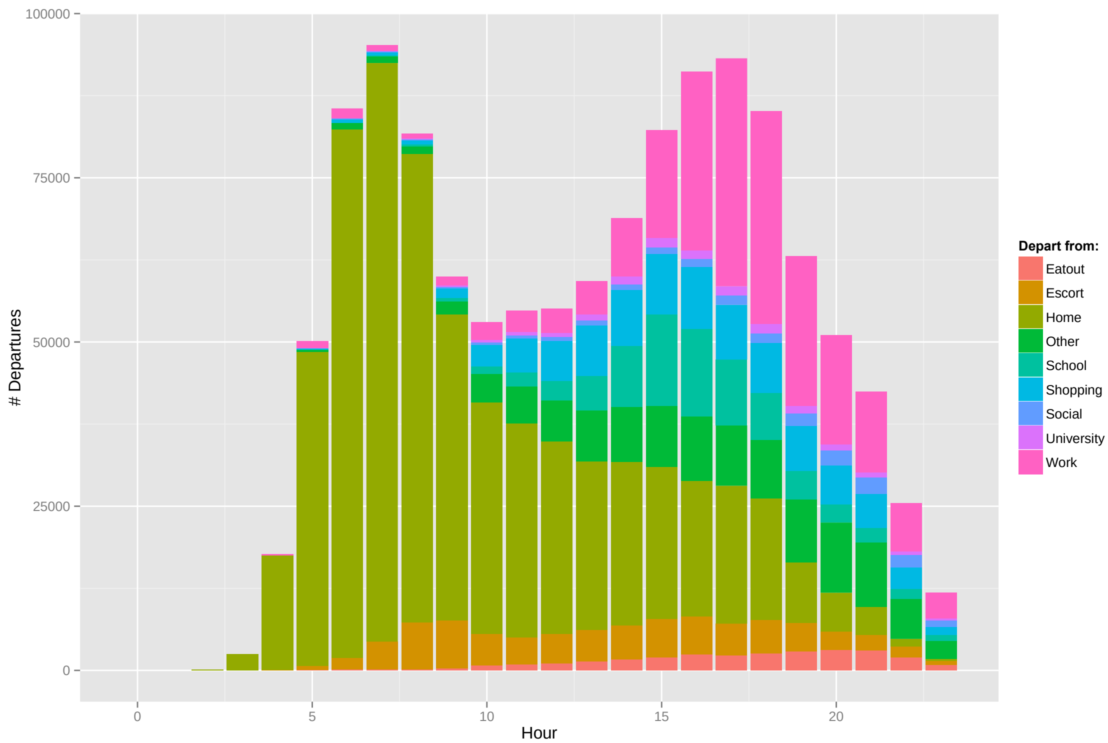

Figure 4.10: Departure times in San Francisco Bay Area application of BEAM by type of activity from which the agent is leaving.

choice modeling in the literature. We took advantage of the work of [41, 146] and [147] to choose an initial set of parameter values that approximate the tradeoffs between the attributes of the chargers and agents in Table 4.4. We could not solely rely on data from the literature because the structure of the models and experimental design in those studies was not identical to the kind of information available to agents in BEAM. For example, in [41], the model was designed to predict a binary choice: would the respondent charge given a situational circumstance (e.g. remaining range in vehicle) and attributes of one charging station (e.g. cost and charger level). But in BEAM, agents can sense multiple charging station alternatives and therefore are confronted with a more complicated decision.

In order to parameterize this more complicated decision, we first conducted a series of sensitivity analyses, which focused mostly on the intercept of each utility function. By adjusting these intercept parameters, we ensured that no single alternative was dominating the other alternatives (or conversely, was dominated by the other alternatives). We also used the sensitivity analysis to ensure that the direction of change in the alternative probabilities moved in the expected direction with changes in the attribute space. An example of one result from this sensitivity analysis is presented in Figure 13. Here we demonstrate that the choice probability of choosing to charge at a single site ("oneSite") or, analogously, of choosing to charge at any of the sites in the choice set ("allSites") decreases as the remaining

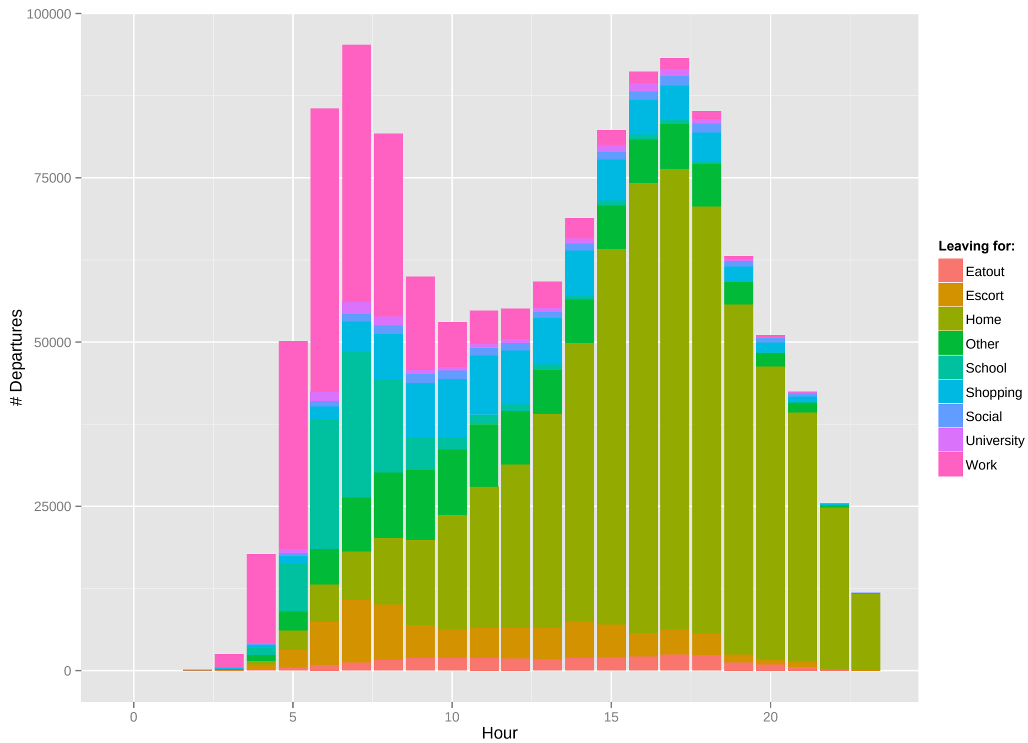

Figure 4.11: Departure times in San Francisco Bay Area application of BEAM by type of activity to which the agent is going.

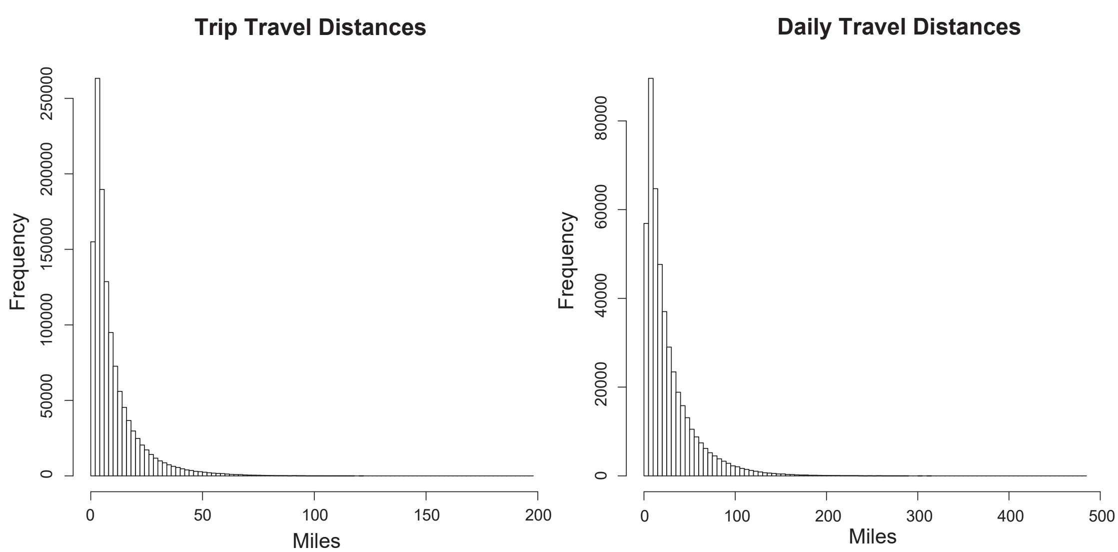

Figure 4.12: Distribution of travel distances in Bay Area application of BEAM.

range in the vehicle increases.

Similarly, the probability of aborting any charging attempt ("abort") increases with remaining range while the probability of adaptive measures that may lead to a charging session decrease "searchInLargerArea" and "tryChargingLater").

Once the gross probabilities of the choices were adjusted to have reasonable values in the judgment of our modeling team, we proceeded to do a more empirical calibration of the Bay Area BEAM model by comparing simulated charging profiles to observed patterns. The calibration process was executed at a spatially aggregated scale due to the fact that the nested logit parameters are spatially lumped and therefore making changes to them would not have an appreciable impact on spatially disaggregated charging patterns. However, we did temporally disaggregate the observed charging profiles.

In Figure 4.14, we show the result of running BEAM with four separate sets of parameters for the nested logit choice model. The x-axis corresponds to observed numbers of chargers in use by hour of the day (hour is represented by color) and the y-axis corresponds to the simulated number of chargers in use. The results are additionally disaggregated by charging level (Level 2 vs. DC Fast which is indicated by point shape).

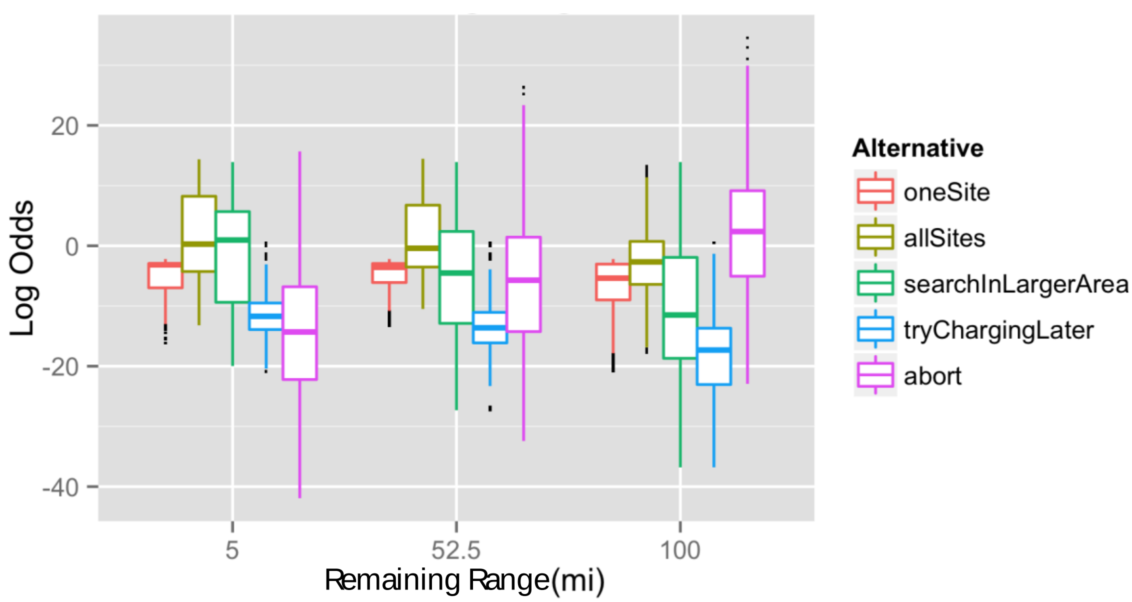

Figure 4.13: Log odds of five alternatives from a nested logit model with preliminary parameters across a wide range of charger and situational attributes. The situational attribute "remaining range" is varied along the x-axis. The box plots represent the distribution of log odds computed as all other model attributes are varied.

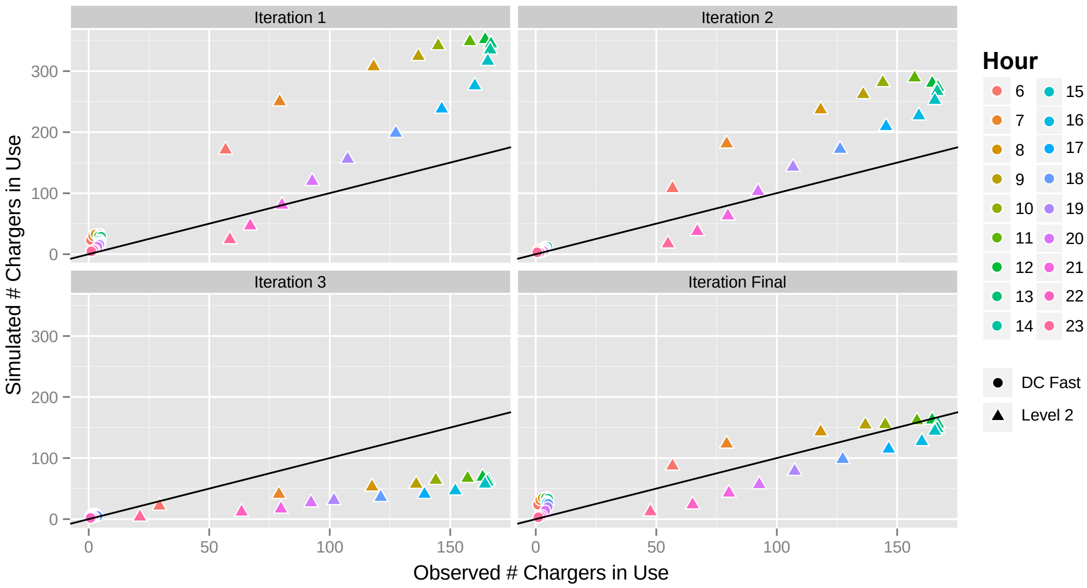

Figure 4.14: Simulated vs. observed charger utilization for four sets of parameter values in the nested logit decision model in BEAM. Each point represents a comparison of the number of public chargers in use by charger level and hour according to BEAM outputs versus observed from charging networks in the Bay Area in mid-2016.

Aggregated Comparison of Simulated and Observed Charging Profiles

The four parameter sets shown in Figure 4.14 are not comprehensive of all the sets explored in the calibration analysis. Therefore, we examined the result of running BEAM with dozens of combinations of parameters. The selected results give an idea of the range of outcomes that we observed by making reasonable adjustments to the nested logit parameters.

Ultimately, the scenario titled "Iteration Final" was taken to be the final set of parameters we used for further analysis (which are the parameter values presented in Table 4.4). While in this report, we call this a "final/calibrated" BEAM model, we acknowledge that this parameter set is, in reality, a starting point for our current work. This means that more work is needed to achieve better agreement between spatially disaggregated charging patterns in BEAM and the observed charger utilization (Figure 4.15). We therefore intend to continue the calibration of the decision model as we improve our modeling assumptions and access more realistic and comprehensive data sources.

Spatially Distributed Comparison of Simulated and Observed Charging Profiles

PEV Charging Behavior

Based on the models of decision-making described in Section ??, Table 4.3, including the preliminarily calibrated nested choice model, we conducted some preliminary analysis with

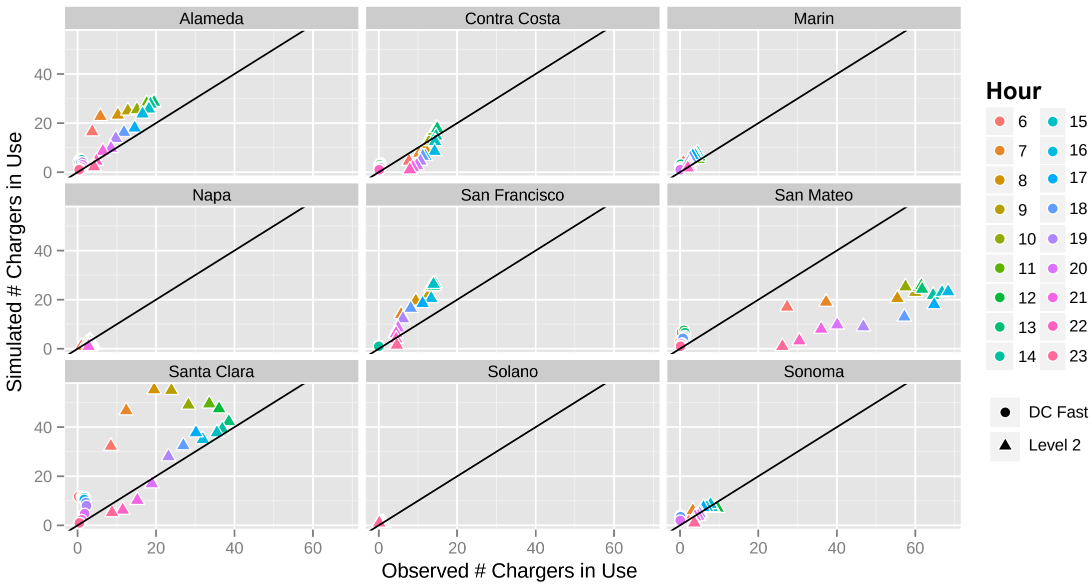

Figure 4.15: Simulated vs. observed charger utilization for the preliminary calibrated nested logit decision model by county in BEAM. Each point represents a comparison of the number of public chargers in use by charger level and hour according to BEAM outputs versus observed from charging networks in the Bay Area in mid-2016.

BEAM to illustrate the value of simulating regional mobility and charging behavior with such a detailed, agent-based, spatially explicit approach.

Impact of Constrained Infrastructure on Charging Profiles

Modelers make a series of simplifying assumptions when simulating PEV mobility and charging demand in order to rapidly produce results for a variety of analytical purposes. One common simplification is to ignore the fact that charging infrastructure in the public sphere is constrained. In order to test the impact of this simplifying assumption, we created two charging infrastructure scenarios for the Bay Area application of BEAM. The “Constrained” scenario is the baseline scenario based on the actual number of chargers installed in the region according to the Alternative Fuels Data Center. The “Abundant” scenario involved siting a very large number of charging plugs (approximately 150 times the number actually installed in 2016) throughout the road network.

The BEAM model was run under both scenarios with the “Always Charge on Arrival” decision model enabled. As shown in Figure 4.16, there is a dramatic difference in the charging profile of the agents when infrastructure is abundant versus constrained. Since the decision model is highly simplistic (always charge if a charger within 2 miles is available) it can readily be concluded that the current charging infrastructure in the San Francisco Bay Area is insufficient to allow all PEVs to charge whenever and wherever they arrive at a destination.

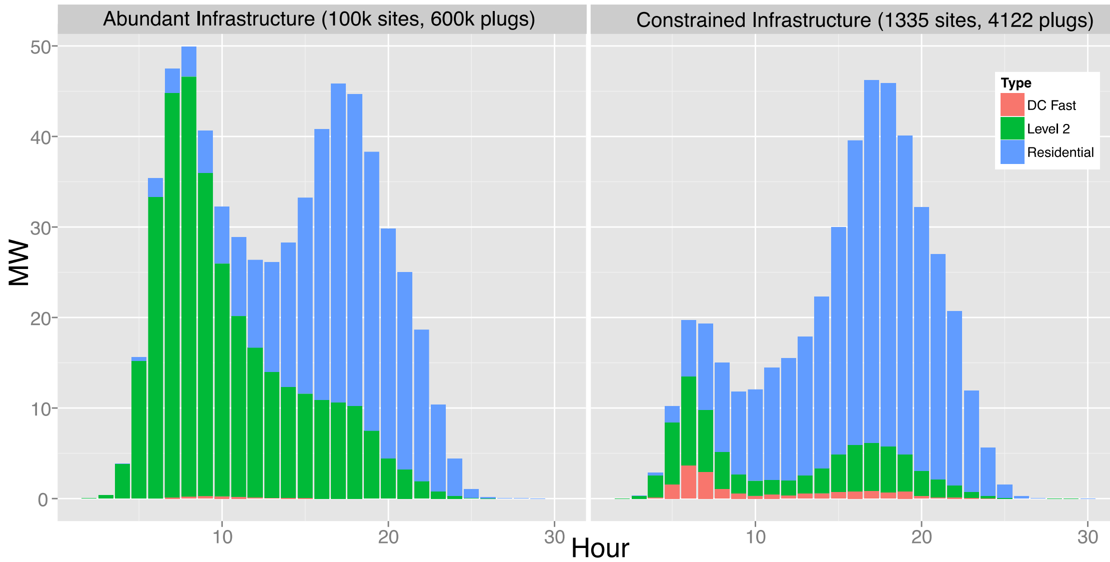

Figure 4.16: Instantaneous charging demand for PEVs in the Bay Area under a scenario with abundant and constrained charging infrastructure. Demand is disaggregated by charger type (Level 2, DC Fast, or residential). The charging decision model used is "Always Charge on Arrival."

Impact of Spatially Dispersed Charging Infrastructure on Charging Profiles

Another common simplifying assumption in some PEV models is to ignore the complication of explicitly representing space in the simulation. The "constrained" infrastructure scenario in Figure 4.16 also provides a useful basis for testing the importance of adopting a spatially explicit model approach as we have done in BEAM. The temporal distributions in Figure 4.17 were produced from the same model run as the "constrained" scenario in Figure 4.16. In other words, the charging infrastructure is based on mid-2016 chargers in the Bay Area and the decision model for charging was "Always Charge on Arrival." Based on the results presented above, it is clear that if agents could access chargers within a reasonable radius of their activity locations, they would. But as shown in Figure 4.17, a large fraction of total charging plugs in the constrained scenario are not being used. The reason is because at any given point in time, the majority of chargers are not co-located with the agents, so they sit idle.

In addition to demonstrating the value of spatially explicit modeling, this result also represents a fundamental challenge to the business viability of installing charging infrastructure. Namely, because lower power chargers need to be installed where vehicles park (in contrast to DC Fast or conventional fueling stations which are destinations for vehicles), they are necessarily sparsely distributed across the landscape, making it very difficult to achieve duty factors high enough to build a thriving business model on supplying chargers.

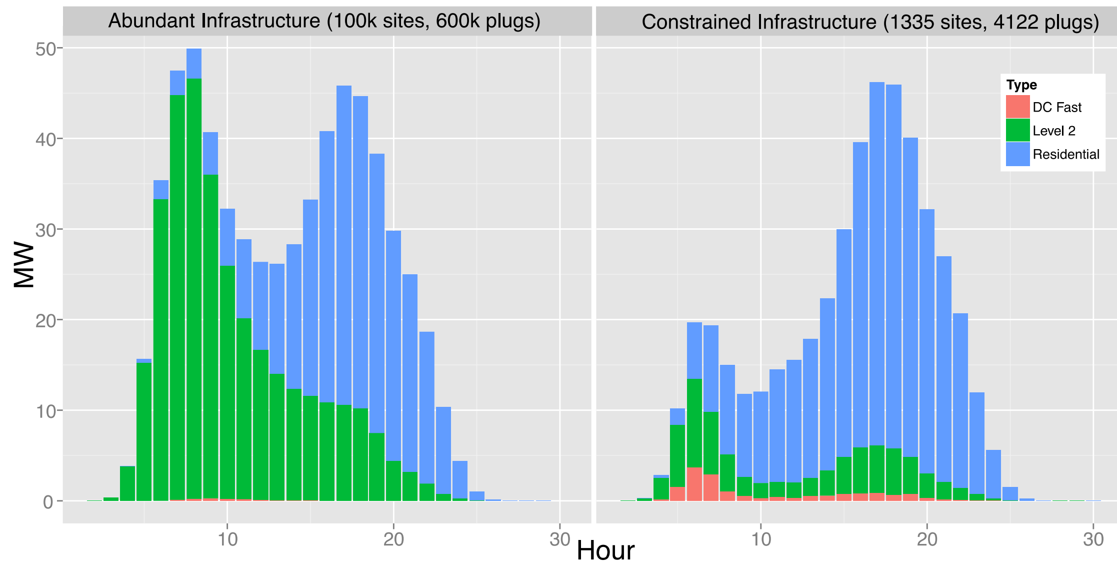

Figure 4.17: Plug availability for the baseline Bay Area BEAM scenario with the "Always Charge on Arrival" decision model. Here, availability is defined as plugs that are not actively charging any vehicle and are accessible by empty parking spaces, though they could be plugged into a vehicle.

Impact of Alternative Models of Charging Decisions on Charging Profiles

Finally, in Figure 4.18, we examine a set of scenarios using the baseline charging infrastructure and then we vary the charging decision model used by the agents. It is clear that the choice model has a large degree of influence on emergent charging profiles.

In the public sector, there is some similarity between the charging profiles under the "Uniform Random" and the "Nested Logit" decision models. With some further parameterization of the uniform random model, it could be possible to reproduce aggregate charging patterns even more closely matching the nested logit profiles. Because this kind of choice model is simpler and faster to execute, it could be preferable when a high degree of granularity in choice mechanism is not of interest to a modeler. However, there are some ancillary benefits to using the nested logit choice model, which we describe in Section 4.6, and believe it could enable a highly computationally efficient methodology to site charging infrastructure without making great sacrifices in the spatiotemporal resolution of the analysis.

4.6 Remaining Research Gaps

Method of incorporating this work into the BaSce analysis

The results from the BEAM-PLEXOS work, when completed, can be used in the next BaSce analysis to estimate all PEV related benefits. Benefits and costs that accrue to the power system due to the deployment of electric vehicles can be estimated in several scenarios including ones where we use the PEV fleet to provide grid services in both one-way control and V2G configurations. The precise reporting metrics need to be further defined.

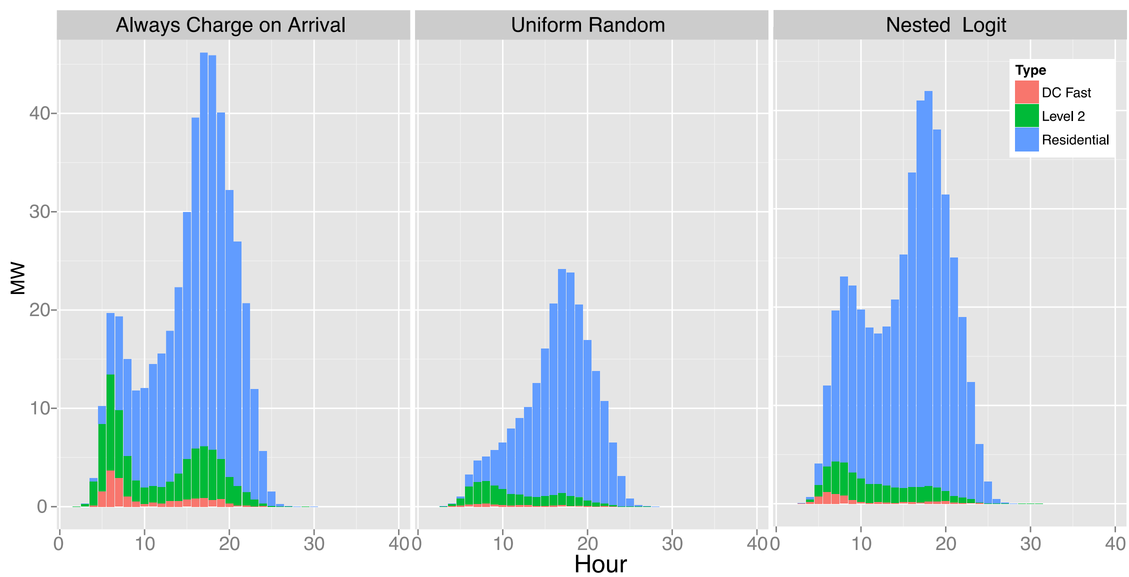

Figure 4.18: Instantaneous charging demand for PEVs in the Bay Area under the baseline infrastructure scenario and three different models of charging decisions. Demand is disaggregated by charger type (Level 2, DC Fast, or residential).

Additional Calibration Work

As described in Section ??, the current preliminary parameterization of the nested logit choice model was insufficient to recreate spatially disaggregated charging pattern observed in the Bay Area. We have two potential refinements to the model inputs and assumptions that could rectify the discrepancy. The first is described in Section 4.4, namely, that if we base our assumptions of the home location of agents on vehicle registration data instead of PEV rebate data, our spatial distribution of charging behavior may become more accurate.

Secondly, the sampling of mobility plans from the full MTC data set were based only on home location. It is also a fact that PEV drivers systematically drive fewer miles on average than drivers of conventional vehicles. We may be able to remove some bias in our model assumptions by weighting our sample of mobility plans by the total miles driven in a day. This can be done based on reported daily mileage from surveys such as [141] or through data licensing with OEMs.

Charging Infrastructure Siting Methodology

Once the Bay Area application of BEAM is fully specified and calibrated, our analysis can develop projections of future PEV fleets and the corresponding charging infrastructure that will serve those vehicles. As we have established in this report, the impact of constrained charging infrastructure is very important to the resulting spatiotemporal charging profiles. Taking a robust approach to charger infrastructure siting is an important step to producing reliable projections of future electricity demand and estimating the potential for load flexibility from PEVs. The following describes some of the challenges associated with siting charging infrastructure and an approach we have developed to overcome those challenges.

The Computational Challenge

As explored in [60] and [58], the problem of robustly siting spatially resolved charging infrastructure in a region is challenging primarily due to computational burden. The approach in those studies was to use a relatively complex, agent-based model of PEV mobility and charging demand to evaluate the efficacy of a hypothetical distribution of chargers. By exploring the decision space (consisting of the number of chargers to be sited in each zone of the model for each alternative level of charger), it is possible to maximize the quality of service provided to the population of PEV drivers subject to a budget constraint.

The advances made by the BEAM model (as presented in this report) permit an unprecedented level of realism and richness in the simulation of PEV mobility and charging infrastructure interaction. However, running a single day of mobility and charging for 60,000 agents takes anywhere from 15 to 60 minutes of time on a modestly powerful personal computer.

In addition, in our previous work, we had to aggregate the travel analysis zones in a region from hundreds of thousands to dozens in order to reduce the dimension of the search space. However, these kinds of simplifications do not allow us to easily account for detailed heterogeneity within a zone despite the fact that our data sources permit such resolution.

We therefore have devised an approach that allows us to site chargers in large increments (tens to hundreds at a time) simultaneously across a region in a manner that distributes the chargers according to need.

Deriving a Metric for Spatiotemporal Charging Infrastructure Need

Where are chargers needed? How much are they needed and when? These are complicated questions to untangle with a high degree of certainty due to the complexities surrounding when, where, and for whom charging is needed. In the process of defining and calibrating the nested logit decision model for BEAM, we have identified the choice model itself as a highly valuable summary of all of the characteristics relevant to the need for charging infrastructure.

Namely, each time a driver makes a decision about charging infrastructure, they collect all of the data needed to understand whether or not that location in time and space is a location with available and high quality charging infrastructure. In transportation engineering, this metric of quality is called "accessibility." It is defined as the log of the denominator in a multinomial logit model. In the case of a nested logit model, it is the log of the denominator of the top-level nest of the model.

For BEAM, we intend to use the "accessibility" of the charging infrastructure in a manner similar to the infrastructure siting approach taken by [148], which involved simulating PEV mobility and then recording the location (like dropping a pin on a map) when the battery reached some low state of charge. In our approach, we associate the accessibility of a charging decision with the time and location when the decision is made. After a model simulation is complete, we take all of the accessibility metrics and do further analysis to recast them into a measure of need for charging infrastructure.

Each accessibility metric is associated with a particular link in the road network. We divide all of the metrics by the length of the corresponding pins to normalize for the heterogeneity in link size. Then we take the arithmetic inverse of the metric by subtracting all of the metrics from the maximum value. The new metric is now a metric of need, where the agent who had the maximum value for accessibility is considered to be in a time and location where there is no need for additional infrastructure.

Finally, the need metrics are then aggregated to the link and hour of day, enabling a spatiotemporal analysis of charging need. In Figure 4.19 we show the temporal distribution of charger need by hour of day and by county. It is clear that charging infrastructure need is well correlated with mobility demand as seen in Figure 4.10.

To use this metric of need to site chargers, we perform a random draw from a discrete probability distribution of length equal to the number of links in the road network and with probability in proportion to the total need on each link. We can repeat the random draw multiple times to site chargers simultaneously. In Figure 4.20, we show the spatial distribution of charger need (in red) and the corresponding result of sampling 500 charging sites from the spatial distribution.

Incremental Siting of Infrastructure

When we employ the siting approach described above, we can do so in a way that reflects a reasonable progression of events, where the penetration of PEVs in the local fleet and composition of that fleet evolve over time along with the introduction of charging infrastructure. Fleet composition in particular will be critical to our analysis, given that BEVs with larger battery capacities are soon to enter the market at competitive price points (e.g. the Chevrolet Bolt and Tesla Model 3 with over 200 miles of range). The charging infrastructure should be co-sited along with these evolving adoption patterns in order to project

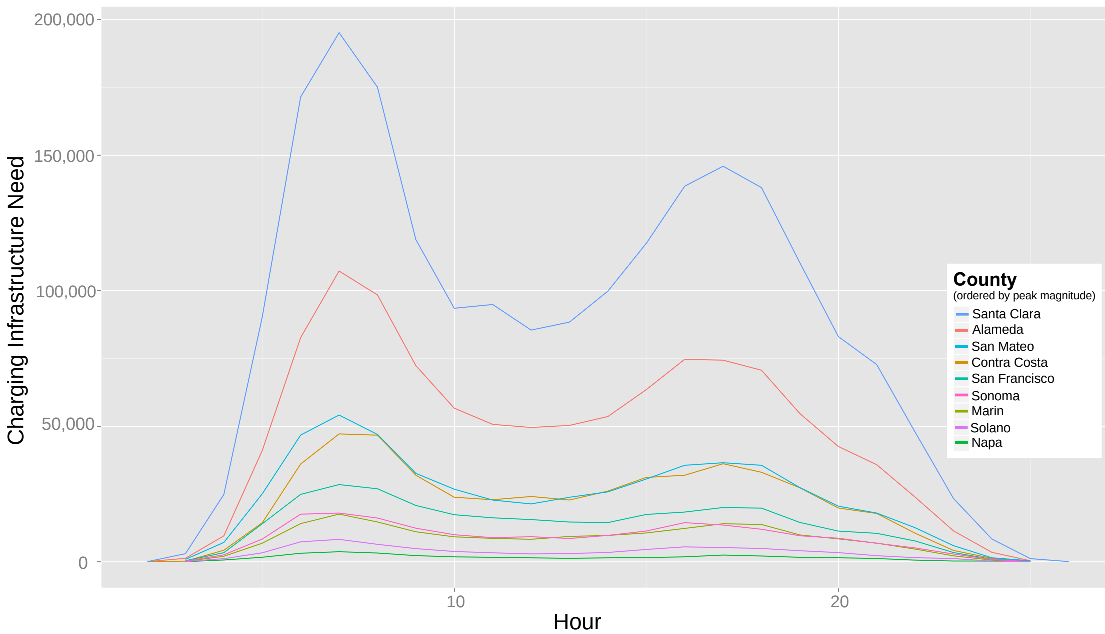

Figure 4.19: Charging infrastructure need by hour of day and county.

a future transportation electric system that reflects the path dependency of how technology and markets evolve over time.

4.7 Conclusion

We find that accurately reproducing observed charging patterns requires an explicit representation of constrained and spatially disaggregated charging infrastructure. Chargers are not ubiquitous and therefore they must be treated as a finite resource in order to analyze realistic load profiles from charging. In addition, drivers balance tradeoffs with regards to time, cost, convenience, and range anxiety when deciding about whether to charge. We find that simulating these decisions explicitly improves modeling accuracy and can provide a useful metric for siting new charging infrastructure.

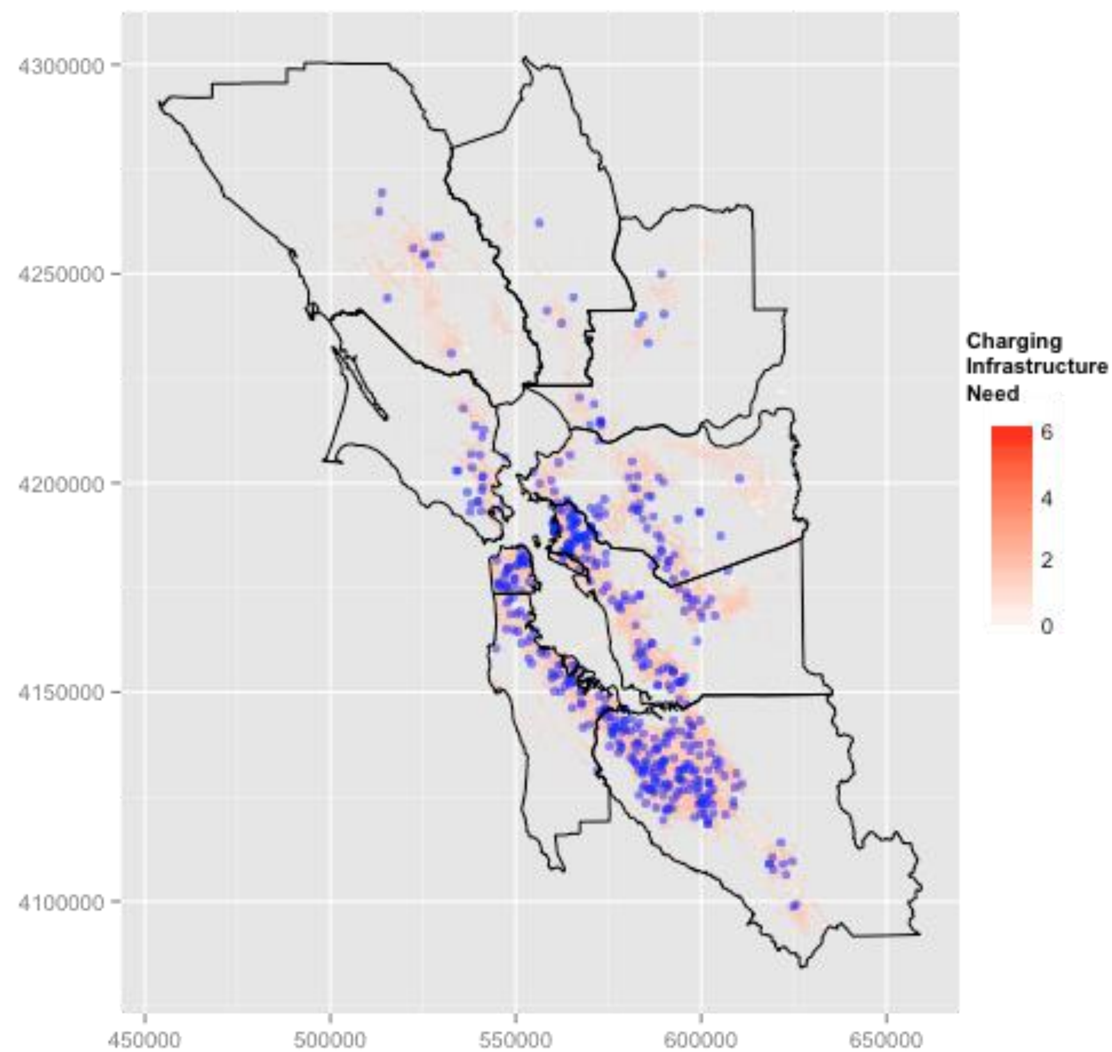

Figure 4.20: Example of siting 500 charging sites (blue circles) in road network by sampling from a probability distribution based on link by link infrastructure need.

Chapter 5

Grid Impacts of Electric Vehicles and Managed Charging in California

5.1 Overview

Similar to Chapter 3, this Chapter also explores the economic value of charging flexibility, but it involves a more comprehensive and refined modeling approach. We use California as a case study to examine the economic value and RE grid integration impacts of different penetration levels of PEVs (ranging from 0.95 million to 5 million PEVs) under various charging strategies. We consider the effects of smart charging and time-of-use (TOU) charging, under a State mandate requiring that utilities produce at least 50% of electricity from renewable sources by 2025. We accomplish this by linking high-resolution travel behavior and grid production cost models that more accurately characterize charging infrastructure, travel demand, and grid dispatch constraints. We find that the flexibility inherent in PEV smart charging patterns can provide substantial benefits to the power sector, primarily in lowering grid operating cost and the amount of RE that must be curtailed (turned down or off from the level that they would otherwise be producing) to avoid over-generation when supply and demand are mismatched. For example, if treated as flexible loads, 2.5 million smart charging PEVs avoid 50% of incremental system operating costs annually and reduce renewable energy curtailment by 27% annually relative to when the same number of unmanaged charging PEVs are added to the grid. Overnight TOU charging provides similar cost savings, though not curtailment reductions, without incurring smart charging implementation costs. Both smart and overnight TOU charging can defer system infrastructure expansion at PEV deployment of 5M, which is the State's goal for 2030.

This work originally appeared in the following publication (reprinted with permission from Julia Szinai, Nikit Abhyankar, and Anand Gopal):

Colin Sheppard, Julia Szinai, Nikit Abhyankar, and Anand Gopal. *Grid Impacts of Electric Vehicles and Managed Charging in California: Linking Agent-Based Electric Vehicle Charging with Power System Dispatch Models.* Lawrence Berkeley National Laboratory, 2019

5.2 Introduction

Widespread electrification of the transportation sector through the adoption of plug-in electric vehicles (PEVs) including battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) can enable oil independence [310], reduce fuel costs for drivers [311], reduce local air pollution, and lower greenhouse gas (GHG) emissions [312], among other benefits. Increasing the level of renewable energy (RE) in the power system in parallel with transportation electrification can increase energy independence, reduce air pollution, and advance economy-wide GHG emission reductions [269]. In this report, we focus on California as case study because the state has been pursuing both transportation electrification and a renewable energy-dominant generation portfolio to reduce its greenhouse gas (GHG) emissions 40% below 1990 levels by 2030, and 80% below 1990 levels by 2050 [313], [190].

In 2012, the governor of California issued Executive Order B-16-2012 setting a state goal of 1.5 million zero emission vehicles (ZEVs), which include hydrogen fuel cell vehicles (FCEVs) and PEVs, by 2025 [270][1]. California has about 440,000 PEVs as of late 2018 on the road [314], which is about half of the U.S. PEV fleet and 8% of the world's PEVs [183]. With expanding model options [315, 316, 317], policy support [270, 318, 319], and planned charging infrastructure investments [320, 189, 321], California is predicted to exceed the governor's goal and have about 2 million PEVs on the road within the 2024–2030 period [186, 322, 323]. Alongside this growing PEV adoption, California's Renewable Portfolio Standard (RPS) requires half of electricity consumption be met by RE sources by 2030 [190] and utilities are several years ahead of schedule in meeting this target [191].

The concurrent growth of RE and PEVs have ramifications for the electricity grid. Intermittent wind and solar photovoltaic (PV) sources constitute the majority of RE [191] in California, thus the California Independent System Operator (CAISO) relies on ramping flexible generators or loads and on RE curtailment (being turned down or off from the level that they would otherwise be producing) to mitigate imbalances between supply and demand [67, 324, 192]. Solar PV and wind have zero marginal cost so, curtailment although a reliable way to maintain grid stability can increase system operating costs [67]. Subsequently, utilities deliver less RE to comply with RPS requirements, necessitating more RE capacity or flexible generation or load resources to compensate [167, 325]. PEVs could either exacerbate or help address RE-related grid challenges, depending on whether charging is unmanaged or managed in some way. If PEVs are unmanaged, charging typically occurs when drivers arrive home from their evening commutes and happens at the fastest rate permitted by the chargers as soon as the vehicles are plugged in [326, 154]. If such loads come online in the late afternoon or evening, they can coincide with the system's peak [172] and increase ramping needs and costs through the use of inefficient and expensive "peaker" power plants [326]. In addition to alleviating such peak loads and costs, by charging at times of low prices and high RE generation, managed PEVs could instead serve as a flexible load to help California's grid avoid RE curtailment and save money.

Numerous studies (for example [163, 2, 171, 4, 3], [172]) have investigated the impacts of managed PEV charging on power systems with RE, but most existing literature on PEV-grid interaction (also known as Vehicle Grid Integration (VGI)) either simplifies PEV charging behavior and charging infrastructure or the dispatch of the power system. These simplifications could lead studies to overestimate the availability and willingness of PEV drivers to

[1]We do not evaluate the impact of FCEVs in this report, because they form a much smaller share of ZEVs in California [270].

provide grid services as well as the value that PEV grid services can add to the grid. The travel demands of drivers, the location and availability of chargers, and the user acceptance of managed charging programs are important in modeling a realistic estimate of value of PEV grid services [154], [1, 5, 179]. In addition, some studies (for example [195]) only include PHEVs, whose hybrid gasoline-electric powertrains diminish the mobility-charging tradeoff and which have a much smaller grid footprint. Robustly representing both BEV and PHEV drivers' constrained charging choices is critical for assessing the feasibility of managed charging strategies because the ability to fulfill mobility needs without compromise is paramount to drivers and charging infrastructure is constrained [154, 175]. In this study, we seek to minimize an economic objective and not necessarily an engineering objective such as load flattening [281]. This reflects the reality that the power sector is operated as a market and economic incentives are the appropriate mechanism to alter consumer behavior. In a recent study [327], the authors take such an approach, but at the scale of individual facilities, here we look at the macroscale utilization of charging flexibility.

To address the gaps in adequately modeling PEV charging, in this report we use a novel agent-based travel behavior model – Behavior, Energy, Autonomy, Mobility (BEAM) – that realistically represents the choices faced by BEV and PHEV drivers given constraints in charging infrastructure [154]. Further, we link the temporally- and spatially-explicit charging constraints and outputs of BEAM to a power systems model, PLEXOS, to simulate the interactions of PEV charging with the electric grid for integrating RE. PLEXOS is a unit commitment and dispatch model by Energy Exemplar [328], and is an electricity industry standard tool for optimizing the dispatch of grid resources. We apply this linked modeling framework to California's forecast of its 2025 power system with a 50% RPS generating portfolio. We consider the following two PEV managed charging strategies in this report[2] as a solution to mitigate the problems with unmanaged charging [163] and high RE (both of which are in some stage of piloting in California [329, 330, 331]):

- **Unmanaged Charging:** the vehicle charges immediately and at full power as soon as it plugs in.
- **Time-of-use (TOU) Charging:** Drivers are incentivized by a lower electricity rate to charge during off-peak hours, usually pre-programming the charging start time through the charger or PEV.
- **Smart Charging:** The PEV participates in a demand response (DR) program whereby an aggregator remotely and directly controls active charging to be on or off through the charger or vehicle software. The aggregator shifts charging to times that provide

[2]Vehicle-to-grid (V2G) charging is also commonly studied as a managed charging strategy. V2G allows for bi-directional power flow between the vehicle and grid such that the vehicle can both discharge excess energy to the grid and charge from the grid. We do not model bi-directional power flow from the vehicle to the grid (V2G) or participation in ancillary services [165], because of the low marginal benefits and greater complexity and cost of these strategies relative to just one-directional charging [167, 119]

the most grid benefit, when prices are low or RE is abundant, bidding the aggregated flexible load of many PEVs into the wholesale electricity market.

Through this integration of BEAM and PLEXOS, we evaluate the achievable potential for PEVs to provide services to the California grid in 2025 via smart and TOU charging strategies, while maintaining drivers' same mobility and convenience and not requiring a change in travel behavior from unmanaged charging. We compare the charging strategies under four scenarios of PEV adoption based on the California Energy Commission's (CEC) forecast of 0.95 million, 1.5 million, 2.1 million, and 2.5 million PEVs for 2025 [323] and an additional "reach" scenario of 5 million PEVs. We focus on grid operating cost savings and RE curtailment reduction between unmanaged and each of the smart and TOU charging strategies, as these metrics are commonly used in the literature (for example in [67, 3, 332, 333, 334, 335]) and are the relevant decision-making criteria for California system planners and utility regulators.

We find that the flexibility inherent in PEV smart charging patterns can provide substantial benefits to the power sector, primarily in lowering grid operating cost and the amount of RE that must be curtailed to avoid over-generation when supply and demand are mismatched. We also find that in California's power system with 50% RPS, overnight off-peak TOU rates can achieve the majority of the system cost savings from smart charging. Our results agree with the literature that these managed charging strategies offers cost savings and avoided curtailment relative to unmanaged charging, but these benefits are more modest than some other prior studies with less realistic power system dispatch and constraints on mobility, charging infrastructure, and driver behavior. While the cost savings and curtailment values are specific to the California system, the relative ranking of the impacts from the managed charging strategies compared to unmanaged PEVs is likely applicable to other systems considering both high PEV and renewable deployment.

5.3 Framework of Model Integration

To evaluate the impact of unmanaged, smart, and TOU charging on the California grid, this paper integrates two models to simulate both PEV mobility and charging behavior (using BEAM) and the operation of the electric grid (using PLEXOS). The framework of model integration is illustrated in Figure **??** and the methodology is further described below.

1. **BEAM Model: PEV Mobility/Charging.** BEAM simulates PEV mobility and charging behavior for three representative weekdays (based on travel demand modeling from the regional transportation planning authority) for about 68,000 PEVs in the San Francisco Bay Area. Charging sessions (defined by the period of time the PEV is plugged in) are simulated as unmanaged, but the time between the end of active charging and the actual unplug event concluding the session is tracked for later use and exported as an input into the next step. See Section 5.4.

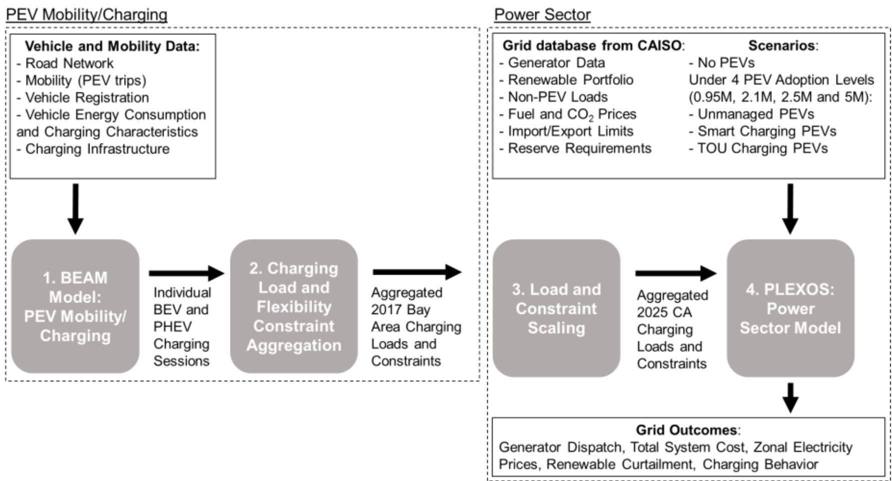

Figure 5.1: Vehicle-Grid Integration Modeling Framework with BEAM and PLEXOS.

2. **Charging Load and Flexibility Constraint Aggregation.** The charging session data are analyzed and aggregated by vehicle type battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV)–into both an unmanaged trajectory of delivered energy (when the vehicle charges immediately and at full power when it plugs in), and an alternate trajectory that represents delaying charging to the maximum extent possible while still delivering the same amount of energy by the end of the session. These trajectories are treated as maximum and minimum constraints that bound possible dispatch of smart charging loads and still ensure the same end state of charge (SOC) of the PEV as with unmanaged charging. Corresponding power constraints on smart charging are also produced based on the number of connected vehicles in each hour and are aggregated by vehicle type. For TOU charging, we represent the response to off-peak TOU rates by forcing charging to begin at staggered times between 10 PM and 2 AM (to avoid inducing a sudden demand spike) for those PEVs that would already be plugged in overnight if unmanaged. We then aggregate the resulting TOU off-peak charging loads by vehicle type. In order to capture the realistic behavior of an average day and to avoid edge effects and assumptions around initial conditions (e.g. that all vehicle begin the day with a full battery), for each of the charging strategies the data from charging sessions from the second day of a three-day BEAM run of representative weekdays are used for the load and constraint aggregation. A full week of data, constructed by calibrating to observed charging data, is then repeated to create an annual data set for each charging strategy.

3. **Load and Constraint Scaling to California Vehicle Adoption Forecasts.** The aggregated unmanaged, TOU loads, and smart charging constraints produced from BEAM in Step 2, based on approximately 68,000 PEVs in the San Francisco Bay Area, are scaled from magnitudes that represent the San Francisco Bay Area PEV

stock in 2017 to that of the whole state of California in 2025. The scaling occurs in two parts, from the Bay Area to each utility zone in California based on respective BEV and PHEV vehicle stock as of 2016, and then from 2016 to California in 2025 based on CEC forecasted adoption levels. The CEC 2025 forecast includes 3 scenarios: 0.95 million, 2.1 million, and 2.5 million PEVs. We use these 3 scenarios and also add a "reach" scenario of 5 million PEVs in the state. We assume that current trends in PEV sales will continue and that 60% of each 2025 adoption scenario will be met by BEVs and 40% by PHEVs.

4. PLEXOS Power Sector Model. The scaled 2025 PEV loads and constraints are loaded into PLEXOS along with power sector data from the database originally used by CAISO for the 2014 Long Term Procurement Planning process and updated by CAISO to reflect more recent changes on the electricity system. For each of the 4 PEV adoption levels ranging from 0.95 million to 5 million PEVs, we run PLEXOS for the four scenarios described below (no PEVs, unmanaged PEVs, TOU charging PEVs, smart charging PEVs) and export as results the total system cost, electricity prices, renewable curtailment and generation, and charging behavior (charging behavior for smart charging is dispatched by PLEXOS but unmanaged and TOU charging loads are the fixed loads from Step 3).

Section 5.4 further describes the models, analytical steps, data, and some of the key assumptions used by each of the steps above.

5.4 BEAM and PLEXOS Model Application and Assumptions

As outlined in Section 5.3, the outputs from BEAM for the San Francisco Bay Area in 2016 are processed and scaled up to each California utility area in 2025 to represent unmanaged, smart, and TOU charging PEVs in PLEXOS, which then simulates the dispatch of generation in a 2025 grid. The sections below discuss this process and critical assumptions and data used in the application of the two models.

BEAM Model: PEV Mobility and Charging

The following is an abbreviated summary of BEAM, which is described in full detail in prior work [154]. The BEAM Framework is a collection of software tools that enable robust, spatially explicit simulation of the transportation-electric system. BEAM is an extension of the open source transportation systems modeling framework Multi-Agent Transportation Simulation (MATSim), which simulates individuals and their detailed interactions with the transportation system. BEAM simulates the daily activity patterns of individual travelers (i.e. where and when people perform activities such as at home, work, shopping mall, etc.).

Agents are assumed to make trips in a PEV and they are programmed with discrete choice models to simulate their charging-related decisions. The charging decisions consider the state of charge of their battery, their remaining mobility needs for the day, the type of location (i.e. home vs work), the number of accessible chargers at a site, the level of the chargers, the cost, and the distance to their activity. The charging infrastructure is explicitly modeled including the number of parking spaces that permit physical access to the chargers, resulting in the formation of queues at occupied chargers.

BEAM Model Inputs: PEV Vehicle Information, Mobility, and Infrastructure

We have applied BEAM to the San Francisco Bay Area in 2016. Mobility data is based on the San Francisco Bay Area Metropolitan Transportation Commission's (MTC) activity-based travel demand model [145, 123]. The number of PEVs (∼68,000) in the Bay Area and their spatial distribution are based on vehicle ownership estimates from the SERA model (Scenarios, Evaluation, Regionalization, and Analysis) developed by the National Renewable Energy Laboratory (NREL) [151]. The vehicle attributes (fuel economy, charging infrastructure compatibility) are based on a combination of resources from Original Equipment Manufacturer (OEM) model specifications and the U.S. Department of Energy (DOE) fuel economy website [143].

We assume all drivers have a charger at home and include a relatively small share of other chargers; we model about 5,400 workplace chargers (mix of Level 1, Level 2, and DC Fast chargers), 1,200 public chargers (mix of Level 1, Level 2, and DC Fast chargers), and 68,000 residential chargers (Level 2) for the San Francisco Bay Area [336]. Charging infrastructure data is from the Alternative Fuels Data Center and ChargePoint [336]. The driver preferences around charging are calibrated to observed charging session data received from ChargePoint from 2016. ChargePoint is the largest charging infrastructure provider in the United States. We assume that the driving behavior in the San Francisco Bay Area is representative of other areas of the state; according to MTC the per capita vehicle miles traveled (VMT) in the San Francisco Bay Area are virtually the same as in Los Angeles [337].

To reflect anticipated technology improvements and subsequently higher PEV utilization by our 2025 study year, we assume the BEAM PEV fleet has battery capacities–and therefore a driving range −1.5 times greater than that of the 2016 fleet. Based on analyses of the positive relationship between the range and electric vehicle miles traveled (eVMT) per typical BEV and PHEV (with greater range drivers will drive more) [338, 339], we also scale up the eVMT of our aggregated fleet to correspond with the larger batteries. With this scaling, BEVs are assumed to drive 11,000 electric-miles and PHEVs are assumed to drive 7,600 electric-miles on average per year. Key PEV fleet and charging infrastructure assumptions used in BEAM are shown in Table 5.1.

Table 5.1: Key Assumptions for PEV Models, Driving, and, Charging Infrastructure.

Vehicles						
Make/Model	Type	Battery capacity (kWh)	Fuel economy (kWh/mi)	L2 Charging limit (kW)	Direct Current Fast Charge (DCFC) Charging limit (kW)	# Vehicles
NISSAN LEAF	BEV	45	0.30	7.0	50.0	17,024
CHEVROLET VOLT	PHEV	28	0.31	7.0	50.0	11,256
TESLA MODEL S	BEV	113	0.33	20.0	125.0	10,308
TOYOTA PRIUS PLUG-IN	PHEV	12	0.29	7.0	20.0	8,961
FIAT 500e	BEV	37	0.29	7.0	50.0	4,370
FORD FUSION	PHEV	11	0.34	3.3	-	4,327
FORD C-MAX	PHEV	11	0.35	7.0	-	3,638
BMW I3	BEV	50	0.27	7.4	50.0	2,718
GEM - Various Models	BEV	19	0.20	-	-	1,983
VOLKSWAGEN E-GOLF	BEV	36	0.29	7.2	50.0	1,854
FORD FOCUS	BEV	50	0.32	6.6	-	1,566
CHEVROLET SPARK EV	BEV	30	0.28	3.3	50.0	1,384
TOYOTA RAV4 EV	BEV	63	0.44	10.0	50.0	970
All other BEVs	BEV	41	0.37	varied	varied	3,052
All other PHEVs	PHEV	17	0.47	varied	varied	878
Electric vehicle miles traveled						
Vehicle Type	**eVMT**	**Comments**				
BEVs	11,000	Average annual electric vehicle miles traveled per vehicle. Used to scale electricity demand for aggregated fleet for whole year, based on assumption that all batteries are 50% higher capacity in 2025 than they are in 2016.				
PHEVs	7,600					
Charging infrastructure						
Market Sector	Level	# Chargers				
Residential	L2	68,000				
Workplace	L1	330				
Workplace	L2	4,900				
Workplace	DCFC	210				
Public	L1	130				
Public	L2	900				
Public	DCFC	160				

BEAM Model Outputs: Charging Session Information

Using all the mobility and infrastructure data described above, the BEAM simulation runs and outputs data from each PEV's charging sessions, defined by the amount of time the PEV is plugged in to the charger (but not necessarily actively charging the whole time), include the following details:

- Time
- Location
- Driver ID
- Charger ID
- Charger type (Level 1, Level 2, DCFC)
- Activity type
- Energy delivered (kWh)
- Maximum power of the charger & vehicle's charge controller (kW)
- End of activity power delivery
- End of the plug session (entire time the vehicle is left plugged in)

Unmanaged, TOU, and Smart Charging Loads and Constraints in BEAM

The charging session outputs described in Section 5.4 are recorded for individual BEVs and PHEVs and are used as described below to estimate loads and constraints for unmanaged, TOU, and smart charging strategies.

Unmanaged Charging Load

Charging sessions are first simulated in BEAM as unmanaged, such that a PEV starts charging as soon as it is plugged in, and we record the cumulative energy delivered during each PEV's session as the unmanaged load.

TOU Charging Load

For the TOU charging case, we represent the response to off-peak TOU rates by forcing charging sessions in BEAM to begin at staggered times (to avoid inducing a sudden demand spike) between 10 PM and 2 AM-approximately the range of start times of California's current residential off-peak rate periods [340, 341, 342]-for those PEVs that would already be plugged in at home overnight if unmanaged. We do not explicitly model a particular TOU electric rate but assume that the price would be sufficiently low to incentivize all drivers to program a timer for charging at off-peak times. We record the energy delivered during each PEV's TOU charging session.

Smart Charging Load and Constraints

To create a realistic, bounded estimate of the impact of smart charging, for this analysis, the flexibility to shift load is limited to shifting within a single charging session, rather than allowing a shift in the time of day of the charging session entirely. A charging session is defined by the time the vehicle is plugged in at a station even if it is not actively charging during this entire plug-time. We limit the shifting to the times that vehicles are plugged in under the unmanaged charging BEAM simulation. Therefore, during the unmanaged charging BEAM simulation, the time between the end of active charging and the actual unplug event concluding the session is tracked and exported.

Implicit in this methodology is that BEAM assumes perfect foresight into the length of the charging session; similar to previous studies [343], a driver would be expected to input their expected parking time and end SOC into the charger and/or vehicle's software. We limit smart charging flexibility to the time windows of unmanaged charging session because 1) we assume that even with incentives, people will not readily shift their charging session to an entirely different time of the day, given that charging infrastructure is not ubiquitously available, 2) drivers do not usually unplug immediately after active charging completes, and 3) there is still flexibility available within the charging session without disrupting mobility or other user preferences.

When the PEV participates in smart charging, the vehicle charges at a different time and/or rate (power) than it would otherwise if unmanaged. However, in constructing the bounding maximum and minimum energy constraints, we treat the end SOC from unmanaged charging in BEAM as a required target for the smart session. This treatment ensures that any management of charging would have no impact on mobility in BEAM.

For three representative PEVs, Figure 5.2 shows an illustrative example of the maximum (earliest) and minimum (latest) smart charging cumulative energy constraints for the first week of the BEAM simulation. The maximum energy boundary corresponds to the same energy as unmanaged charging, when active charging begins immediately. The minimum energy boundary corresponds to delaying active charging until the last possible moment while still reaching the same target SOC. The two curves remain flat in between charging sessions when no charging load occurs. Within the boundaries of these two curves, any monotonically increasing trajectory can be achieved with smart charging while still reaching the target SOC, subject to the maximum charging power of the vehicle and charging equipment. We record the energy values of these maximum and minimum constraints and the power limits of the vehicle and/or charger.

Unlike the unmanaged and TOU charging strategies whose loads are determined entirely by the BEAM simulation and passed through as fixed loads to PLEXOS, the final smart

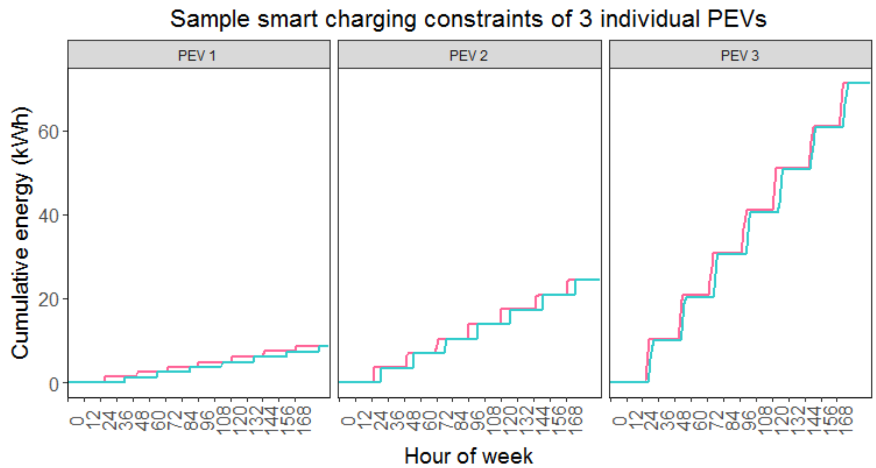

Figure 5.2: Example Maximum and Minimum Cumulative Energy Constraints for Smart Charging.

charging loads are the result of the PLEXOS optimal dispatch within these constraints from BEAM. As described in more detail in Section 5.4, as part of the optimization in PLEXOS we also enforce a constraint to conserve total energy shifted by the end of each month for the aggregation of vehicles to account for any edge effects that could occur by any charging sessions occurring overnight at the end of a month.

Aggregation of Charging Loads and Constraints to SF Bay Area

Following the methodology of Xu et al. [343], for each charging strategy, we aggregate the energy outputs (and energy and corresponding power constraints for smart charging) by summation across the individual vehicles modeled for the San Francisco Bay Area in BEAM. For example, for smart charging, the aggregated maximum cumulative energy delivered to a fleet by hour 10 is equal to the sum of the maximum energy delivered to each vehicle in that fleet by hour 10. For each charging strategy we do this type of summation separately for BEVs and PHEVs for the entire San Francisco Bay Area.

The aggregated Bay Area constraints from a typical weekday (the second day of a three-day BEAM run of representative weekdays) are used to construct a full week of constraints based on the weekly load shapes from the observed ChargePoint data set described in Section 5.4. This construction occurs by repeating the hourly load profiles from BEAM seven times to create a week and then scaling the profiles separately by charger type (residential, workplace, and public) and weekday/weekend to match the normalized daily average load profiles from ChargePoint by charger type and day of week. Finally, these weekly power and energy constraints are repeated to complete a data set spanning an entire year for use in PLEXOS.

Scaling of Charging Loads and Constraints to CA Vehicle Penetration Scenarios

The aggregated charging session loads and constraints from Section 5.4 are simulated in BEAM for approximately 68,000 vehicles (PHEV and BEV combined) in the San Francisco Bay Area in 2016. We scale these outputs to represent the eight separate California utility zones modeled in PLEXOS in the forecast year of 2025. The factors used to scale to the eight utility zones are based on the ratio of the number of BEVs and PHEVs in the Bay Area counties included in BEAM relative to the number of BEVs and PHEVs in the eight utility areas modeled in PLEXOS, using California's CVRP data, which covers the whole state and includes data on county and utility area of each rebate recipient [318]. The factors used to scale from a 2016 estimate of PEV penetration to 2025 are derived from the ratio of the California total cumulative number of BEVs and PHEVs in 2016 relative to the projected 2025 vehicle penetration levels from the CEC's 2015 California Energy Demand (CED) forecast and the added "Reach" bookend scenario as shown in Table 5.2 [344]. The PEV penetration forecasts represent 4% (0.95 million), 8% (2.1 million), 10% (2.5 million) and 20% (5 million) of today's light-duty vehicle stock (approximately 25.2 million) in California.

The CEC's aggregate 2025 vehicle population forecast is for PEVs and does not show the split of the population between PHEVs and BEVs. Therefore, we assume that current trends in PEV sales will continue and that 60% of the 2025 stock level will be met by BEVs and 40% by PHEVs, which is the split of PEV rebates currently seen in the CVRP database [318]. Table 5.2 shows the resulting scaled 2025 annual load values summed across all utility zones in California for the unmanaged charging case in each of the PEV penetration scenarios. The total loads for the smart and TOU cases are within 1% of the total unmanaged load due to rounding and the load shifting efficiencies assumed for smart charging.

Table 5.2: Scenarios of 2025 California PEV penetration and Energy.

Scenarios of 2025 California PEV penetration and energy				
	Low	Mid	High	"Reach"
Total California Annual PEV Unmanaged Charging Load (GWh)	3,016	6,668	7,938	15,876
Total Stock of PEVs	950,000	2,100,000	2,500,000	5,000,000
Stock of BEVs (60%)	570,000	1,260,000	1,500,000	3,000,000
Stock of PHEVs (40%)	380,000	840,000	1,000,000	2,000,000
PEVs % of Current CA Auto Stock	4%	8%	10%	20%

PLEXOS Power Sector Model

The purpose of this analysis is to assess the broader electric system and RE integration impact of PEV managed charging, and in general of the forecasted penetration of PEVs at the bulk power system level in California. In order to do so, we use PLEXOS, an industry standard unit commitment and economic dispatch (also referred to as production cost) software developed by Energy Exemplar, Inc. [328]. There are several examples in the literature of the use of PLEXOS as a way to model the grid impacts of PEV penetration and different charging regimes [54, 171, 170].

PLEXOS performs a unit commitment and economic dispatch simulation (deterministically and not stochastically) using mixed-integer programming to minimize the total system cost, subject to several operational constraints including generator unit commitment, generator ramping, start and shutdown times, minimum stable generation levels, carbon price/emission caps, hydropower energy limits, import/export restrictions, transmission line bounds, etc. In this analysis, we use a version of the PLEXOS database originally created by CAISO for the state's 2014 Long Term Procurement Plan (LTPP) regulatory process and then revised by CAISO to include certain modeling assumptions and data for a 50% RPS. We use this database in order to simulate the operating practices and energy markets of the CAISO and the rest of the Western Electricity Coordinating Council (WECC) in the year 2025. More details on the database are in Section 0. We use the PLEXOS 7.4 R01 x64 edition, and the Xpress-MP solver 28.01.13 for the optimization.[3]

We run the model one month at a time consecutively for the 12 months of 2025. Each run first optimizes over a time horizon of one month to accommodate the generators with monthly energy limits, such as large hydro plants, and then conducts daily chronological optimizations to balance load by dispatching generation for each hour. Through this process, PLEXOS co-optimizes for energy and ancillary services to meet load and ancillary services requirements and achieve a minimum cost result [334]. Together the result is an hourly solution that includes power plant dispatch, cost, zonal electricity prices, transmission line flows, imports, and exports. The solution represents the day-ahead CAISO market and does not separately model the real-time CAISO market.

In the following sections, we provide an overview of our methodology of representing aggregate PEV fleets in PLEXOS, the application to the CA power sector, and the scenarios we use for our analysis.

Unmanaged and TOU Charging in PLEXOS

For the unmanaged and TOU charging scenarios, for each utility zone we add the aggregated and scaled 2025 PEV load from Section 5.4 to the non-PEV load (which are already developed by state agencies for other grid planning studies) as a fixed load profile in PLEXOS.

[3]We set the model performance MIP relative gap to 0.5 percent, with a max time of 4,000 seconds. The MIP gap is a measure of the quality of the integer solution by indicating the difference between the best known integer solution and the best known bounding linear solution (through the branch-and-bound algorithm).

Smart Charging in PLEXOS

The smart charging aggregated PEV fleet from Section 5.4 is added to PLEXOS as a combination of "inflexible"[4] load plus a dispatchable storage resource. We add the "inflexible" PEV load profile to the non-PEV load for each utility planning area or zone in the same way as described above for unmanaged charging. Then we configure a dispatchable storage resource similar to [171] which can both generate and consume energy in response to fluctuations in electricity market conditions. At the start of each monthly simulation, the storage resource is full. If the storage resource is not dispatched by the PLEXOS optimization, the smart PEV load equals the load defined for the unmanaged scenario. But when the storage resource generates (discharges energy), this has the net effect of reducing the load demanded by the smart PEVs and therefore the cumulative energy delivered to the PEVs falls below the maximum energy constraint. When the storage resource consumes (charges), the PEVs use more net energy than the unmanaged scenario and the cumulative energy begins to return toward its maximum constraint.

We constrain the total size (in GWh) of the smart charging storage facility to be the largest difference between the maximum and minimum energy constraints of the aggregated PEVs in each utility zone. We limit the storage resource's hourly SOC to be greater than the hourly difference between the maximum and minimum cumulative energy constraints of the aggregated vehicles. We also enforce time-varying maximum power constraints on discharging the storage resource, corresponding to the unmanaged load. The maximum power for charging the storage resource is constrained by the vehicle and charger capacity of all grid-connected PEVs in each time period. We set the round-trip efficiency of the storage resource to 99% instead of 100%, such that PLEXOS first dispatches a zero-marginal-cost generator before the flexible smart charging load. Lastly, because we run our PLEXOS simulation one month at a time, we account for any edge effects by constraining the aggregation of vehicles to return to the original SOC by the end of each month. With this monthly constraint to rebalance, and the storage efficiency of 99%, the total energy of smart charging over the course of the month is 1% higher than the energy from the unmanaged scenario.

Grid Assumptions and Input Database

We have populated PLEXOS dispatch model with the grid data and assumptions as described below.

Overall geographic area and spatial resolution We use a variant (most recent publicly available at the time of the analysis) of the 2014 Long Term Procurement Plan (LTPP) PLEXOS database from the CAISO, which was also vetted by a number of stakeholders and staff of the California Public Utilities Commission (CPUC) and CEC [334]. A number

[4] "Inflexible" is in quotes to remind the reader that we are using a combination of inflexible load and storage in PLEXOS to model a flexible load. The word "inflexible" in this context should not be interpreted as fixed load that can't be shifted.

of other studies have been conducted based on versions of the same original 2014 LTPP database or earlier versions [67, 333, 345, 346]. For this analysis, we use a version (released in November 2016) that the CAISO updated to conduct a special study of the grid impact of a 50% RPS and analyze the impact of additional bulk energy storage for the 2015–2016 Transmission Planning Process [325, 335].

The geographic scale covers the entire WECC area and we run the model at the hourly temporal level for one year.[5] There are 25 zones in the model, including eight in CA based on utility planning areas: Imperial Irrigation District (IID), Los Angeles Department of Water and Power (LADWP), Pacific Gas and Electric (PG&E) Bay Area, PG&E Valley, Southern California Edison (SCE), San Diego Gas and Electric (SDG&E), Sacramento Municipal Utility District (SMUD), and Turlock Irrigation District (TIDC) citebib50. Key assumptions on the grid inputs are listed in the following section. Additional assumptions CAISO originally used in assembling this data are described in the CAISO testimony for the 2014 LTPP CPUC proceeding [334], and in the CPUC ruling on the 2014 LTPP planning assumptions and scenarios [347]. Modifications CAISO made to the original 2014 LTPP database are also described in [325, 335].

There are number of limitations of the particular PLEXOS database we used in this study. Because the model was built primarily for planning purposes, the model is run as a combined unit commitment and economic dispatch for the day-ahead without a separate real-time market to reflect CAISO operations. This simplification does not capture the uncertainty of the energy market due to changes between a day-ahead dispatch and real-time (such as in the load or in renewable generation) and assumes perfect foresight of the day-ahead market [333]. Additionally, the model is run deterministically and only uses one set of renewable profiles and therefore does not capture any uncertainty in the energy mix to meet the 50% RPS. This database is also a zonal PLEXOS model, therefore, the transmission network is broadly represented as paths between utility zones and does not cover individual lines. Although the zonal representation improves the computational time of the model, because of this simplification, we cannot examine the impacts the addition of PEV is expected to have on transmission congestion. Lastly as elaborated in a previous study that used PLEXOS [333], because of the aggregation of the transmission network, and the use of marginal costs as a proxy for generator bids for energy and reserves (not reflecting any individual generator's particular bidding strategy), the electricity prices produced by the model generally under-estimate hourly prices.

Load and Distributed PV Generation The California loads and distributed rooftop solar PV estimates for the analysis came from the 2014 California Energy Demand (CED) Forecast (2015 – 2025) developed by the CEC [335, 348]. The original load for the California

[5]The original 2014 LTPP PLEXOS database was constructed by CAISO for 2024. CAISO updated this version with loads for 2025, but did not change the model horizon or file labels from 2024 to 2025 in PLEXOS. In order to maintain consistency with CAISO's database, for this study we maintained the PLEXOS model horizon for 2024, but refer to the results as for the year 2025 because the load is from the 2025 CEC forecast.

balancing areas modeled in the PLEXOS database, net of distributed solar PV and energy efficiency (EE), is 297,686 GWh. We then remove the 6,108 GWh of PEV load included in the original load forecast to avoid double-counting when adding the PEV loads from BEAM [344]. Non-CA loads come from the WECC Transmission Expansion Planning Policy Committee (TEPPC) 2024 Common Case.

Renewable Generation For all PLEXOS runs we use the RE profiles that CAISO created to test the final 50

Table 5.3: Renewable Capacity and Annual Energy Production in 50% RPS Scenario from CAISO (includes RPS-eligible out-of-state capacity)

Biogas	Biomass	Geothermal	Small Hydro	Large Solar PV	Small Solar PV	Thermal Thermal	Wind	Total	
Capacity (MW)	228	635	2,076	986	19,316	2,073	1,021	14,649	40,986
Energy (GWh)	1,511	4,120	15,775	3,104	53,611	4,995	2,412	39,779	125,307
% of RPS Energy	1.2%	3.3%	12.6%	2.5%	42.8%	4.0%	1.9%	31.7%	100.0%

Renewable Curtailment We allow for California solar PV, wind, and solar thermal generation to be curtailed. Curtailment can be invoked because of local or system congestion, but typically occurs when there is over-generation. Over-generation is usually caused when supply from must-run resources such as nuclear, combined heat and power (CHP), and minimal levels of thermal generation exceeds load plus exports [350]. In PLEXOS, RE generates until the electricity price reaches a negative floor price and is curtailed [50]. We use a floor price of −\$150/MWh, which is the current floor for economic bids in the CAISO market [350].

Reserve Requirements and Frequency Response Standard CAISO developed load, wind, and resource profiles based on CEC load and resource assumptions [334], as well as NREL data [335]. Using these profiles, the CAISO conducted a statistical analysis to calculate the regulation and load-following reserve requirements for the hourly PLEXOS database. These reserve requirements are based on variability and forecast error in load, wind, and solar resources [351]. Regulation reserves in each hour are meant to cover the maximum difference between the actual minute-by-minute CAISO generation requirement and the 5-minute-ahead forecast [334, 351]. Load-following reserves in each hour must be sufficient to cover the maximum difference between the hourly schedule and the 5-minute-ahead net load forecast [334, 351]. In addition, spinning and non-spinning reserves (3% of load) were included in the CAISO inputs [334]. We use the reserve requirements that CAISO calculated for this analysis corresponding to the 50% RPS profiles because we do not make any additional changes to the wind and solar profiles, and the changes in the PEV load shapes (between the original PEV load that we remove and the inflexible PEV load we add) are not significant enough to change the forecast error of the load.

In our analysis, per CAISO's updated 2014 LTPP database, we allow for renewable generators to provide up to 50% of their energy as downward load-following reserves, satisfying up to 50% of the load-following down requirement [335]. A recent study assessing a 50% RPS in CA found that allowing renewable generators to provide downward reserves can greatly reduce the amount of renewable curtailment and lower emissions from fossil generators that would otherwise be used [191]. The assumptions and scenarios recommended for the 2016 LTPP also include a scenario to test the impact of allowing renewable generators to provide operating reserves [352].

Per the recommendations of the 2016 LTPP assumptions, our analysis also removes a requirement for 25% local generation and instead replaces that with a frequency response requirement. To comply with the new NERC BAL-003-1 standard, the frequency response requirement is that at all times CAISO must 752 MW of headroom (available capacity). Half of the headroom requirement is met by storage and/or combined cycle generators, while the other half is to be met by hydro resources [352]. The elimination of the 25% local generation requirement is also a sensitivity tested to increase flexibility of the system by several other studies [67, 332].

Stationary Storage We include 1,325 MW of stationary storage (transmission connected, distribution system connected, and behind-the-meter connected) ordered by the CPUC storage mandate by 2020 [353, 334]. The storage resources are modeled in the CAISO data with a round-trip efficiency of 83.3%, and 873 MW of the transmission and distribution connected storage is modeled with the ability to provide ancillary services [334].

Demand Response The non-PEV related DR modeled in the CAISO database only reflects event-based DR to lower the peak energy usage during contingencies, when high trigger prices are reached (some DR resources have limits on the number of hours each month they can be called) [334]. Non-event based DR is already embedded as a modifier to the load forecast described in Section 5.4. We only include these DR resources to be consistent with CAISO's data, but by 2025 there may be a much higher DR penetration, and possibly additional DR products, to reflect the large DR resource potential and need for load flexibility that has been identified in the recent CPUC Demand Response Potential Study [192].

Conventional Generators We include the conventional thermal and hydro generators as specified in the CAISO updated 2014 LTPP database. Hydro generators are either run-of-river (and modeled with a fixed generation profile) or dispatchable (and constrained by weekly maximum and minimum energy levels). The data that the CAISO used to characterize thermal generators originated from the CPUC Scenario Tool, CAISO Master Generating Capacity list, and the WECC's TEPPC 2024 Common Case [334, 335]. This information includes start-up, shut-down, variable operations and maintenance (O&M), fixed O&M, heat rate, emissions rate, energy limits (for hydro), and any other related cost information. CAISO has also included several generic conventional generators in its database to represent

CPUC authorized procurements of new generation in CA that is expected to be built by 2024 [347]. A list of conventional generators that have been approved and are included in the PLEXOS database is in the 2016 LTPP scenarios documentation [352].

Fuel and Carbon Dioxide Emissions Prices Fuel prices vary based on the location of the generators. Natural gas price forecasts for California come from the CEC, and the natural gas and coal prices for the rest of WECC come from the TEPPC Common Case [334, 335]. Based on CAISO's own forecast of GHG price we assume emissions cost $20.75/metric ton CO2-eq, a value within the historical range of prices under the CA AB32 cap and trade program. Per the CAISO's methodology, for fossil resources imported from outside of CA, except dedicated imports, a CO2 cost adder (determined by the California emissions price times average emissions rate of 0.435 metric ton/MWh) is added to the transmission wheeling charge [334]. The transmission adder is 20% of this value for Bonneville Power Administration (BPA), which primarily produces hydropower [334].

Imports and Exports We constrain California's out-of-state net-exports such that exports minus imports cannot be more than 2000 MW in any given hour [352]. This allows for some excess RE to be exported rather than curtailed [67, 332]. We also model some dedicated imports to California entities, including from certain fossil and large hydropower resources, and 70% of out-of-state RPS renewable resources [334].

Retirement of Diablo Canyon Nuclear Plant In 2016, PG&E announced that it will not seek relicensing of its Diablo Canyon nuclear power plant (about 2,200 MW of capacity). The current license expires in 2024 for one unit and 2025 for the other [354]. For the purposes of extrapolation of our results to future years, we turn off both Diablo units in PLEXOS for all of 2025.

Vehicle-Grid Integration Scenarios: PEV adoption levels and charging strategies

We assume California reaches its 50% RPS target (approximately 125 TWh of RE) and we run the hourly PLEXOS model for the whole western U.S. grid for the four PEV charging cases below for 2025, the target year for some of California's vehicle electrification goals [311]:

- No PEVs
- All PEVs charging unmanaged
- All PEVs participating in smart charging
- All PEVs responding to an overnight off-peak TOU rate.

For each case, we test four levels of PEV adoption (Table 5.2). The PLEXOS optimization dispatches the generators to minimize cost while meeting the load, yielding as output the California total system cost, RE curtailment, generation, zonal electricity prices, and smart charging profile (the unmanaged and TOU charging profiles do not change with grid dispatch).

5.5 Results and Analysis

After running PLEXOS with the three cases described in Section 5.4, we analyze several grid-related outcomes of vehicle-grid integration (VGI): PEV smart charging dispatch, total system operating costs, and renewable generation and curtailment. We produce results for all of WECC, but the discussion of results in the following sections focus on California.

Smart Charging Dispatch Compared to TOU and Unmanaged Charging

Before analyzing the statewide grid impacts, we first compare the different PEV charging profiles and how they relate to several key system metrics. As mentioned, the unmanaged and TOU charging loads are directly passed-through as the aggregated and scaled loads from BEAM, and do not change with PLEXOS dispatch. Smart charging loads, however, are the result of the PLEXOS dispatch optimization, within the aggregated constraints from BEAM. Figure 5.3 shows the charging loads for the various strategies and the corresponding system metrics with a 2.5 million PEV adoption level, averaged across three seasonally representative months of winter, spring, and summer grid operation.

On average, BEAM simulates PEVs primarily leaving home around 7am, with a steady stream of remaining PEVs departing home between 7am and 4pm [145]. Row B shows that the majority of the unmanaged PEV load subsequently occurs between 3pm and 11pm, after the predominant commute home and coinciding with the typical evening peak of the system's load net of PV, solar thermal, and wind generation (Row A). TOU charging, by design, is concentrated overnight at home starting at 10pm and lasting until the early morning (Row B), avoiding peak load times (Row A) but also most times of RE curtailment (Row C). Row B shows that smart PEVs, dispatched by PLEXOS and subject to all the constraints as modeled in BEAM, charge in the late morning (delayed residential charging) and the late afternoon (delayed workplace charging or residential charging as drivers arrive home) to reduce RE curtailment, surging again as soon as prices drop around 11pm. This pattern follows the timing of low-priced generation shown in Row D: solar during the middle of the day and wind plus baseload plants overnight. However, even when there are high levels of RE curtailment and negative pricing in the middle of the day, which would be ideal times for PEV loads, daytime smart charging is likely limited by the relative scarcity of workplace and public chargers. Most load flexibility is in the middle of the night when drivers are parked for longer periods at their homes (and where everyone has a charger under our assumptions).

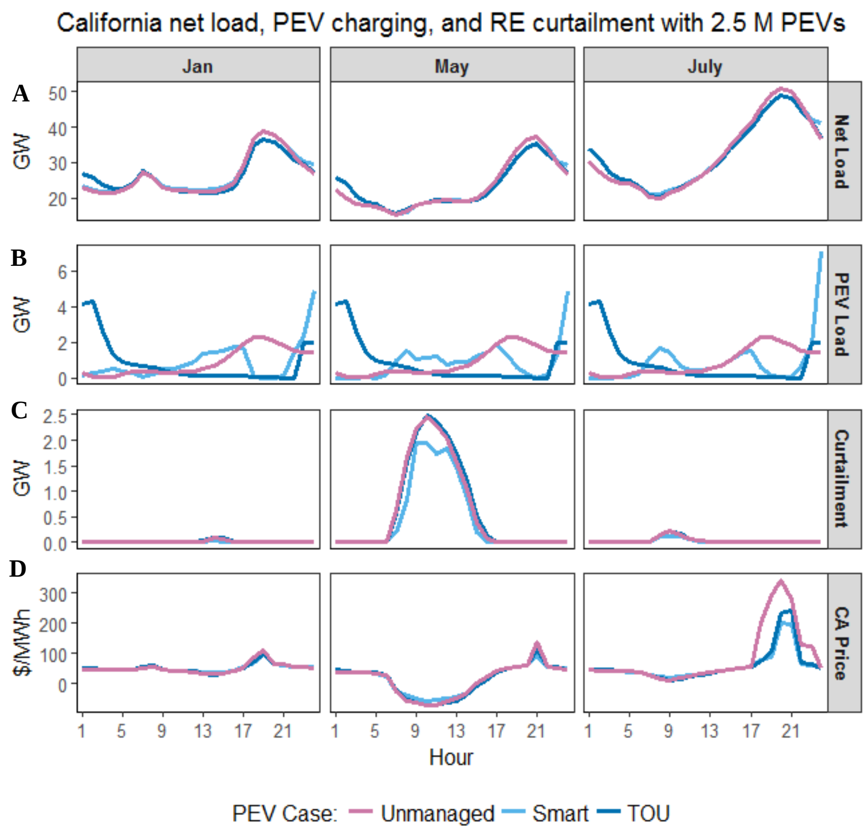

Figure 5.3: California net load, PEV charging, and RE curtailment with 2.5 M PEVs.

Total System Cost

Total System Cost Calculation

One of the key PLEXOS results is an estimate of the total system cost, often referred to as production cost. Total system cost is a commonly used metric (for example in [67, 332, 333, 334, 335]) calculated with dispatch models to estimate a system's total operating cost to meet its load. In general, the system cost is calculated from a societal perspective of the wholesale electricity market and is comprised of generation costs (including fuel, startup and shut down, and variable O&M) and emissions cost. Because annually California is a net importer of electricity from neighboring regions [334], we also include the costs of imports and the revenue from exports (negative costs) in our calculation of total system costs. However, because our analysis holds the generation and other infrastructure of the system as fixed as we add PEV loads, our estimate of the total system cost does not include capital costs (for building new power plants, transmission or distribution or other infrastructure to enable flexible load). We also do not include capacity payment costs, or other annual maintenance costs for the system, which would comprise a more complete assessment of the costs of producing and delivering electricity to the end-user. A calculation of retail rate impacts of

PEVs to the customer is also outside of the scope of this analysis.

In order to estimate the California-wide system cost, we first sum the total system cost for all the utility zones within the state. We then add costs of both "unspecified net imports" (net imports of power from unspecified generators that would be purchased on the spot market to balance load) and "dedicated imports" (power from specific generators that is dedicated to be sent to Californian utilities per long-term contracts). For unspecified imports we add the product of net interstate power flows and the electricity price in the region receiving the power per the method of [332]. For dedicated imports, we add the generation cost of the amount of power sent to California from the specific, contracted generators.

Total System Cost Result

Relative to the base case with no PEVs, the total system cost rises with all scenarios of PEV adoption levels and charging strategies because of the increased generation needed to meet the added load. However, as noted by Richardson [30], the PEV charging strategy employed affects the total cost increase to the system from the added load. For the same number of vehicles, smart charging avoids 47% or about $80 million (with 0.95 million PEVs) to 51% or about $700 million (with 5 million PEVs) of these incremental costs per year compared with unmanaged charging, as show in Figure 5 and in Table 5.4. Compared to what the total system cost increase would be with unmanaged PEV charging, TOU charging avoids 34% or $60 million (with 0.95 million PEVs) to 42% or about $580 million (with 5 million PEVs) of incremental costs (Figure 5.4, Table 5.4).

Table 5.4: California Total System Cost (Absolute) and System Cost Value of Smart and TOU relative to Unmanaged Charging.

No PEVs	0	$6,508	NA	NA	NA	NA	NA	NA	NA
Low	0.95	0	$6,687	$6,603	$6,626	$83	47%	$60	34%
Mid	2.1	0	$6,986	$6,764	$6,806	$222	46%	$179	38%
High	2.5	0	$7,110	$6,806	$6,865	$304	50%	$245	41%
Reach	5	0	$7,893	$7,185	$7,317	$707	51%	$576	42%

Smart charging incurs lower system costs in California relative to unmanaged charging, in part because peak load is reduced and more PEV load is served by RE (Figure 5.3) and because net imports decrease from out-of-state. TOU charging decreases system costs relative to unmanaged charging because of reduced load (Figure 5.3)–and thus reduced ramping primarily from natural gas generation–during evening peak demand hours. Under both managed charging strategies, the system dispatches less traditional and expensive DR to reduce peak loads and also displaces some use of stationary storage, increasing the option value, or the opportunity for future use, of these flexible resources for other grid needs.

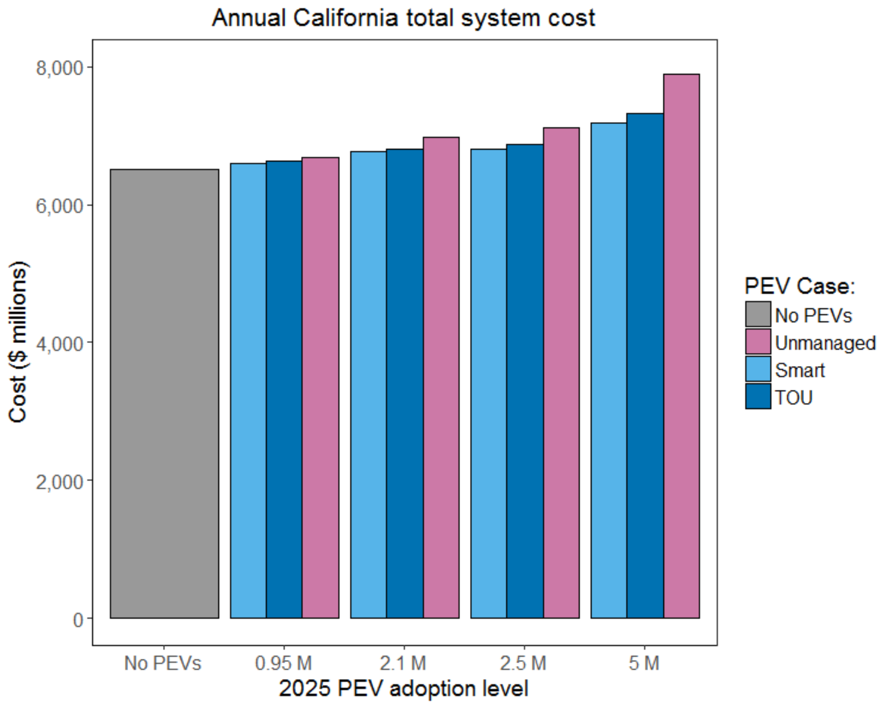

Figure 5.4: California 2025 Annual Total System Cost.

System Cost Benefits per Vehicle

While not all of the avoided system costs benefits achieved by smart or TOU charging would necessarily be returned to the PEV driver (depending on the business model and incentives of the PEV smart charging aggregator and the utility rate structure), if we divide the cost savings by the number of PEVs modeled, this represents an average savings of $88/PEV per year with 0.95 million PEVs and $141/PEV per year with 5 million PEVs on the system (Figure 5.4). PEVs that charge during off-peak TOU periods achieve 72% to 81% of these cost savings resulting from smart charging. On average, that translates to annual system cost savings from TOU of $63/PEV per year with 0.95 million PEVs and $115/PEV per year with 5 million PEVs (Figure 5.5). A review of the VGI and V2G literature shows that PEVs participating in different electricity markets show a typical profit in the range of $100–300 per vehicle. The values we see in this study are below or in the lower end of this range, likely because unlike the majority of prior studies, we include more realistic constraints on driver mobility behavior and charging infrastructure, as well as a full power systems dispatch model.

System Cost Spikes and Deferred Generating Capacity Expansion

The system cost results also show that, compared with unmanaged charging, smart or TOU charging can also defer the addition of new generating capacity. Once 5 million PEVs

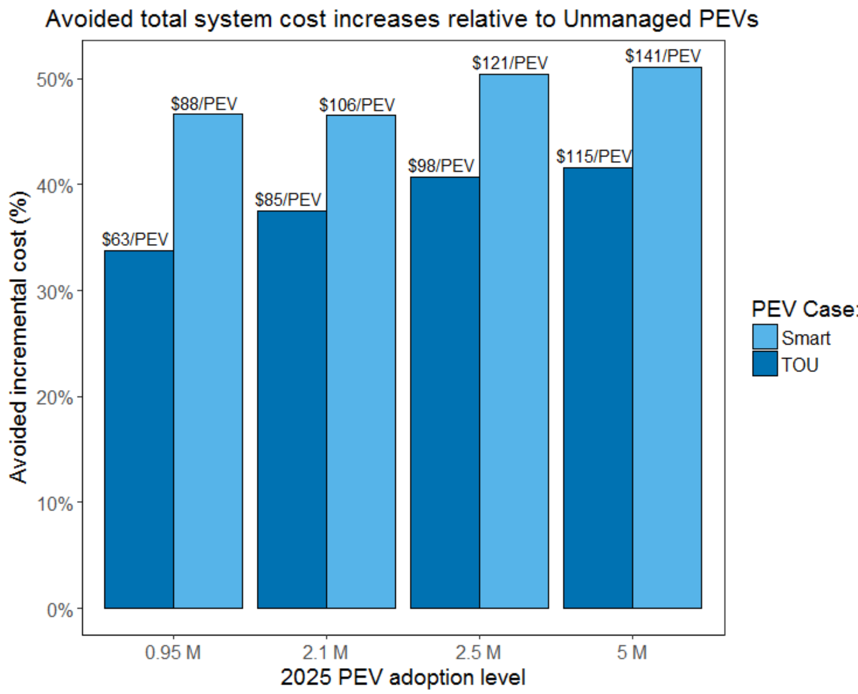

Figure 5.5: Avoided Cost Benefits from Smart and TOU Charging Relative to Unmanaged PEVs.

are added, in the case of unmanaged charging, the PEV load stresses the system peak to the point that about 2,600 MWh of load are unserved in California over the course of 2 days in July, while the load of 5 million PEVs participating in smart or TOU charging can still be accommodated by existing generators without any unserved load. In our simulation, in such a case when there is not enough generation to meet load (either within a utility region or through more imports), a region's electricity price spikes up to the level of a market ceiling price set at $2000/MWh. Because we calculate the total system cost to include price times net flow of electricity into the region, part of the high total system cost for unmanaged charging with 5 million PEVs (shown in Figure 5.3 and Table 5.4) is driven by the high imports during spikes of California regional market prices near or at the price ceiling. The high system cost with unmanaged charging shows that the system reaches a saturation point close to 5 million PEVs and that, without the management of PEV charging to avoid peak times and prices, added generation or transmission line capacity or other load management resources are needed to avoid unserved loads.

Renewable Curtailment and Renewable Generation

Smart charging shifts load to times with excess RE when power is priced at or below zero (Figure 5.3). This operational flexibility allows the grid to extract more value from the RE plants that have already been built [191]. Compared with unmanaged charging, smart charging lowers annual curtailment by an additional 148 GWh or 12% (with 0.95 million PEVs) to 478 GWh or 48% (with 5 million PEVs) (Figure 5.5). Lowering curtailment can increase investor confidence in developing future RE projects and enable emissions reductions [348]. TOU charging actually results in more curtailment than does unmanaged charging because the RE generation coincides less with overnight PEV load (Figure 5.3).

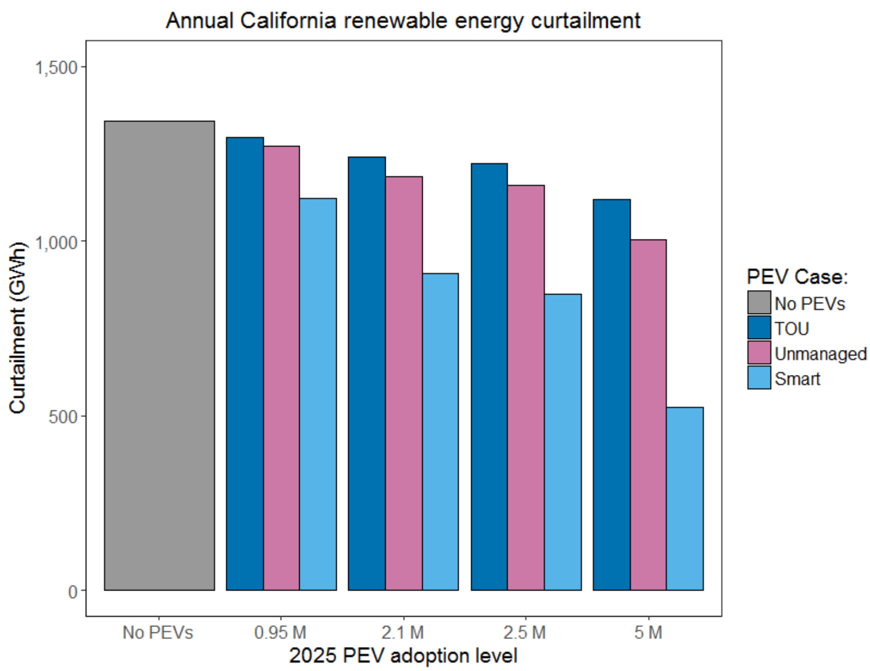

Figure 5.6: Annual California renewable energy curtailment.

RE curtailment is highest in Spring, especially in the month of May, and smart charging reduces that challenge significantly. For example, in the 2.5 million PEV scenario, smart charging reduces RE curtailment in May to 3.3% of solar and wind generation compared with 4.9% in the case with no PEVs (Figure 5.6). While annual RE curtailment even with unmanaged charging is only 1.3% (0.95 million PEVs) to 1.0% (5 million PEVs) of RE generation, with possible future RE targets higher than 50% RPS, smart charging could play a significant role in reducing curtailment and thus overall system costs.

5.6 Conclusion

As illustrated in Figure 5.1, this study unifies 1) the BEAM model, which produces realistic PEV charging simulations incorporating driver behavior, mobility patterns, and detailed charging infrastructure constraints, with 2) PLEXOS, which optimizes the power system dispatch with the addition of PEVs to estimate transmission-level impacts of unmanaged and managed PEVs. We evaluate the system cost and RE curtailment impacts of the addition of

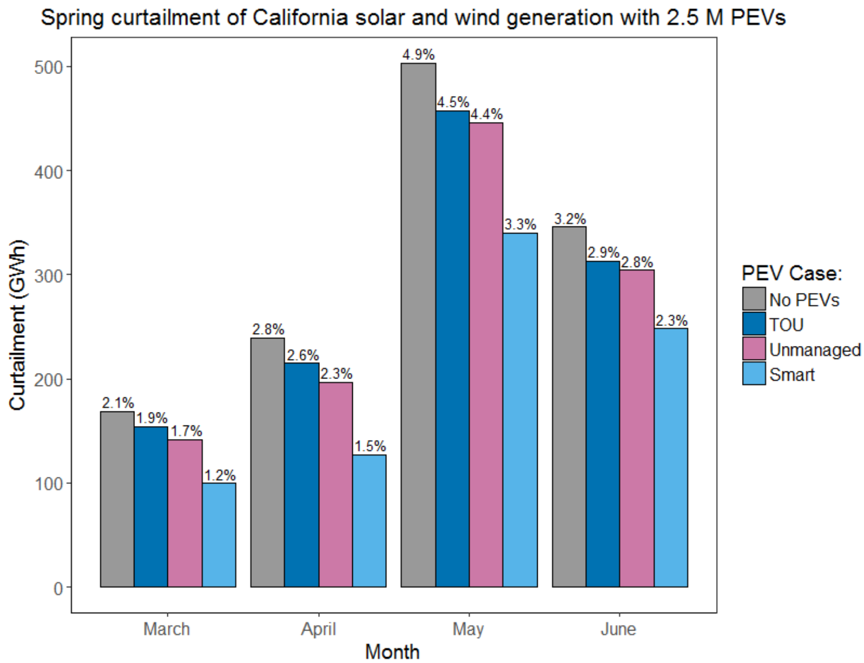

Figure 5.7: RE curtailment during spring months.

0.95 million (4% of California's current vehicle stock) to 5 million (20% of California's vehicle stock) PEVs under unmanaged, smart, and TOU charging strategies on the California power system with the assumption that the state meets its 50% RPS mandate.

Key Findings

We find that integrating PEVs in an unmanaged charging scenario, compared to TOU and smart charging, has the following grid impacts for California in terms of total system cost and RE:

System Costs

- When PEVs are added to the grid, the charging strategy employed affects how much grid operating costs increase. Smart charging avoids 47% (with 0.95 million PEVs) to 51% (with 5 million PEVs) of the California system costs increases from unmanaged PEV charging. These costs reflect the wholesale operating costs to generate energy and do not include capital costs, transmission and distribution costs, and any other incidentals that comprise the full cost of producing and delivering electricity, or of retail electricity rates for customers.

- About 80% of these benefits can be gained through TOU charging without the implementation cost of smart charging controls and administration; 34% (with 0.95 million

PEVs) to 42% (with 5 million PEVs) of system cost increases can be averted if PEVs already plugged in at home only charge overnight based on current TOU off-peak rate schedules.

- Smart charging has the potential to provide value (by avoiding system operating costs) of about $90 to $140/PEV per year compared to unmanaged charging. TOU has the potential to provide value of about $60 to $120/PEV per year.

- The benefits of both managed charging strategies are non-linearly related to PEV adoption, and the benefits increase as the power system approaches its generation and transmission capacity limits. If 5 million PEVs participated in smart or overnight TOU charging, capital costs of new generators or transmission could be deferred without leaving load unserved during peak hours of the year.

RE Curtailment

- Among the PEV charging strategies we consider, smart charging reduces California's RE curtailment the most-by an additional 12% (0.95 million PEVs) to 48% (5 million PEVs), relative to unmanaged charging.

- In contrast, nighttime TOU charging increases curtailment relative to unmanaged charging because of a load mismatch with times of high RE generation. With smart charging, the ability of PEVs to reduce RE curtailment is limited by the number of multi-hour, midday charging opportunities without queues at workplace or public chargers.

These grid impacts are specific to the California system and will also ultimately depend on the evolution of the generation mix, curtailment-reduction policies (such as better coordination with neighboring balancing areas [355]), distributed energy resources (such as other "smart" loads), and flexible supply-side resources (such as stationary battery storage). Nonetheless, most regions with aggressive PEV adoption can benefit from smart or TOU charging strategies to avoid operating and capital costs by reducing peak loads, provided that they overcome any challenges of deploying managed charging program successfully.

Remaining Research Gaps

There are many areas remaining for further research on the impacts of managed charging on the grid, including:

- Testing different PEV adoption forecasts and different PEV fleet composition (e.g. vehicles with longer range).

- Testing different charging infrastructure scenarios, including the emphasis on fast versus slow charging, and added workplace charging infrastructure.

- Testing more accurate estimation of charging power constraints of the varying available charging infrastructure.
- Using California and/or National Household Travel Survey data to scale PEV charging demand and flexibility in a manner that reflects regional variations in mobility and charging infrastructure.
- Finding correlations between charging demand and mobility profiles (i.e. daily VMT) and including these relationships when scaling demand.
- Simulating the participation of aggregated PEV fleets in other grid services such as regulation and load-following through vehicle-to-grid.
- Testing different renewable renewable generation mixes.
- Testing the impact of competing sources of grid flexibility including increased storage and demand response, varied curtailment assumptions, and higher net export limits.

Finally, there are also many policy changes happening concurrently in California and WECC, which could impact the conclusions of this study. For example, California is already coordinating with neighboring balancing areas through the Energy Imbalance Market, which could alleviate some of the curtailment problems highlighted here [350]. CAISO may also expand to other parts of WECC, and there may be an increase in DR and load management from other end-uses besides PEVs to cope with curtailment. Lastly, there is a push to move residential electric customers in California to opt-out TOU rates in the next few years [356], which may incentivize load shifting during these curtailment periods, without the use of actively managed PEVs.

Chapter 6

Dispatch of Shared Autonomous Electric Vehicles During Power Outages

6.1 Overview

In this Chapter, we present a novel methodology to assess the impact of integrating shared, autonomous, electrified fleets for mobility services with the electric grid. We envision a future where autonomous plug-in electric vehicle (PEV) fleets can be dispatched as both a taxi service and a source of on-demand power serving customers during power outages. We develop a PDE-based scheme to manage the optimal dispatch of an autonomous fleet to serve passengers and electric power demand during outages as an additional stream of revenue. We use real world power outage and taxi data from San Francisco for our case study, modeling the optimal dispatch of several fleet sizes over the course of one day; we examine both moderate and extreme outage scenarios. In the moderate scenario, the revenue earned serving power demand is negligible compared with revenue earned serving passenger trips. In the extreme scenario, supplying power accounts for between $1 and $2 million, amounting to between 32% and 40% more revenue than is earned serving mobility only, depending on fleet size. While the overall value of providing on-demand power depends on the frequency and severity of power outages, our results show that serving power demand during large-scale outages can provide a substantial value stream, comparable to the value to be earned providing grid services.

This work originally appeared in the following publication:

C. Sheppard, L. N. Dunn, S. Bae, and M. Gardner. "Optimal dispatch of electrified autonomous mobility on demand vehicles during power outages". In: *2017 IEEE Power Energy Society General Meeting.* July 2017, pp. 1–5. DOI: 10.1109/PESGM.2017.8274221

6.2 Introduction

Motivation and Background

Fully autonomous plug-in electric vehicles (PEVs) have tremendous potential to change the future of mobility. In particular, fleets of autonomous vehicles providing on-demand mobility services will likely play a major role in transportation systems [302]. While the impact of these changes on travel demand is uncertain, it is clear that safety, energy efficiency, and cost of travel will be substantially improved in the future. It is also clear that autonomous on-demand fleets of PEVs will require continued innovation in methods for systems optimization and control.

Autonomous PEV fleets could play an important role in providing flexibility services to the future electric grid. Another potential source of ancillary value provided by these vehicles is supplying electricity to buildings during power outages, when occupants are willing to pay more for energy to avoid damages associated with lack of electric service. The current work examines the additional revenue attained by a fleet of autonomous electric vehicles providing both a mobility-on-demand service and backup power during outages.

Relevant Literature

The current personal vehicle ownership paradigm involves gross under-utilization of vehicles, as personal vehicles sit idle for most of the day. This under-utilization makes PEV batteries an excellent source of load flexibility, as grid-connected vehicles can charge or discharge as needed while not in use. Numerous studies examine the capabilities [298, 303, 300, 301] and economics [309, 308, 300] of using electric vehicles to provide grid services. However, Sheppard and Bae conclude that privately owned vehicles can earn only about \$100 per year (on average) providing ancillary services [308].

Furthermore, technology development and gradual deployment of semi-autonomous safety features suggest that the future of transportation is autonomous. Once autonomous vehicles are deployed at scale, the current paradigm of personal vehicle ownership is likely to change. Although a right-sized, autonomous, commercially operated fleet is likely to be much less flexible than privately owned vehicles, centralized control can increase the magnitude and reliability of aggregate response when price signals are adequate.

Sheppard and Bae demonstrate that electric vehicles can earn limited revenue providing ancillary services. However, energy is most valuable during power outages, when customers are willing to pay more for electricity to avoid costs associated with loss of power (e.g., food spoilage, business closure, reduced manufacturing capacity) [305].

Focus of this Study

We propose a PDE-based approach, as described in [298], to simulate the optimal dispatch of autonomous on-demand PEVs serving time varying, spatially distributed demand for trips and backup power. The fleet is dispatched to maximize profit earned from serving both trips and power. The revenue earned for each trip serviced or kWh provided depends on the origin and destination of the trip, and the location of the power outage. We consider several fleet sizes, examining differences in vehicle dispatch, state of charge, revenue earned, and unserved demand for trips/power. Key contributions of this work include the geospatial modeling of vehicle mobility, charging & discharging, and inclusion of backup power as an ancillary revenue stream.

6.3 Technical Description

Modeling Aggregations of Autonomous Electric Vehicles

Table 6.1: Nomenclature

Symbol	Description
x	PEV Battery SOE ($dx = 0.2$)
t	Time ($dt = 10min$)
N_n	Number of nodes (3)
N_b	Number of spatial bins
E_{max}	Battery energy capacity ($10kWh$)
η	Power conversion efficiency during charging (0.86) [299]
$u_i(x,t)$	Density of charging PEVs in node i
$v_i(x,t)$	Density of idle PEVs in node i
$w_i(x,t)$	Density of discharging PEVs in node i
$\sigma_{I_i \to C_i}(x,t)$	Flow of PEVs in node i from Idle to Charging
$\sigma_{I_i \to D_i}(x,t)$	Flow of PEVs in node i from Idle to Discharging
$\sigma^o_{I_i \to I_j}(x,t)$	Flow of PEVs from Idle state of node i to Idle state of node j without passengers
$\sigma'_{I_i \to I_j}(x,t)$	Flow of PEVs from Idle state of node i to Idle state of node j with passengers
$q_C(x,t)$	Instantaneous charging power
$q_D(x,t)$	Instantaneous discharging power
$\mathbb{Z}$	Set of Transportation Network Nodes (I, II, IV)
T	Time horizon of the optimization ($50min$)
$\rho_{dis}(i)$	Price of servicing load during power outages by node($/kWh)
$\rho_{mob}(i,j)$	Price of servicing mobility demand from node i to node j ($/trip/minute)

We adopt and extend the scheme developed by [298] for tracking and controlling an aggregation of electric vehicles. The core advantage of the scheme is the recognition that in an autonomous PEV fleet, only the location of vehicles and their state of charge are critical to know at any point in time. Instead of representing individual vehicles explicitly and developing a combinatorial approach to control, we aggregate all vehicles in a node and represent the aggregate distribution of vehicle state of energy (SOE). Vehicles in any node i can be in one of three states: charging, idle, or discharging, which we represent by the state variables $u_i(x,t)$, $v_i(x,t)$, and $w_i(x,t)$, respectively. The system is then characterized by the following coupled partial differential equations (see Table 6.1 for further nomenclature):

$$
\begin{aligned}
\frac{\partial u_i}{\partial t}(x,t) &= -\frac{\partial}{\partial x}\left[q_C(x)u_i(x,t)\right] + \sigma_{I_i\to C_i}(x,t) \\
\frac{\partial v_i}{\partial t}(x,t) &= \sum_{j\in\mathbb{Z}}\Big[\sigma'_{I_i\leftarrow I_j}(x,t) + \sigma^o_{I_i\leftarrow I_j}(x,t) \\
&\qquad -\sigma'_{I_i\to I_j}(x,t) - \sigma^o_{I_i\to I_j}(x,t)\Big] \\
&\qquad - \sigma_{I_i\to C_i}(x,t) - \sigma_{I_i\to D_i}(x,t) \\
\frac{\partial w_i}{\partial t}(x,t) &= -\frac{\partial}{\partial x}\left[q_D(x)w_i(x,t)\right] + \sigma_{I_i\to D_i}(x,t)
\end{aligned}
$$

Where:

$$
\begin{aligned}
q_C(x) &= \frac{7}{E_{max}}\eta\frac{1}{60} \\
q_D(x) &= \frac{-7}{E_{max}}\frac{1}{60}
\end{aligned}
$$

The equations make use of an advection term (when the time derivative is linearly related to the spatial derivative) to represent how SOE changes over time for vehicles in the charging or discharging states, with SOE advecting toward 1 or 0, respectively. The model is spatially disaggregated, so the three PDEs are repeated for every node in the system and indexed by i.

Flow terms $\sigma_{I_i\to C_i}(x,t)$ and $\sigma_{I_i\to D_i}(x,t)$ capture the transport of vehicles between the three distributions within each node. Additional flow terms capture transport between the Idle curves of distinct nodes. For a given node i and any other node j, four separate terms are used to represent trips with and without passengers (σ' and σ^o respectively) and departing trips versus arriving trips ($\sigma_{I_i\to I_j}$ and $\sigma_{I_j\leftarrow I_i}$ respectively).

The inter-nodal flow terms are then constrained through the optimization scheme such that departures from a node i to node j are equivalent to the arrivals of vehicles from i to j at a future time and with a lower SOE, corresponding to the travel time and energy requirements of that trip. The distinction between trips with and without passengers becomes critical in the context of the economic optimization that places monetary value on transporting people over moving empty vehicles.

Optimization Formulation

Objective

The objective of the optimization is to maximize the operational profit of dispatching the fleet of autonomous on-demand PEVs:

$$\begin{aligned}
\max_{\substack{\sigma_{I_i \to C_i} \\ \sigma_{I_i \to D_i} \\ \sigma_{I_i \to I_j}}} K &= \sum_{i \in \mathbb{Z}} \int_{t=0}^{T} \left[\frac{\rho_{dis}(i)}{60} Q_{dis,i}(t) + \right. \\
& \left. \sum_{j \in \mathbb{Z}} \rho_{mob}(i,j) Q_{mob,i,j}(t) - \frac{C}{60} Q_{ch,i}(t) \right] dt \\
Q_{dis,i}(t) &= \int_0^1 7 w_i(x,t) dx \\
Q_{ch,i}(t) &= \int_0^1 7 u_i(x,t) dx \\
Q_{mob,i,j}(t) &= \int_0^1 \left(\sigma'_{I_i \to I_j}(x,t) \right) dx
\end{aligned}$$

Where $\rho_{mob}(i,j)$, $\rho_{dis}(i)$, and C are the fares charged to passengers, the price charged to serve load during outages, and the cost to purchase electricty from the grid, respecitvely. The constant 60 converts kWh to kW-minutes and the constant 7 is the charging and discharging rate of each vehicle.

Constraints

The equations of state are discretized using a first-order upwind scheme for numerically solving hyperbolic PDEs. They appear in the formulation as a set of equality constraints. In addition to the equations of state there are other constraints on the flows which we use to enforce realistic transport between nodes and the overall conservation of vehicles in the system.

Firstly, we constrain the size of the flows between states u, v, and w to be no greater than the number of vehicles in those states:

$$\begin{aligned}
-\sigma_{I_i \to C_i}(x,t) &<= u_i(x,t)/\Delta t \\
\{\sigma_{I_i \to C_i}(x,t) + \sigma_{I_i \to D_i}(x,t) & \\
+\sigma'_{I_i \to I_j}(x,t) + \sigma^o_{I_i \to I_j}(x,t) & \\
-\sigma'_{I_i \leftarrow I_j}(x,t) - \sigma^o_{I_i \leftarrow I_j}(x,t) \} &<= v_i(x,t)/\Delta t \\
-\sigma_{I_i \to D_i}(x,t) &<= w_i(x,t)/\Delta t
\end{aligned}$$

We also require that as charging vehicles reach an SOE of 1 or as discharging vehicles reach an SOE of 0, they immediately flow to the Idle state.

$$\begin{aligned}-\sigma_{I_i \to C_i}(1,t) &= u_i(1,t)/\Delta t \\ -\sigma_{I_i \to D_i}(0,t) &= w_i(0,t)/\Delta t\end{aligned}$$

Next, we require that trips be conserved between origin-destination pairs but shifted in time and SOE.

$$\begin{aligned}\sigma'_{I_i \to I_j}(x,t) &= \sigma'_{I_j \leftarrow I_i}(x - \Delta x_{i,j}, t + \Delta t_{i,j}) \\ \sigma^o_{I_i \to I_j}(x,t) &= \sigma^o_{I_j \leftarrow I_i}(x - \Delta x_{i,j}, t + \Delta t_{i,j}) \\ &\{(i,j) \in \mathbb{Z} \times \mathbb{Z}\}\end{aligned}$$

The values of Δx and Δt for each node (I, II and IV) are derived empirically based on real San Francisco taxi fare data collected over the course of a month in June 2012. We assume a decline in personal vehicle ownership accompanies deployment of autonomous vehicles. We account for increasing reliance on mobility-on-demand services by scaling travel demand by a factor of 10 relative to 2012. We averaged trip durations and trip distances for trips from each node i to each node j, scaling the average distance by 5.05 km/kWh to derive $\Delta x_{i,j}$ and taking the average time as $\Delta t_{i,j}$. The derived values are shown in Table 6.2.

Vehicle dispatch is constrained such that the number of vehicles servicing passenger trips or power demand cannot exceed mobility and power demand at that time step.

$$\begin{aligned}Q_{dis,i}(t) &\leq D_{dis,i}(t) \\ Q_{mob,i,j}(t) &\leq D_{mob,i,j}(t)\end{aligned}$$

The demands $D_{dis,i}$ and $D_{mob,i,j}$ are exogenously defined and described below. The choice of inequality constraints when constraining $Q_{dis,i}$ and $Q_{mob,i,j}$ serves three purposes: 1) it allows the solution of the optimization to prioritize between serving the two types of demand; 2) it enables simulations where the fleet of vehicles is not sized to meet the peak demand in the system; and 3) it allows the system to be used in an application where power outages occur spontaneously and without foresight.

Finally, we require that the vehicles have sufficient state of energy to make trips:

$$\begin{aligned}\sigma'_{I_i \to I_j}(x,t) &= 0, \quad x < \Delta x_{i,j} \\ \sigma^o_{I_i \to I_j}(x,t) &= 0, \quad x < \Delta x_{i,j}\end{aligned}$$

Table 6.2: Flow Constraints

Node Flows ($i \to j$)	**Derived** Δx (kWh)	**Derived** Δt (s)
$1 \to 1$	0.42	476
$1 \to 2$	0.82	792
$1 \to 3$	0.83	773
$1 \to 4$	0.93	1000
$2 \to 1$	0.84	760
$2 \to 2$	0.38	489
$2 \to 3$	1.26	992
$2 \to 4$	0.77	698
$3 \to 1$	0.82	773
$3 \to 2$	1.33	1130
$3 \to 3$	0.46	643
$3 \to 4$	0.86	813
$4 \to 1$	0.93	956
$4 \to 2$	0.77	725
$4 \to 3$	0.81	664
$4 \to 4$	0.37	403

Application

Spatial Discretization

We have divided the City of San Francisco, CA into a highly simplified 4-zone, equal-area network (Figure 6.1). As described above, we analyzed taxi data to characterize the constraints related to mobility and the prices used in the objective. Below we describe how power outages are characterized from real world data. We observe very little demand for mobility and backup power in Node III; due to additional computational complexity of modeling a four node system, we exclude Node III from the current analysis.

Demand for Backup Power

We estimate the magnitude and location of power outages using real outage data collected from the Pacific Gas & Electric Company website. These data report the number and spatial distribution of outages in the region; we aggregate outages spatially by node. We estimate the magnitude of unserved load based on the number of customers affected, expected distribution by customer type (i.e., residential, commercial, industrial), and average power demand by customer type (as reported in EIA form 861). We use local population and economic census data to estimate the distribution of customer types affected by outages in each node.

We examine two days of outage data, including one extreme outage scenario (December 31, 2014) and one moderate outage scenario (September 29, 2014). Figure 6.2 shows the

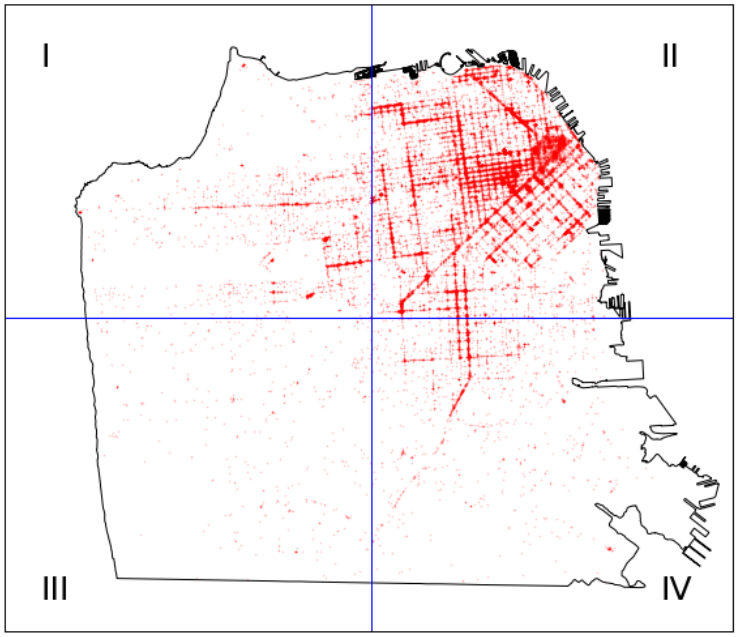

Figure 6.1: We divide San Francisco into 4 equal-area nodes. Origins and destinations of taxi trips over one month (June 2012) are plotted as red dots.

estimated power demand at each node for both scenarios. We highlight that demand in the Extreme outage scenario exceeds demand in the Moderate outage scenario by two orders of magnitude.

Finally, we estimate the value of providing backup power on demand. To do so, we compute the cost of damages incurred due to outages in each node for both outage scenarios using the ICE Calculator [305], a tool commonly used by electric utilities to estimate the economic benefits of reliability-enhancing measures. Inputs for the damage calculations include: when the outage occurs, the type and size of the affected customers, and the duration of the outage. Table 6.3 gives the estimated value of backup power in each node for the two outage scenarios in $ per unit energy delivered (kWh) and $ per time step (10 minutes). Although power demand is much higher in the Extreme outages scenario, the cost per kWh is greater in the Moderate outages scenario.

Table 6.3: Cost of power outages in each node for Extreme and Moderate outage scenarios per kWh delivered, and per time step (10 minutes).

Node (i)	**Extreme**		**Moderate**	
	($/kWh)	($/time step)	($/kWh)	($/time step)
I	20	23	14	16
II	9	11	32	37
IV	15	18	46	54

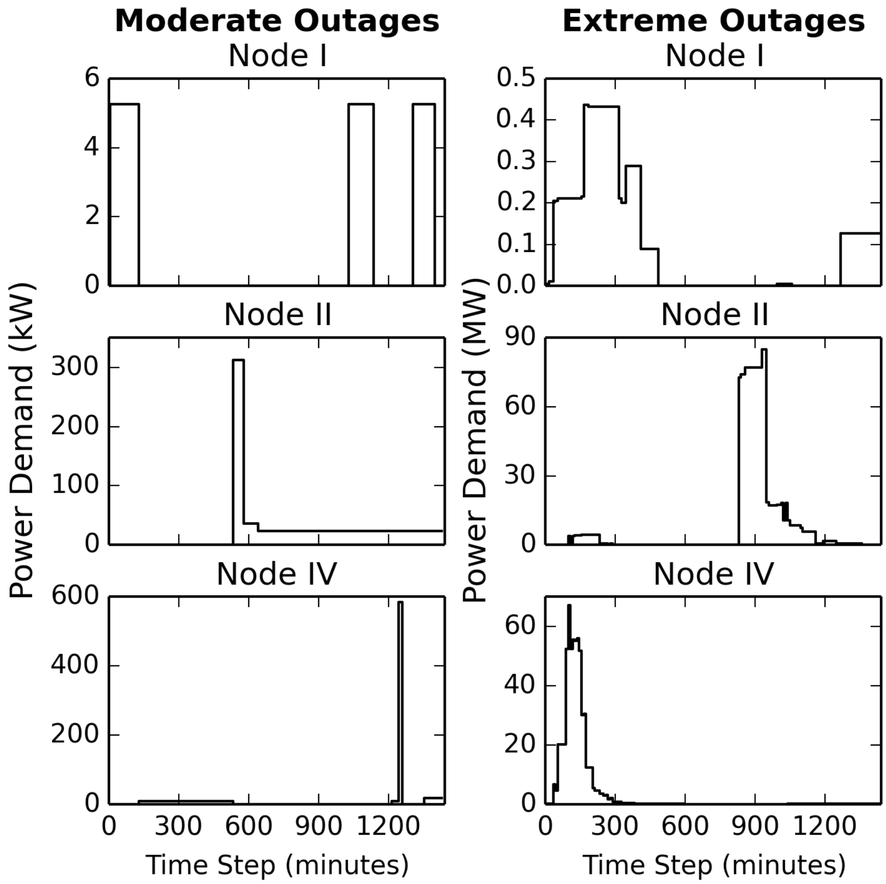

Figure 6.2: Power demand at each node (I, II, IV) in the Moderate (left) and Extreme (right) outage scenarios, represented by September 29, 2014 and December 31, 2014, respectively. For readability, demand is presented in kWh in the Moderate scenario, and in MWh in the Extreme scenario.

For comparison, Table 6.4 lists the fares associated with passenger trips to and from each node in terms of dollars per unit energy consumed (or $ per time step). These fares are empirically derived from the San Francisco taxi data. The value earned per kWh serving passenger trips is remarkably similar to the value earned per kWh of power demand served.

6.4 Results

We present simulation results for the two outage scenarios with various fleet sizes, including 7.5, 10 and 15 thousand vehicles for the Moderate outage scenario, and 7.5, 15 and 40 thousand vehicles for the Extreme outage scenario. The following sections detail various

Table 6.4: Cost of passenger trips per unit energy for each origin-destination pair.

Origin	**Destination**	**Cost**	
		$/kWh	$/time step
I	I	25	11
I	II	19	8
I	IV	20	9
II	I	18	8
II	II	26	10
II	IV	19	7
IV	I	20	9
IV	II	19	7
IV	IV	24	9

components of the results to facilitate discussion of different components of the analysis, including both revenue earned and fleet size.

Revenue

Figure 6.3 presents the revenue earned in each scenario by the entire fleet and per vehicle. Contributors to overall revenue include: the cost to charge (G2V), revenue earned serving trips (Trips), and revenue earned serving power demand (V2B). The total revenue earned (Total) in each scenario and maximum possible revenue (Max) are also shown. The maximum possible revenue includes servicing all passenger trips and all power demand, with no charing costs.

Charging costs are almost negligible compared with the revenue earned because the cost of charging (0.25 $/kWh) is small compared with the revenue earned serving power and trip demand (see Tables 6.3 and 6.4).

Next we consider the revenue earned at each node serving power and mobility demand in the Extreme outages scenario, shown in Figure 6.4. Very little revenue is earned at Node I; this is attributable to limited demand for trips and low power demand. Nodes II and IV have higher demand for passenger trips, and experience power outages in the afternoon and morning, respectively.

The revenue peaks at Nodes II and IV, coincide with the power outages at those nodes (see Figure 6.2). At Node II, the revenue earned per kWh served ($9) is small compared with revenue earned serving passenger trips. As such, revenue during the outage at Node II increases only for over-sized fleets (15,000 and 40,000 vehicles).

At Node IV, the revenue earned serving power demand is $15, which is still less than the revenue to be earned serving passenger trips. However, the outage occurs early in the morning, when demand for passenger trips is low. Thus we observe an increase in revenue at Node IV during the outage for all three fleet sizes.

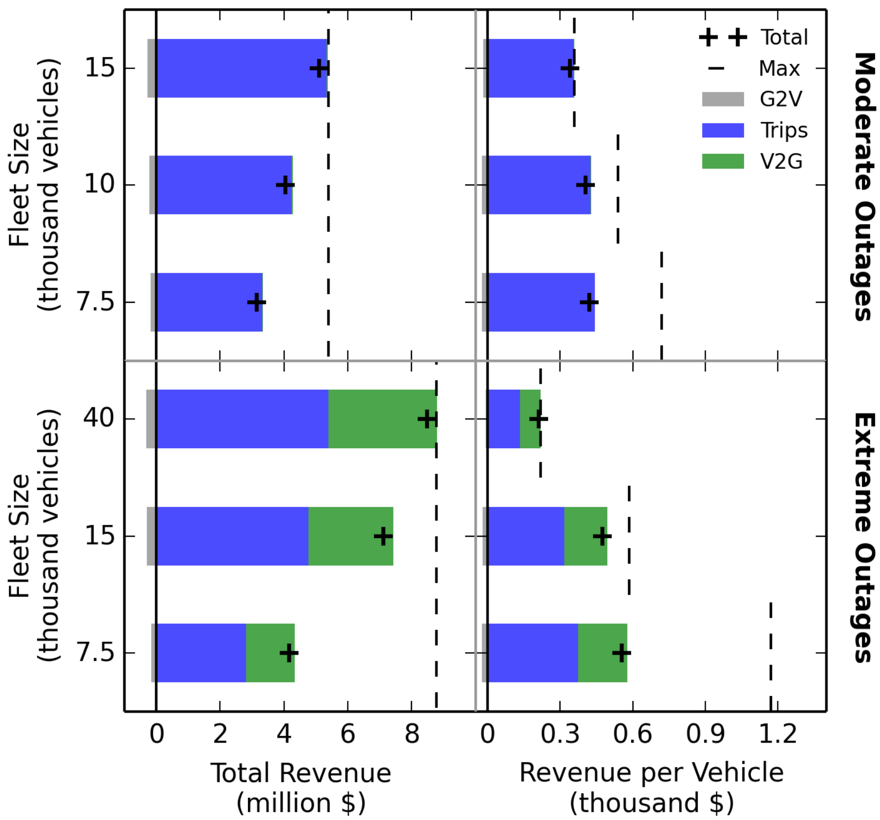

Figure 6.3: Revenue earned by entire fleet (left) and per vehicle (right) in the Moderate (top) and Extreme (bottom) outage scenarios. Revenue components include: cost to charge (G2V), revenue earned serving passenger trips (Trips), and revenue earned serving power demand (V2B). The total revenue (Total) and maximum possible revenue (Max) are also shown.

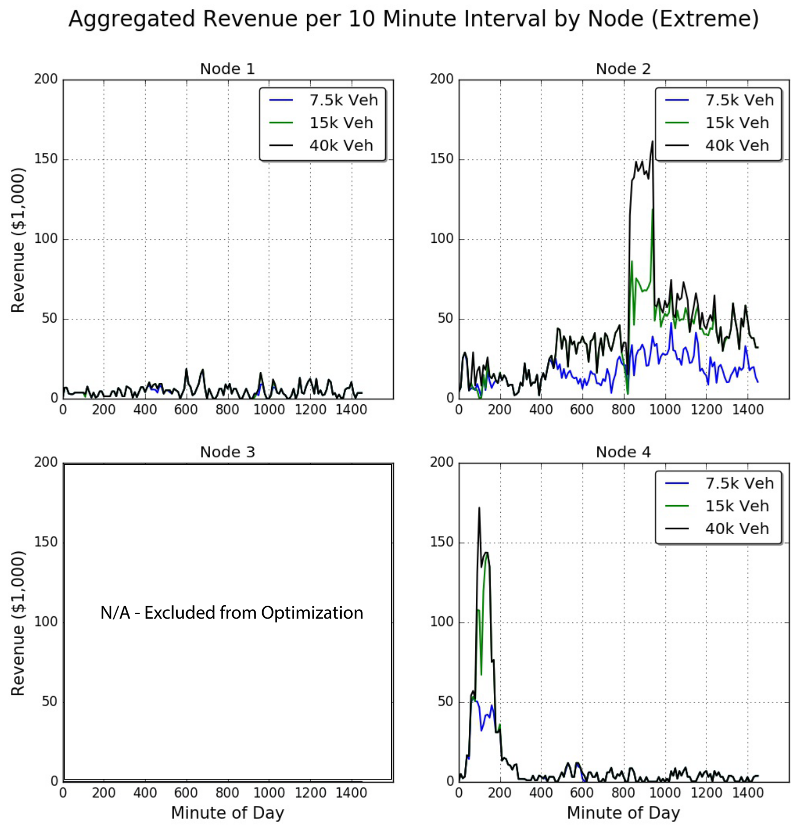

Figure 6.4: Revenue earned at each node serving power and mobility demand in the Extreme outages scenario with 7.5, 15,000 and 40,000 vehicle fleets.

Fleet Size and Vehicle Dispatch

Next we consider the benefits and drawbacks of different fleet sizes. Nearly all demand for mobility and power can be served with a 40,000 vehicle fleet in the Extreme scenario, and a 15,000 vehicle fleet in the Moderate scenario. Figures 6.5 and 6.6 show the number of vehicles in each state in the Extreme outages scenario with 40,000 and 7500 vehicles. States include: in transit with and without passengers, charging, discharging, and idle.

Figure 6.5 reveals that a 40,000 vehicle fleet spends most of the simulation in the idle state; the fleet is only fully utilized between 800 and 900 seconds, when demand for power peaks. Low revenue per vehicle in Figure 6.3 provides further evidence that the 40,000 vehicle fleet is under-utilized. On the other hand, the 7500 vehicle fleet in Figure 6.6 earns less revenue overall, but spends very little time in the idle state. In fact, the vehicles spend more time charging than in any other state; faster charging infrastructure would increase fleet utilization, and should be evaluated as an alternative to increasing the fleet size.

In Figure 6.4, the 7500 vehicle fleet earns less revenue at Node II than the larger fleets for

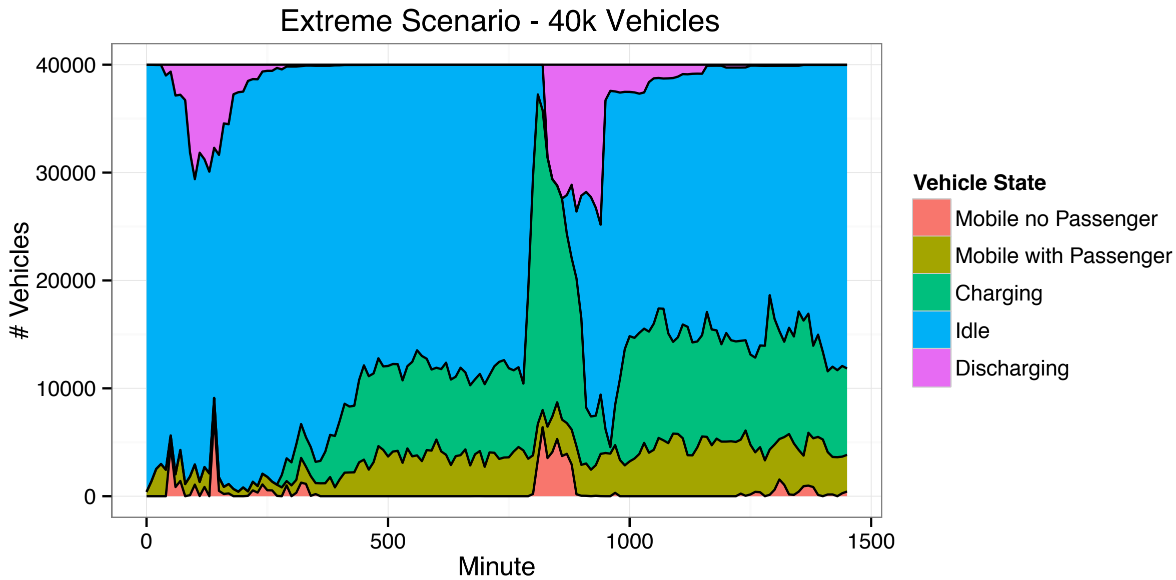

Figure 6.5: Number of vehicles in each state at each time step in the Extreme outages scenario with a 40,000 vehicle fleet. States include: in transit with and without passengers, charging, discharging, and idle.

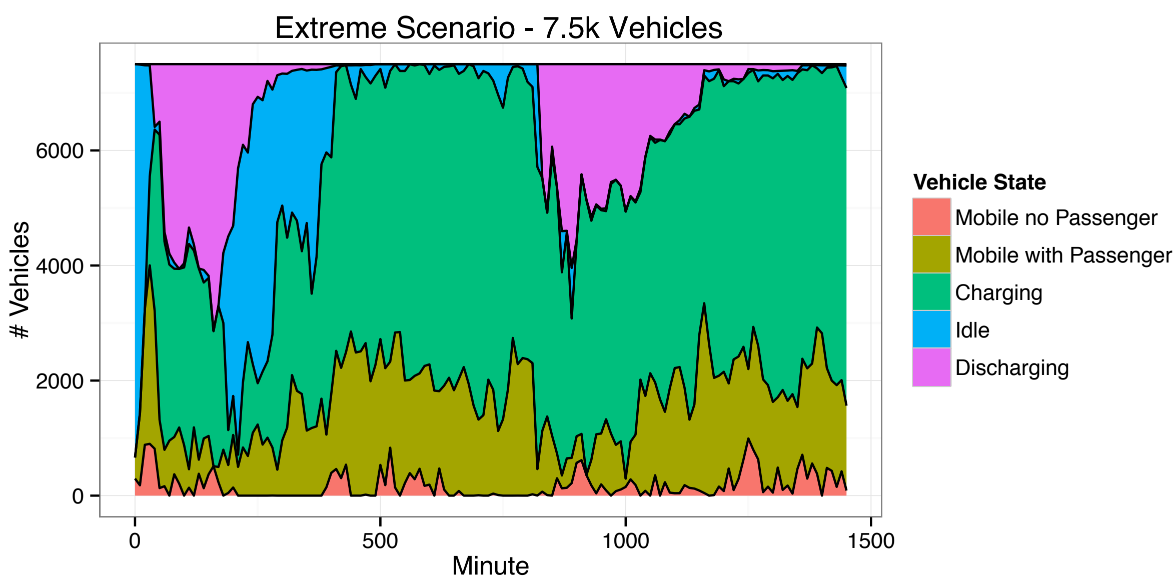

Figure 6.6: Number of vehicles in each state at each time step in the Extreme outages scenario with a 7500 vehicle fleet. States include: in transit with and without passengers, charging, discharging, and idle.

almost the entire simulation. This result suggests that the 7500 vehicle fleet is under-sized. Figure 6.7 shows the dispatch of a 15,000 vehicle fleet serving mobility only in the Moderate outages scenario. The results indicate that with charging constraints, upwards of 15,000 vehicles are needed to meet all of the demand for mobility.

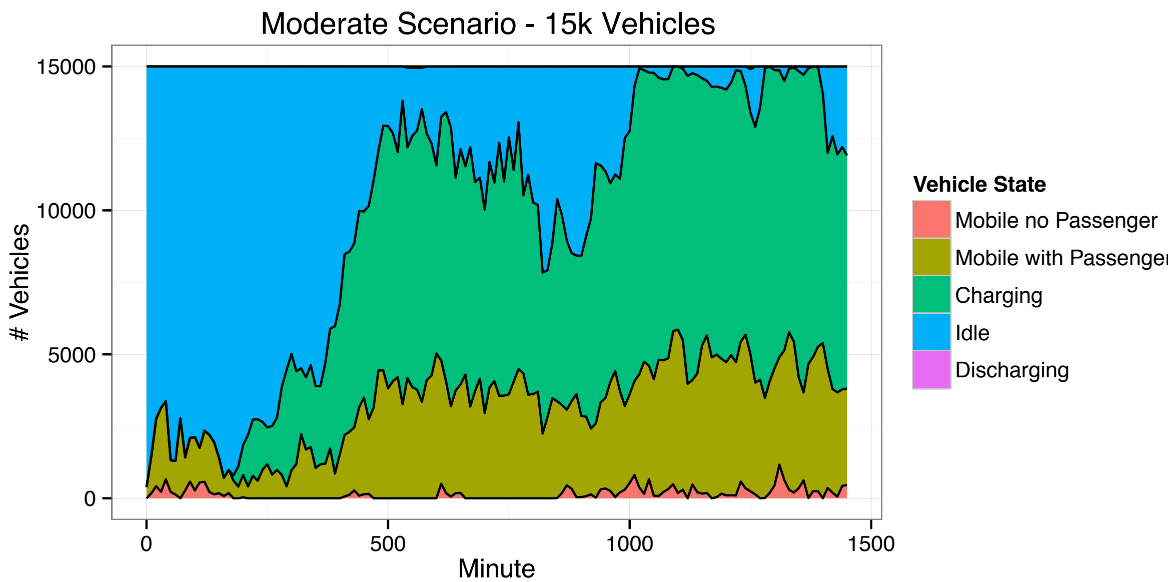

Figure 6.7: Number of vehicles in each state at each time step in the Moderate outages scenario with a 15,000 vehicle fleet. States include: in transit with and without passengers, charging, discharging, and idle.

6.5 Discussion

The fundamental question underlying the current work is whether on-demand backup power provides a substantial value stream for the fleet. To answer that question, we must consider the relative frequency of Extreme and Moderate outage days, and the marginal increase in revenue associated with serving power demand in addition to passenger trips.

We consider several scenarios for the number of Extreme verses Moderate outage days in a year. We then compute the marginal annual revenue earned serving both power and mobility demand, compared with serving mobility only. We treat the Moderate outages scenario as a mobility-only case, as the revenue earned serving power demand in that scenario is negligible.

We calculate the marginal revenue earned serving power demand by taking the difference between a year with Extreme outages and a year with only Moderate outages for equivalent fleet sizes. The results, summarized in Table 6.5, suggest that fleet operators can earn \$1400-\$3400 (or ∼1-3%) more revenue per vehicle per year serving power demand during outages, depending on fleet size and the number of major power outages.

Table 6.5: Increase in annual revenue from serving power demand in addition to mobility for fleet sizes of 7.5k and 15k.

Extreme	**New Revenue** ($/year/vehicle)		**Percent Increase** (%)	
Days	7.5k	15k	7.5k	15k
10	1400	2000	0.9	1.6
12	1700	2300	1.0	1.8
14	2000	2600	1.2	2.0
16*	2200	2800	1.4	2.2
18	2500	3100	1.5	2.4
20	2800	3400	1.7	2.6

* Actual number of days with major power outages in the Pacific Gas and Electric Company service territory in 2014 [307].

These results are sensitive to numerous assumptions in our analysis, including but not limited to: outage cost, outage frequency/duration, vehicle battery size, battery discharge rate, optimization window, and foresight into demand for power and passenger trips.

State of Energy

Figure 6.8 shows the aggregate SOE of the fleet with respect to time for the various fleet sizes and outage scenarios. We initialize the fleet with an aggregate SOE of 0.5. For all fleet sizes, the aggregate SOE then drops to below 5% before any charging occurs. Figures 6.5 and 6.6 show that charging begins at about 250 and 50 minutes, respectively. The entire fleet operates at a very low SOE, cycling out of charging before vehicles reach full SOE.

The fleet operates at a low SOE because the current model dispatches the fleet based on a planning horizon of only 50 minutes. We assume no knowledge of demand for trips or power more than 50 minutes ahead of time, and assign no penalty for entering the next planning horizon with low SOE. Thus the fleet is dispatched to maximize profit within each 50 minute window, and vehicles spend only as much time charging as is needed to serve near-term demand for trips and power. Furthermore, when vehicles are not needed to meet demand within the planning horizon, charging is less cost effective than remaining idle (at zero cost) with low SOE.

Future work will examine more realistic assumptions around vehicle charing. Examples could include a penalty for failing to achieve some minimum SOE at the end of each planning horizon, or a fee charged upon entry into the charging state, incentivizing vehicles to charge until reaching full SOE.

6.6 Summary

We demonstrate a method for simulating a fleet of autonomous PEVs in San Francisco dispatched to serve mobility and electricity demand during power outages throughout the city. We use a PDE-based approach to model the aggregate state of energy of fleet as

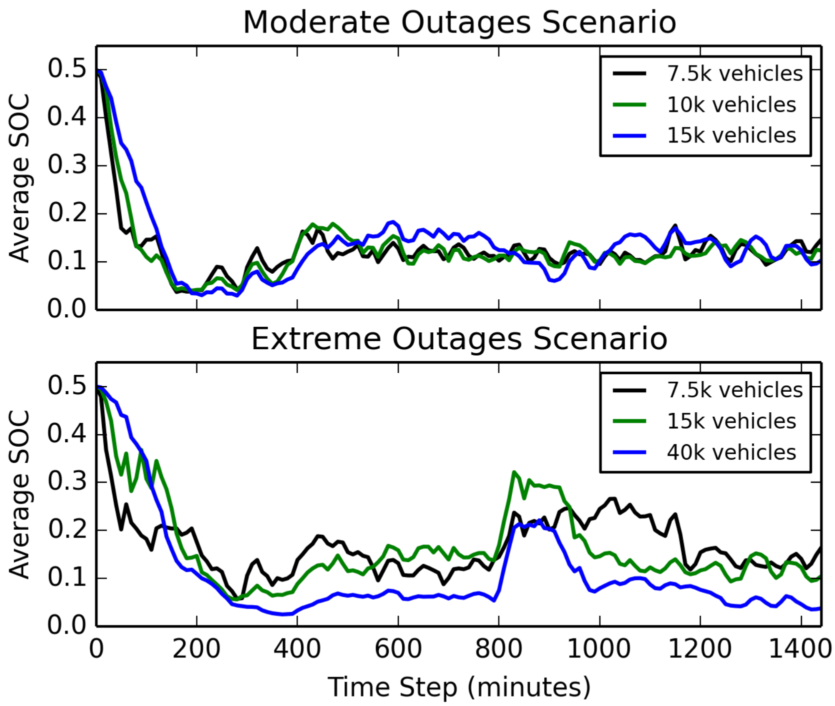

Figure 6.8: Aggregate fleet state of charge over time for 7500, 10,000, and 15,000 vehicle fleets in the Moderate outages scenario and 7500, 15,000 and 40,000 vehicle fleets in the Extreme outages scenario.

vehicles charge, discharge, and travel throughout the system. We optimize vehicle dispatch over a 50 minute planning horizon, assuming perfect foresight into both mobility and power demand within that time frame. We consider two outage scenarios, including both Moderate and Extreme outages based on real outage data for San Francisco. Finally, we compute the revenue earned in each scenario with various fleet sizes, ranging from 7500 to 40,000 vehicles. We find that serving power demand increase fleet revenue by \$1400-\$3400 per vehicle, or 30-40%, in the Extreme outages scenario. Given that power outages are rare, these results translate to ~1-3% more revenue per year, depending on the number of major power outages in a year.

Chapter 7

National Planning for Shared Automated Electric Vehicles

7.1 Overview

In this Chapter, we present a model capable of jointly optimizing both the planning and operation of a fleet of shared, electric, automated vehicles for an entire region. The model treats the size of the PEV fleet and the amount of charging infrastructure as decision variables, allowing for heterogeneous vehicle ranges and charger levels. The model minimizes operational costs by choice of the timing of fleet recharging while requiring that mobility demand is served and energy conservation is maintained. Planning costs are simultaneously minimized by amortizing the cost of the fleet and charging infrastructure to a daily time period. The model is run based on travel demand from the National Household Travel Survey and covers the entire United States at the scale of Census Divisions with the largest four U.S. states treated separately. Demand is disaggregated by urban versus rural as well as by travel distance and time of day. Initial results indicate that the distribution of vehicle types, charger levels, and the scheduling of recharging are all quite sensitive to cost assumptions and therefore further work is required to refine economic assumptions.

This work originally appeared in the following publication (reprinted with permission from Alan Jenn, Gordon Bauer, Brian Gerke, Jeffrey Greenblatt, and Anand Gopal):

Colin Sheppard, Alan Jenn, Gordon Bauer, Brian Gerke, Jeffrey Greenblatt, and Anand Gopal. "A joint optimization scheme for the planning and operations of a regional electrified fleets of ride hailing vehicles serving mobility on demand." In: *Transportation Research Record* (2019)

7.2 Introduction

The transportation sector represents the fastest-growing segment of the world's greenhouse gas (GHG) emissions, with cars accounting for 8.7% of global energy-related carbon dioxide emissions in 2013, and car sales set to more than double by 2050 [252]. In 2017, the transportation sector became the largest emitter of greenhouse gases in the United States, overtaking emissions from the electric power industry [201]. Transportation, therefore, represents one of the primary challenges to achieving deep decarbonization of the U.S. economy [182, 269].

Plug-in electric vehicles (PEVs) have emerged as a market-ready technology with the potential to dramatically reduce the carbon intensity of private transportation [253, 254]. Prior research has proven the capability of PEVs to meet the travel needs of the majority of drivers in the U.S.[276, 277]. Nine U.S. states (California, Connecticut, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island and Vermont) have established zero-emission vehicle mandates which combined will lead to deployment of 12 million vehicles, mostly PEVs, in the US by 2030 [270, 271, 272].

Simultaneously, other important trends are emerging in the transportation sector. This study attempts to align these trends in a coupled evaluation of electric vehicles with shared, autonomous on-demand mobility services. In the remainder of the introduction, we examine future trends in transportation and discuss their potential impact on electrification followed by an overview of analytical approaches that have been employed to model PEV usage which we draw upon for this work.

Future trends in transportation

Automation and Shared Mobility

The transportation sector is transforming through the introduction of on-demand mobility and through vehicle automation[261]. Increased use of smartphone-enabled shared mobility services through transportation network companies (TNCs) such as Uber and Lyft, are already implicated in reductions in private vehicle ownership [262]. Automation, too, may result in significant changes in how people use vehicles and their associated energy consumption. Self-driving vehicles are already on the roads, serving passengers in the United States without a human backup driver in the vehicle [211]. Synergy among these "three revolutions" [256, 216] could result in deep GHG reductions [258].

However, adoption of PEVs has been relatively slow for several reasons, including technological uncertainty, slow charging, range anxiety, and higher capital costs compared to other types of vehicles[255, 257]. The leading developer of vehicle automation technology, Waymo, has entered an agreement to purchase 20,000 PEVs by 2020 [212]. While there is still a great deal of uncertainty around the impact that automated vehicles (AVs) will have on the transportation system in the coming decades [213, 215], there is little doubt that they will soon be a part of the transportation system and could dramatically disrupt conventional modes of mobility. There are a wide variety of business models that could make use of AVs [206]. The success of these business models will depend on their relative cost structures [207], regulatory burden [229], consumer acceptance [230], and a host of other factors. However, there is growing consensus that without sharing rides, i.e., more than one passenger per vehicle, the end result of vehicle automation could increase undesirable outcomes like vehicle miles traveled, congestion, energy consumption, and emissions [214, 216, 228].

Shared, automated electric vehicles (SAEVs)[208] could offer on-demand transportation in electric and self-driving cars similar to the service provided by current TNCs but likely at much lower cost and carbon intensity. Because each SAEV need only have enough seats (known as "right-sizing") and battery range for the trip requested and charging can be split over many short periods in between trips, the shared mobility paradigm could enable the use of smaller cars with shorter battery range, thus overcoming the barriers of slow charging speed and high capital cost[258, 259, 248].

Furthermore, because shared vehicles typically travel many more miles annually than private vehicles, deployment of SAEVs would increase the per-vehicle GHG reductions relative to private ownership and spread the capital costs over more miles. SAEVs deployed in 2030 could reduce GHG emissions per mile by more than 90% relative to privately-owned conventional vehicles while substantially increasing cost-effectiveness [258]. A recent Rocky Mountain Institute report predicted that the marginal cost of SAEVs could fall below that of conventional private vehicles leading to market dominance by 2050 [260]. It is possible that such cost savings will increase overall vehicle miles traveled as a result of induced demand, but some studies have predicted that the efficiency gains would outweigh any resulting potential increases in emissions [261].

Charging Infrastructure and Vehicle Grid Integration

Public PEV charging infrastructure is a critical component to accelerate the adoption of PEVs [202, 203, 204], however there is a weak business case for the private sector to invest in chargers in the context of personally owned PEVs [205]. Governments across the world have therefore initiated campaigns to support the planning and installation of charging infrastructure to varying degrees [50, 188, 189, 272, 249].

PEV charging introduces a significant new load to an electric system that is already challenged to meet peak electricity demand multiple times each year, as well as incorporate increasing levels of intermittent wind and solar generation. As intermittent renewable capacity increases, the incidence of renewable energy (RE) curtailment increases which raises the overall system cost of supplying electricity [67]. In addition, some utilities must meet a renewable energy production standard to satisfy regulatory mandates, so renewable curtailment forces them to either acquire more RE or introduce sources of grid flexibility to relieve the curtailment [167].

Many studies have assessed the benefits of coordinated PEV charging on electric power system operations, [163, 171, 198]. If charging is properly coordinated, it can provide a dual benefit of decarbonizing transportation while lowering the capital costs for widespread renewables integration and reducing the need for energy storage [278, 279, 280, 281]. The capability of PEVs to enhance the integration of renewable energy sources, including wind [282, 283, 284, 285, 286, 287] and solar, [288, 289, 290, 291, 292, 293] into the existing power grid has been widely discussed.

Analytical Approaches

PEVs models typically fall into two groups: trip-based models and activity-based models. Trip-based models typically summarize or infer travel patterns from travel survey data and use them to characterize the need for PEV charging infrastructure and the temporal opportunities to charge [231, 232, 233]. Such approaches cannot account for the individual mobility constraints of travelers and they typically require an assumption that charging infrastructure is unlimited.

The most common form of activity-based PEV models make use of travel diaries from surveys or GPS data logging which are then provided as input to energy and charging simulations that estimate the energy consumption and state of charge of a PEV batteries and therefore the necessity or propensity to recharge at the conclusion of trips [237, 238, 239, 240].

Agent-based models — a subset of activity-based models — treat travelers individually and require a representation of each individual's activity schedule in order to model the travel necessary to engage in those activities. Several previous studies have employed agent-based modeling techniques to explore the feasibility of a fleet of automated taxis operating in an urban environment [208, 207, 263, 264, 265, 266, 267, 268]. Building on these results, [248] developed an agent-based model to predict the system costs of a fleet of SAEVs operating in New York City (NYC) and design a heuristic process to size the fleet and dispatch the vehicles to serve demand that is derived from trip data or stochastically created. We refer to this model as the Bauer, Greenblatt, Gerke (BGG) model.

Previous studies have shown that electric taxi fleets are viable options under certain circumstances. However, those studies have chosen fixed values for various fleet parameters. To our knowledge, [248] was the first study that explores a variety of vehicle, operational, and infrastructure parameters to identify the fleet configuration with lowest cost, and the corresponding environmental and energy impacts. It also assumed that taxis can relocate to charge whenever they are idle, which may reduce both the required battery range and overall cost as well as the impact of the vehicle fleet on the power grid.

In this work, we use a hybrid analytical approach. We develop a trip-based optimization model that can scale to a national scope and we develop key assumptions and parameters for this trip-based model by applying the BGG model in nine urban regions.

7.3 Approach

The primary contribution of this analysis is the optimization model. This model treats the size of the PEV fleet and the amount of charging infrastructure as continuous decision variables (relaxing the problem from mixed-integer to quadratic), allowing for heterogeneous vehicle ranges and charger levels. The model minimizes operational costs by choice of the timing of fleet recharging while requiring that mobility demand be served and energy conserved. Planning costs are simultaneously minimized by amortizing the cost of the fleet and charging infrastructure to a daily time period. For a full model specification, see Section 7.3.

In addition to developing the optimization model, we also curated a set of empirically-derived inputs and assumptions for the model application. While more work is needed to refine the model and assumptions (see Section 7.3), we believe that useful insights can already be gleaned from the results of the modeling workflow. These are discussed in detail in Section 7.4.

In Figure 7.1, we illustrate the source of all major model inputs and assumptions including intermediate modeling and analysis used in their derivation. Each model input is described in further detail below, beginning with the specification of the optimization model.

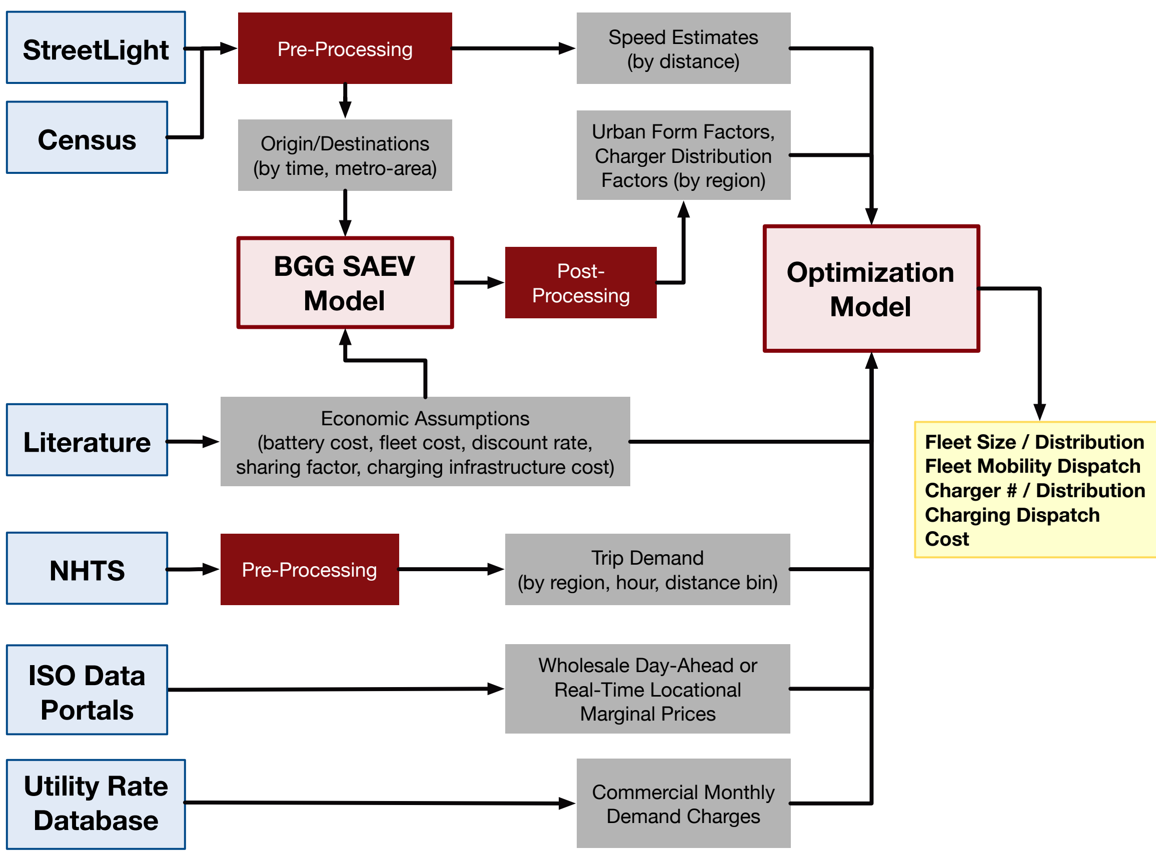

Figure 7.1: Sources of data (blue), data processing (dark red), models (light red), intermediate data (grey), and model outputs (yellow) in the overall modeling and processing workflow.

Model Specification

The dimensions of the model include time, t, region r, vehicle battery size b, charger level l, and trip distance d. The model is quadratic in the objective as well as the constraints and therefore can be efficiently solved with a second-order cone programming solver.

Objective

The objective is to minimize the amortized daily cost of the fleet, the infrastructure, and of fleet operations.

$$\min Z = \sum_r \left(\sum_t C_{tr} + I_r^c + I_r^V \right) \tag{7.1}$$

Where C_t is the operations cost in hour t and region r, I_r^c is the amortized daily charging infrastructure cost, and I_r^v is the amortized daily fleet cost.

Constraints

Operations Cost: cost of electricity energy and capacity, as well as mileage-dependent vehicle maintenance.

$$C_{tr} = \sum_b \left(\sum_l P_{btlr}\tau_{tr} + \beta_v \sum_d \rho_d D_{bdtr} \right) + P_r^{max}\beta_r / N_T \tag{7.2}$$

Where P_{btlr} is the energy dispensed for charging by vehicle class b in time t using level l in region r, τ_{tr} is electricity price (\$ / kWh), β_v is the per-mile vehicle maintenance cost, ρ_d is the average travel distance in miles per passenger trip for distance bin d, D_{bdtr} is the allocated demand for trips, P_r^{max} is the maximum power demanded over the time horizon, β_r is the average demand charge for the region (\$/kW/day), and N_T is the number of time steps in the simulation (this turns the demand charge which is levied once per day into an hourly cost). In reality, demand chargers are usually levied on a monthly basis, so this daily charge neglects the fact that day to day variation would likely lead to a higher monthly payment than a simulation based on a single day. This can be compensated for through sensitivity analysis or increasing the number of simulated days, a task for future work.

Infrastructure Cost: in this constraint, the charger distribution factor accounts for spatial mismatch between vehicle locations and available charger locations as well as overbuilding necessary to decentralize chargers. In other words, for a given number of vehicles charging, we require additional charging infrastructure assuming that not all chargers are sited in the right location at the right time.

$$I_r^c = \sum_l N_{lr}\gamma_l\delta_l\theta_l^c \tag{7.3}$$

Where δ_l is the charger distribution factor, γ_l is the power capacity of the charger (kW), and θ_l^c is the amortized daily charger cost (\$/kW):

$$\theta_l^c = \frac{\phi_l^c r(1+r)^{L^c}}{(1+r)^{L^c} - 1} \tag{7.4}$$

Where ϕ_l^c is the capital cost of charger of level l, L^c is the lifetime of the charger in days, and r is the daily discount rate.

Fleet Cost: in this constraint, battery costs are considered separately from the rest of the vehicle.

$$I_r^V = \sum_b V_{br}^* (\theta^v + \theta^b B_b) \tag{7.5}$$

Where V_{br}^* is the fleet size, θ^v is the amortized daily vehicle cost (without a battery), θ^b is the amortized daily battery cost ($/kWh), B_b is the battery capacity (kWh).

$$\theta^v = \phi_{om}^v + \frac{\phi^v r (1+r)^{L^v}}{(1+r)^{L^v} - 1} \tag{7.6}$$

$$\theta^b = \frac{\phi^b r (1+r)^{L^b}}{(1+r)^{L^b} - 1} \tag{7.7}$$

Where ϕ_{om}^v is the daily variable O&M cost for the vehicle, ϕ^v is the capital cost of the vehicle, and L^v is the lifetime of the vehicle in days. And where ϕ^b is the capital cost of the battery ($/kWh) and L^b is the lifetime of the battery in days.

Energy to Meet Demand: the energy consumed by the fleet is a function of the number of trips served, the conversion efficiency of the vehicles, the urban form (which determines the length of empty vehicle trips) and ride sharing. We model the effect of urban form and sharing as multipliers on the energy efficacy of serving mobility demand.

$$E_{bdtr} = \frac{D_{bdtr} \mu_r \eta_b \rho_d}{\sigma_d} \tag{7.8}$$

Where E_{bdtr} is the energy consumed serving mobility of vehicle type b and trip length d in hour t and region r, σ_d is the sharing factor or the average number of passengers per vehicle trip, μ_r is the urban form factor or one plus the ratio of empty vehicles miles driven to vehicle miles driven with passengers, and η_b is the conversion efficiency of the vehicle power train (kWh/mile).

Vehicles Moving: the number of vehicles actively serving trips is related to trip demand and the sharing factor. The term $\frac{\rho_d}{\Delta t \nu_{dt}}$ corrects for the length of the time period, allowing, e.g. 1 vehicle to serve 2 trips in an hour if the distance to speed ratio is 1/2.

$$V_{bdtr}^m = \frac{D_{bdtr} \rho_d}{\sigma_d \Delta t \nu_{dtr}} \tag{7.9}$$

Where V_{bdtr}^m is the number of vehicles of type b serving mobility demand of trip length d in hour t and region r, ν_{dtr} is the average velocity of vehicles, and Δt is the length of the time period in hours.

Vehicles Charging: we relate the number of vehicles charging to the power consumed by the capacity of each charger type.

$$V^c_{btlr} = \frac{P_{btlr}}{\gamma_l} \tag{7.10}$$

Where V^c_t are the number of vehicles charging in hour t, and γ_l is the charging rate (kW / charger).

Charging Upper Bound: we assume the batteries in fleet start full and therefore can only be replenished up to the cumulative amount consumed by the previous hour.

$$\sum_{\hat{t}=0}^{t} \sum_{l} P_{b\hat{t}lr} \leq \sum_{\hat{t}=0}^{t-1} \sum_{d} E_{bd\hat{t}r}, \quad \forall btr \tag{7.11}$$

Charging Lower Bound: charging must keep up with consumption as limited by the capacity of the batteries. Energy must be supplied by charging in the previous hour to be used in the next hour. This constraint prevents the aggregate state of charge of the vehicles from becoming negative. By constraining only the aggregate state of charge and not constraining individual vehicle states of charge, we are assuming that the fleet can be managed to maintain all individual vehicles appropriately. In practice there could be solutions to the aggregate problem that are challenging to satisfy with the individual vehicles.

$$\sum_{\hat{t}=0}^{t-1} \sum_{l} P_{b\hat{t}lr} \geq \sum_{\hat{t}=0}^{t} \sum_{d} E_{bd\hat{t}r} - V^*_{br} B_b, \quad \forall btr \tag{7.12}$$

No Charge At Start: the first hour of the day needs to have no charging to allow for the convention that charging can only occur after some energy is consumed by the fleet.

$$P_{btlr} = 0, t = 0, \quad \forall blr \tag{7.13}$$

Terminal State of Charge: the aggregate state of charge of batteries must again be full at the end of the day. This constraint would be too restrictive if the end of the day is defined as midnight (since there is still a fair amount of VMT during that hour). We therefore shift our day boundary to the lowest VMT level of the day, which typically occurs at 4am.

$$\sum_{t} \sum_{l} P_{btlr} = \sum_{t} \sum_{d} E_{bdtr}, \quad \forall br \tag{7.14}$$

Demand Allocation: demand must be served by some composition of vehicles.

$$\sum_b D_{bdtr} = DD_{dtr} \tag{7.15}$$

Where DD_{dtr} is exogenous demand in hour t (person trips).

Fleet Dispatch: together vehicles serving trips, charging, and idle cannot exceed the fleet size.

$$\sum_d V^m_{bdtr} + V^i_{btr} + \sum_l V^c_{btlr} \leq V^*_{br} \tag{7.16}$$

Max Charging: vehicles charging cannot exceed the number of chargers.

$$\sum_{bd} V^c_{bdtl} \leq N_{lr} \tag{7.17}$$

Where N_{lr} is the number of chargers charging at power level l in region r.

Max Demand: this constraint relates the maximum power consumed for each region to the power drawn in each time period. Because P^{max}_r is in the objective function, there will be no slack in the optimal solution, ensuring it will be equal to the maximum power demanded by the fleet.

$$P^{max}_r \geq \frac{\sum_{bl} P_{tblr}}{\Delta t}, \quad \forall tr \tag{7.18}$$

NHTS Data

We applied the model at a national level based on estimates of hourly demand for private vehicle trips on a typical day, as derived from the 2017 National Household Transportation Survey (NHTS) [294]. NHTS respondents log trip distance, timing, and vehicle type for all household members on a specified day. The responses are weighted according to demographics to yield a typical mobility profile over a single day across the United States.

To produce our trip-demand model inputs, we partitioned the country into thirteen broad geographic regions, made up of the nine US Census Divisions,[1] with the four largest states (California, Florida, New York and Texas) separated out into their own individual regions [2]. Hereafter, we refer to these regions interchangeably as "regions" or as the Census-Division-Large-State (CDLS) subdivision. In addition, we subdivided the trips according to an NHTS

[1] These are New England (NE), Mid-Atlantic (MAT), South Atlantic (SAT), East-North-Central (ENC), West-North-Central (WNC), East-South-Central (ESC), West-South-Central (WSC), Mountain (MTN) and Pacific (PAC).

[2] we use "NL" to refer to the remainder of the divisions containing the large states, "NL" stands for "Not Large"

data field that specifies whether a given respondent is in an urban or a rural area. This yields a total of 26 regional data sets (thirteen CDLS regions, each with urban and rural subregions). Within each region, we take all trips in private vehicles,[3] and compute weighted counts in eight bins of trip distance[4], with counts computed independently for typical weekdays and weekend days. This specifies the distribution of total daily trip demand by trip distance within each region.

To investigate the dynamics of vehicle charging and the related effects on the grid, we must also estimate the time variation of trip demand throughout the day. One straightforward approach would further subdivide the regional and distance bins by hour to produce hourly distributions of trip demand by distance. However, the NHTS dataset is insufficiently large to support this level of granularity without introducing substantial noise into the trip demand estimates, especially for longer trips and less populous regions. To circumvent this issue, we separately computed hourly trip distributions (by the hour in which the trip initiated) for each distance bin, subdivided by urban vs. rural and weekday vs. weekend, but aggregated up to the entire United States, rather than subdivided by CDLS. We then apply these hourly trip distributions to the total trip counts computed within the more granular CDLS regions to produce estimates of the hourly trip volume by distance within each region. The resulting hourly trip distributions thus capture geographical variations in overall trip volume at the detailed CDLS level, while assuming regional differences in the hourly profile of trip demand are insignificant (indeed, disaggregating this calculation into the four US census regions showed regional differences that were noisy but consistent). Figure 7.2 shows the resulting trip distributions.

StreetLight Data

In order to determine realistic values for urban form factor and charger distribution factor for the optimization model, we coupled trip data obtained from StreetLight Data with the BGG model. StreetLight Data is a company that aggregates data from cell phones and GPS devices to produce transportation metrics like travel times and volumes.

First, we obtained shapefiles from the Census Bureau website with census tracts for a series of combined statistical areas, as shown in Table 7.1. We then uploaded these shapefiles to the StreetLight Data portal, and obtained two types of data. "Trip attributes" files contained distances, times and speeds between each pair of census tracts. Data was only provided for zone pairs with a significant number of trips, as determined by StreetLight Data. "Trip Counts" data contained the volume of trips between each census tract origin and every traffic analysis zone (TAZ) with a significant volume, again as determined by StreetLight. The data also contained significant trip counts between each origin TAZ and destination census tract.

[3]specifically, the following NHTS vehicle type codes: car, SUV, van, pickup truck, motorcycle, RV, and rental car.

[4]mileage intervals specified by $(0, 2]$, $(2, 5]$, $(5, 10]$,$(10, 20]$, $(20, 30]$, $(30, 50]$, $(50, 100]$, and $(100 - 300]$

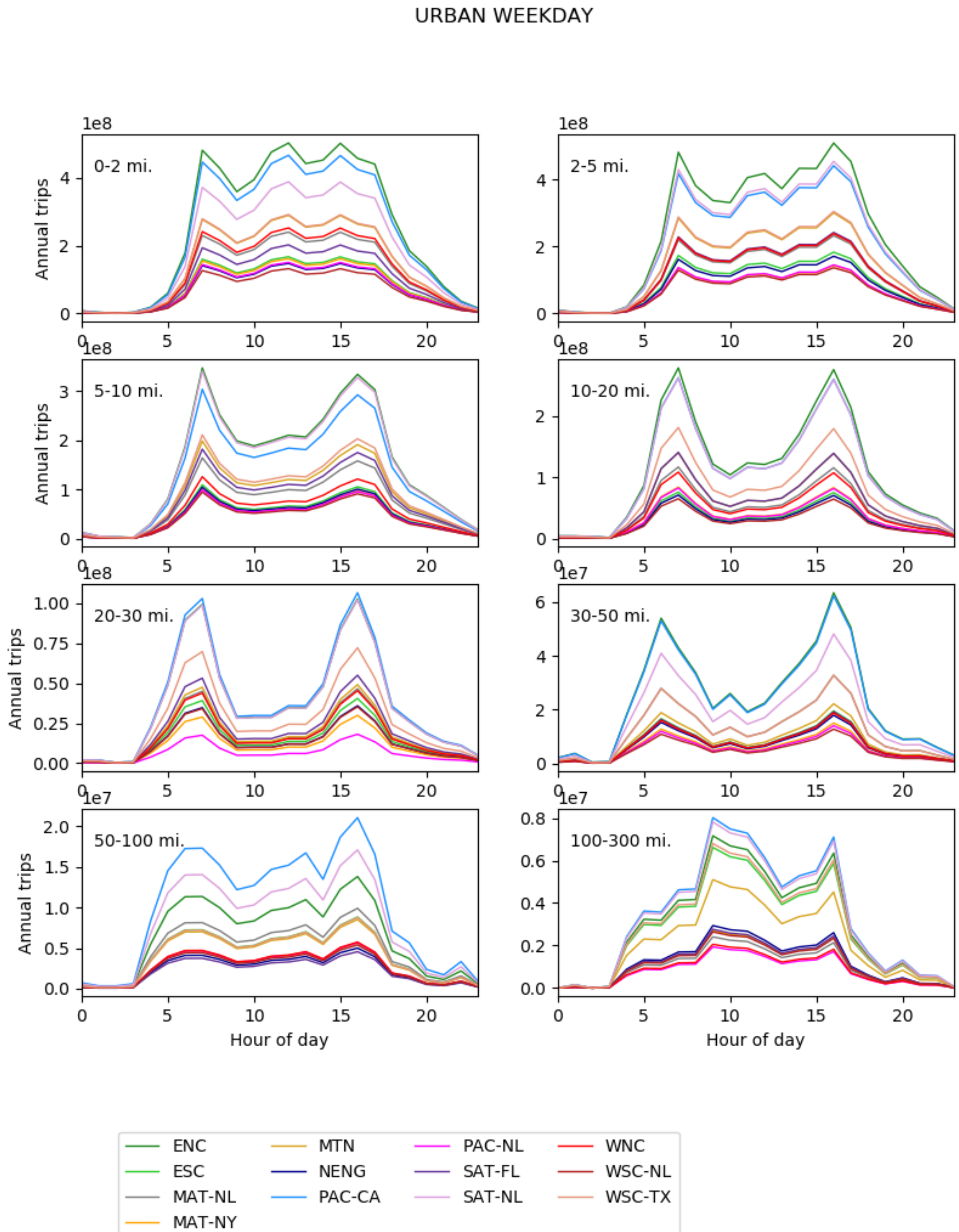

Figure 7.2: Hourly trip distributions (by hour of trip initation), for weekdays, in bins of trip distance, as estimated from the 2017 NHTS for urban areas in 13 CDLS geographic regions.

Table 7.1: Combined statistical areas used for multi-city simulations with the BGG model.

Name	Area (1000 km^2)	Census Division	Population (1000s)
Buffalo-Cheektowaga, NY	7.4	New York	1214
Charleston-Huntington-Ashland, WV-OH-KY	13.8	South Atlantic	680
Dallas-Fort Worth, TX-OK	42.7	Texas	7846
Fort Wayne-Huntington-Auburn, IN	8.2	East North Central	631
Lafayette-West Lafayette-Frankfort, IN	4.4	West South Central	252
Martin-Union City, TN-KY	3.4	East South Central	70
Rockford-Freeport-Rochelle, IL	5.5	East North Central	434
Seattle-Tacoma, WA	31.8	Pacific	4765
Virginia Beach-Norfolk, VA-NC	10.8	South Atlantic	1829

Since Streetlight trip attributes were binned into larger intervals (e.g. percent trips with durations between 10-20 minutes, or 5-10 miles), the first processing step was to interpolate distributions with increased resolution, binning distributions by 1 min, 0.1 mi, and 1 mile per hour for trip duration, distance, and speed, respectively. To interpolate missing values, we found the average distributions from the three nearest zones, along with data from the nearest zones in the hour before and after. This process was repeated iteratively until over 99% of all O-D pairs had data in all hours for all three attributes.

While this interpolation process introduces a source of error into our model, we consider it acceptable for two reasons: all trip data between census tracts comes from zone pairs with actual data, and in previous work [248], we found that modifying trip relocation times by distributions with mean zero did not significantly change our results.

Trip counts were binned by hour, so we interpolated the data to estimate the number of trips starting in each minute. Trips starting outside of the CSA were removed to avoid double-counting trips between regions.

These pre-processing steps resulted in trip counts for each origin-destination pair by minute, and distributions of duration, distance, and speed for each origin-destination pair by hour. We used this data as input for the BGG model.

The BGG model proceeds chronologically over one day of data, repeating until the fleet's aggregate battery capacity at the end of the day is within 5% of that at the beginning of the day. In each minute, trips are assigned to the nearest vehicle, and idle vehicles are routed to charge or rebalanced in anticipation of future demand [248]. Travel times and distances between each taxi and trip or charging point are imputed by drawing random values from the corresponding distribution obtained from StreetLight Data. To ensure a reasonable relationship between time, distance, and speed for each trip, distances are re-sorted in order to best match the relationship between draws for duration and speed. If a trip can only be served by a vehicle with insufficient battery capacity, the vehicle's range is increased by 50-mi increments until capacity is adequate. If no vehicle can serve a trip within a 10-min wait time, a new vehicle is added to the fleet. Thus, both battery range and fleet size increase organically over the course of the simulation, providing estimates of the minimum values required to serve demand.

Simulations were conducted for each city with 100k, 200k, 400k, and 800k trips, and with both 15kW and 50kW charging power. Locations of chargers were determined by k-means clustering of trip origins and destinations, which was determined to work as effectively as the siting algorithm described in [248]. Simulations were then run with sufficient chargers to recharge the fleet assuming 25% empty miles and 50% charger utilization, then again assuming 100% charger utilization. In each case, every charger was occupied during peak charging times, so we concluded that a charger distribution factor δ_l of 1 would be sufficient.

While the simulation ran, we recorded the empty distance traveled for each trip and charging event, and aggregated across census tracts to determine the urban form factor μ_r in both rural and urban areas of each city. Following the definition used by NHTS, rural areas were considered to be all census tracts within a CSA not contained within an urbanized area or urban cluster, as determined by the Census Bureau. As shown in Figure 7.3, we found that urban form factor increases roughly with the square root of area per trip. Using ordinary least squares regression techniques, we extrapolated these ratios to all other CSAs and urbanized areas in the country based on population and area. Finally, we took population-weighted means to extrapolate from cities to determine the urban form factor for each census division.

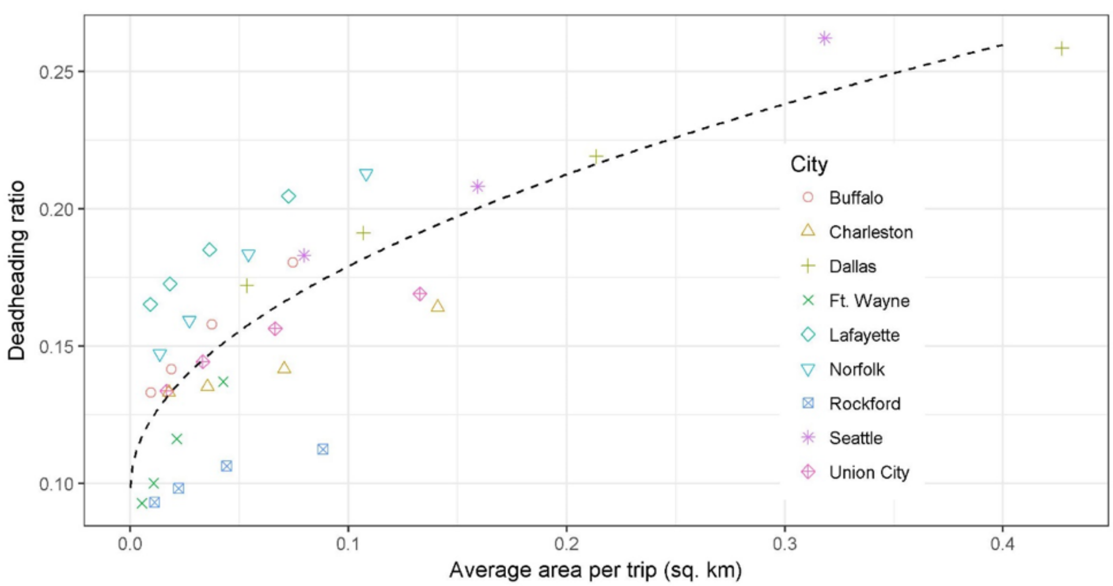

Figure 7.3: Ratio of empty miles to passenger miles in each simulated CSA versus the ratio of CSA land area to number of trips, with square-root regression line.

Power Sector Data

In order to model the fleet operations with reasonable electricity cost estimates, we developed different pricing scenarios that vary over a range of potential economic conditions on the grid. We downloaded real time locational marginal price data (or, if unavailable, day ahead price data) from five Independent System Operators (ISOs) across the United States. The ISOs were CAISO, NYISO, PJM, ERCOT, and MISO. Data were downloaded for the entire year of 2017 as well as the first half of 2018. Across all five ISOs and all locational pricing nodes, we took the median price from each hour of the day across the entire data set. In addition, we took median prices for each combination of ISO and month and used some of the resulting price profiles in one sensitivity analysis (Section 7.4). We then subtracted the average of the price profiles and added \$0.09/kWh to produce a price shape that keeps the hourly variation in price from the wholesale sector, but has an average daily price equivalent to the average commercial retail electricity rate in the U.S. as estimated by the Energy Information Agency [295]. This hybrid approach allows the overall cost to reflect the end-user cost of purchasing electricity while also allowing the fleet to take advantage of price arbitrage opportunities throughout the day. The loads from these fleets will be very large in aggregate, so it is reasonable to expect they will somehow be able to participate in wholesale power markets.

The final price assumption for the base scenario is shown in Figure 7.4 along with 4 other pricing scenarios. The "CAISO-Duck" scenario is based on the California median price of electricity in March, 2017; the "ERCOT-Summer" scenario is based on Texas prices in July, 2018, and the "NYISO-Winter" scenario is based on New York in January, 2018.

Based on data from the Utility Rate Database [296], we estimated a median national retail rate for demand charges in the U.S. We subsetted the data to commercial rate schedules and then took the demand charge price from the primary monthly period (i.e. if multiple time-of-use periods are defined, we only used the first period in the database) and found the median to be \$7.7/kW/month. The interquartile range was from \$3 to \$10.7, demonstrating substantial variability in prices nationwide. We found however, that model results are largely insensitive to this assumption.

Key Assumptions

In Table 7.2, we list all key assumptions used for the Base scenario of the optimization model.

Gaps and Shortcomings

There are several gaps in the model specification and assumptions that should be kept in mind when considering model results. In future research many of these shortcomings will be addressed.

Table 7.2: Key modeling assumptions used to define the Base scenario.

Input	Symbol	Value(s)
Charger Types and Power	γ_l	L010=10kW, L020=20kW, L050=50kW, L100=100kW, L250=250kW
Charger Capital Cost	ϕ_l^c	L010=\$5k, L020=\$11k, L050=\$35k, L100=\$95k, L250=\$425k
Charger Lifetime	L^c	10 years
Charger Distribution Factor	δ_l	1.0 for all types
Demand Charge Price	β_r	\$7.7/kW/month
Energy Price	τ_{tr}	See Figure 7.4
Annual Discount Rate	r	0.05
Number of Distance Bins	$Card(d)$	10
Urban Form Factor	μ_r	See Figure 7.10
Sharing Factor	σ_d	1.5
Vehicle Capital Cost	ϕ^v	\$30,000 (includes cost of automation)
Vehicle Daily Fixed O&M	ϕ_{om}^v	\$0.64
Vehicle Per-Mile O&M	β_v	\$0.09
Battery Capital Cost	ϕ^b	\$150/kWh
Vehicle/Battery Lifetime	L^v,L^b	3.4 years
Battery Capacity	B_b	75mi range=19.7kWh, 150mi range=41.1kWh, 225mi range=64.4kWh, 300mi range=89.4kWh, 400mi range=124.0kWh
Conversion Efficiency	η_b	75mi range=0.262kWh/mi 150mi range=0.274kWh/mi 225mi range=0.286kWh/mi 300mi range=0.298kWh/mi 400mi range=0.310kWh/mi
Speed by Distance Bins	ν_{dtr}	1.1 to 3.6mi = 18mph, 13.4 to 14.1mi = 32mph 24.1mi = 38mph, 35.5mi = 40mph 60.3 to 69.6mi = 45mph, 159.9mi = 48mph

- This model is only concerned with the distant hypothetical future where SAEVs are a dominant mode of transportation. In future work, we will add personally owned EVs and their respective impact on vehicle grid interactions to the model in order to analyze the transition to such a future.

- Price is exogenously defined. In reality, the load and charging flexibility of a SAEV fleet would be enough to influence the cost of generating power. In future work we will make power production costs endogenous to the model.

- Mobility demand is exogenously defined. In reality, demand for mobility responds to the cost, travel time, and convenience of the transportation alternative both when competing against other modes but also with respect to long term shifts in land use and travel patterns. In future work we will more closely align our demand assumptions with detailed regionally travel demand analyses that do account for these feedbacks.

- The time used across all of the regions is in local time. While this should not impact the dynamics of fleet dispatch to serve mobility, the resulting charging profiles are inappropriately assumed to be additive by hour.

- The mobility assumptions only cover a typical weekday, a more accurate planning model would include weekend/holiday in the model and weight the operational costs of these days to produce an annualized cost.

- The speed distributions are exogenous and fixed, we therefore are ingoring the impact of congestion on travel times. This is a major feedback that can only be addressed through more extensive use of detailed travel demand models that simulate traffic flow.

- Electricity price is based on a median price and the simulation only runs for one day. Electricity prices are highly variable by day and season. An improved model would include multiple days in the simulation representative of a full year.

- The model does not consider temporal overheads associated with charging (e.g. maneuvering to spot, plugging in, etc.) and with maintenance (e.g. cleaning the vehicle interior). These processes could be approximated by derating the charging power associated with each charger level.

- The model ignores the impact of C-rate and battery degradation on system cost and performance. In particular, we ignore the fact that in high power charging, the charging rate must be reduced past a vehicle state of charge of 80% before charging can commence.

- The model ignores the difference in battery lifetime among vehicles with different sized batteries. These would not age at the same rate, and should therefore be disaggregated.

- The model does not attempt to optimize the seating capacity of the vehicles.

- We neglect medium/heavy duty vehicle electrification that will likely take place along with passenger vehicle PEVs and have impacts on aggregate electricity consumption and peak load.

- We assume a constant sharing factor across the model, but it likely varies by region, trip distance, and time of day.

- We estimate the variability of urban form factor by region, but it likely also varies by trip distance and time of day.
- We neglect the cost of parking. This is due primarily to the challenge of estimating regional average parking costs in addition to the fact that under a high penetration SAEVs, parking would become much less limited in general, making current parking prices unrepresentative of future costs.

7.4 Results and Discussion

In light of the gaps described above, we present the preliminary results of running the model for the entire United States. These results should be interpreted as generally indicative of the characteristics of a national SAEV fleet, not as a high-confidence prediction.

Base Scenario

We present high level summary metrics for the cost minimizing configuration of vehicle fleet, charging infrastructure, and charging profiles resulting from the Base scenario in Table 7.3 at both the national and regional scales.

If all U.S. mobility were satisfied by SAEVs with a sharing factor of 1.5, a fleet of only 12.5 million vehicles and 2.4 million charge points would be required, consuming 1,142 GWh of energy per day (or 8.5% of daily U.S. electricity demand) with a peak load of 76.7 GW (or 11% of the U.S. non-coincident peak) at a cost of \$0.27/mile. The distribution of power capacities in the charging infrastructure is strongly weighted toward 50kW chargers (Table 7.3), but the solution includes substantial numbers of lower power chargers as well, roughly split between 10kW and 20kW chargers.

The regionally disaggregated results tend to follow predictable patterns that are closely related to the population of the region, and therefore demand for mobility. When comparing demand for charging in specific regions to current-day electricity demand, the result can be quite different from the national average. For example, the 2017 peak load in CA is 50GW and the simulated charging peak is 6.5GW, or 17% of the current peak. This represents a large increase in load and the management of the fleet charging would be of major consequence to the grid operator.

The distribution of vehicle types and charger power by region are shown in Figure 7.5. There are clear, systematic differences in fleet composition between urban and rural subregions, with a greater reliance on longer range vehicles in the rural areas where trip lengths are longer (12.4 miles on average versus 7.8 for urban). The charging infrastructure requirements in rural regions often include 100kW chargers while the urban regions can be satisfied by lower power chargers.

In Figure 7.6, the bulk dispatch of the vehicle fleet between moving, charging, and sitting idle is shown over the course of the day. The total size of the fleet is determined by the afternoon peak for mobility demand (4pm rush hour). Despite the steep drop in demand for mobility into the evening hours, overnight charging of the fleet doesn't begin until after midnight (hour 25) taking advantage of the steadily decreasing marginal electricity price (Figure 7.4).

In Figure 7.7, the daily profile of aggregate energy stored in the batteries of the fleet is shown, disaggregated by vehicle type. The batteries are assumed to start the day full and this energy is used to meet the morning rush hour with some modest recharging in the early hours of the day. After the 7am mobility peak, roughly half of the fleet that is not needed for serving mobility is continuously recharged until the afternoon rush begins at 3-4pm. This charging replenishes the energy in the fleet sufficiently to allow mobility to be served through the afternoon rush into the late evening with very little charging. We acknowledge that the aggregate state of charge depletes almost to zero which is unlikely to be acceptable to fleet managers. In future analysis we will constrain this lower bound to allow for energy reserves and operational flexibility.

Finally, Figure 7.8 shows the distribution of charging by charger power capacity over the course of the day. During peak charging hours, all chargers are in use. During most of the rest of the day, the distribution of charging is roughly proportional to the charging infrastructure distribution.

Also of note in the regional results is the per-mile cost does not vary in a consistent manner between urban vs. rural regions. Vehicle cost is the largest contributor to overall cost (Figure 7.9). The variation in urban vs. rural regions is therefore largely driven by the composition of the fleet, which ultimately is a result of the particular distribution of mobility demand for each region. Based on a regression analysis, 45% of the variation in the difference in cost between urban and rural regions can be explained by the relative differences in the demand for person trips and for person miles traveled in the regions. The differences in urban form factor between urban and rural regions (Figure 7.10) were not predictive of the cost results. The other potential explanation for the variation include the timing of mobility, an effect that will be explored in future research.

Table 7.3: Optimal system configuration and operational statistics for the Base scenario.

Region	Demand (GWh/day)	Peak (GW)	VMT ($\times 10^6$)	Fleet ($\times 10^3$)	Chargers ($\times 10^3$)	L010/L020/L050/L100 ($\times 10^3$)	% of US Demand(Peak)	Cost ($/mi)
National	**1142**	**76.7**	**3012**	**12,529**	**2401**	**599/680/1102/19**	**8.5(11)**	**0.266**
ENC-Rural	67.2	4.64	176	599	166	91/0/74/0	0.5(0.69)	0.246
ENC-Urban	109	7.16	291	1275	232	29/109/93/0	0.81(1.1)	0.271
ESC-Rural	43.3	3.05	116	366	99	53/0/40/4	0.32(0.45)	0.238
ESC-Urban	45.3	2.99	172	499	86	7/33/44/0	0.34(0.44)	0.211
MAT-NL-Rural	15.7	1.1	28	140	41	24/0/17/0	0.12(0.16)	0.319
MAT-NL-Urban	51.2	3.33	135	593	106	13/49/44/0	0.38(0.49)	0.271
MAT-NY-Rural	12.4	0.868	30	120	30	16/0/14/0	0.092(0.13)	0.262
MAT-NY-Urban	34.1	2.26	78	407	69	7/30/31/0	0.25(0.34)	0.302
MTN-Rural	20.6	1.41	49	172	40	21/0/13/5	0.15(0.21)	0.254
MTN-Urban	57.2	3.86	168	753	131	29/50/51/0	0.43(0.57)	0.267
NENG-Rural	17.8	1.23	32	164	38	17/0/21/0	0.13(0.18)	0.321
NENG-Urban	30.7	2	58	371	72	14/35/23/0	0.23(0.3)	0.347
PAC-CA-Rural	10.9	0.723	24	79	17	5/0/10/1	0.081(0.11)	0.249
PAC-CA-Urban	119	7.76	360	1362	227	10/106/110/0	0.89(1.2)	0.247
PAC-NL-Rural	10.5	0.722	28	79	23	12/0/9/1	0.078(0.11)	0.227
PAC-NL-Urban	29.8	1.98	81	347	57	4/23/29/0	0.22(0.29)	0.266
SAT-FL-Rural	6.92	0.485	21	69	13	4/0/8/0	0.052(0.072)	0.233
SAT-FL-Urban	56.2	3.81	93	736	110	6/47/55/0	0.42(0.57)	0.403
SAT-NL-Rural	64.7	4.56	140	570	162	94/0/63/4	0.48(0.68)	0.277
SAT-NL-Urban	110	7.33	300	1277	209	26/68/113/0	0.82(1.1)	0.266
WNC-Rural	35.6	2.39	103	294	78	38/0/40/0	0.27(0.36)	0.224
WNC-Urban	42.6	2.85	105	570	95	20/37/38/0	0.32(0.42)	0.304
WSC-NL-Rural	19	1.2	45	178	26	0/4/22/0	0.14(0.18)	0.267
WSC-NL-Urban	27.3	1.78	81	350	57	2/34/21/0	0.2(0.26)	0.262
WSC-TX-Rural	26.5	1.82	62	210	56	28/0/25/2	0.2(0.27)	0.251
WSC-TX-Urban	78.8	5.33	225	938	150	18/48/83/0	0.59(0.79)	0.260

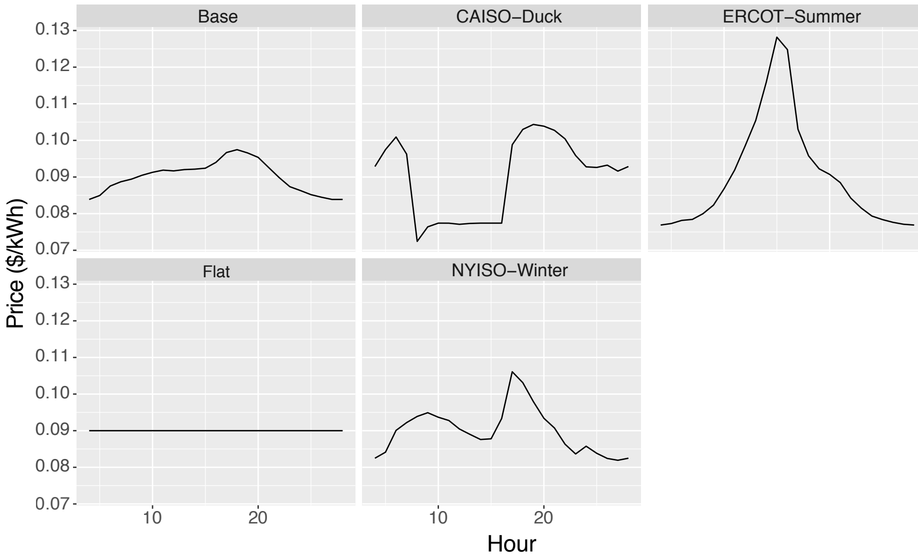

Figure 7.4: Diurnal electricity price used in price shape experiment. Shapes are derived from 2017-2018 wholesale marginal pricing data from various Independent System Operators. Each profile has an average price of $0.09/kWh.

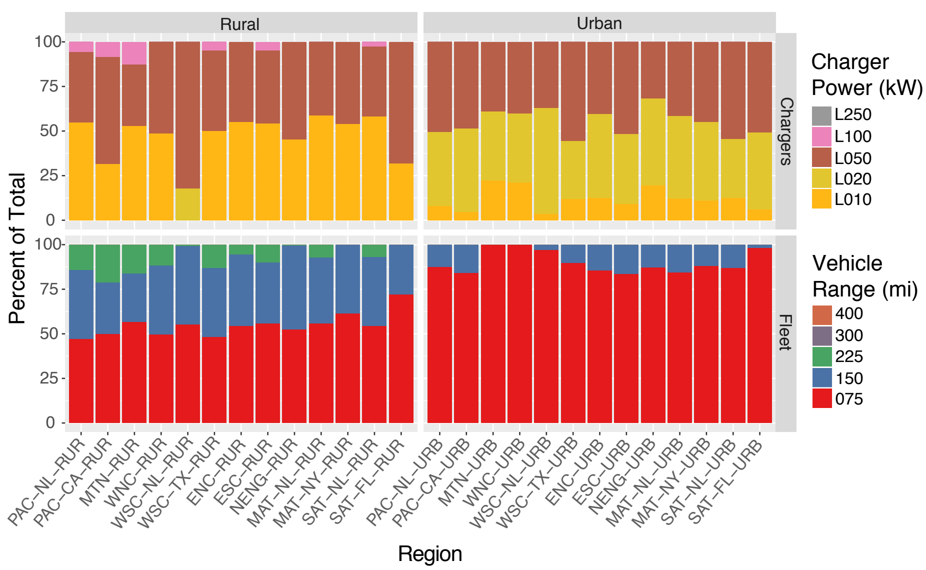

Figure 7.5: Optimal distribution of fleet vehicles and charging infrastructure for base scenario.

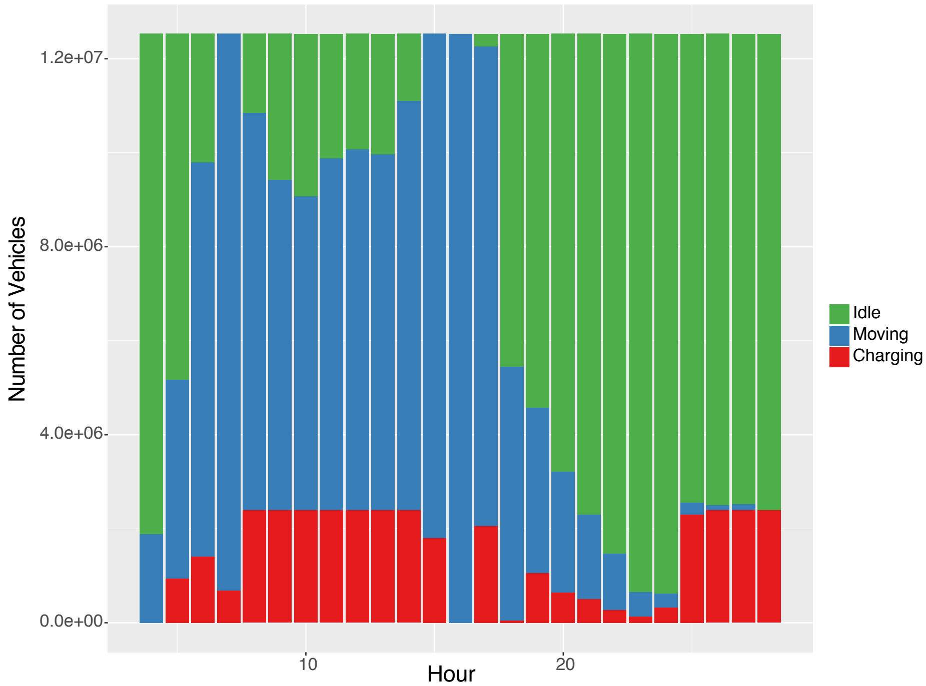

Figure 7.6: Vehicle dispatch by hour between moving (i.e. serving mobility demand), charging, or sitting idle.

Illustrative Sensitivities

We conducted several sensitivity experiments to assess the response of the optimal solution to key model inputs and assumptions.

Ride Sharing

The first analysis involves varying the assumption of ride sharing, as this is a parameter that is widely recognized to have a dramatic impact on system outcomes. In Figure 7.11 the fleet and charger composition are shown for each scenario in the experiment. Because the sharing factor is a simple multiplier on demand, the optimal solution is identical in all respects except that many decision variables are simply scaled. Across all metrics of interest (fleet size, charger requirements, electricity demand, etc.) the solution is scaled in proportion to the sharing factor.

While these results are uncomplicated, they do highlight the power of sharing in a future transportation system. It has immense potential to improve the efficiency of mobility and to decrease the negative impacts. Because sharing is not evenly distributed, we will assess how the sharing factor changes across regions and time in future research.

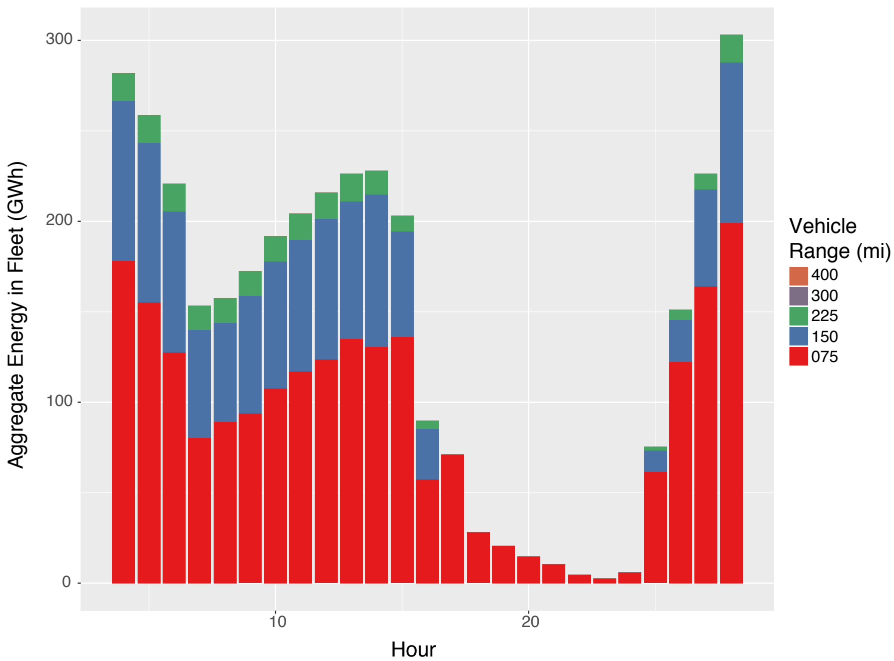

Figure 7.7: Aggregate energy stored in national fleet batteries by vehicle range by hour of day.

Battery Cost

In a separate sensitivity, we varied the cost of batteries (Figure 7.12). Higher cost batteries lead to a fleet with shorter range vehicles and vice versa. These shifts cause the total battery capacity procured for the fleet to vary from the base solution by +68% for \$25/kWh batteries and by −4% for \$250/kWh batteries. In other words, expensive batteries incentivize a reduction in the total purchase of batteries which can only be achieved by distributing them among shorter range vehicles. The total fleet size also increases very slightly with higher battery costs ($< 1\%$); this we attribute to the increased need for some vehicles to charge during the afternoon rush. Conversely, at lower battery costs — less than or equal to the base cost of \$150/kWh — when the fleet mix includes longer range vehicles, the need for charging at 4pm vanishes.

The change in fleet composition also changes the composition of the charging infrastructure. There are three distinct trends, from \$25-75/kWh, there is a substitution of 20kW for a combination of 50kW and 10kW chargers. From \$75-150/kWh, the 50kW chargers increase at the expense of lower power charging. From \$150-250/kWh, 100kW chargers enter the solution, composing 5-10% of the total power capacity of the infrastructure. In general, as the fleet shifts toward shorter-range vehicles, there is an increased reliance on higher power chargers. Faster chargers allow lower range vehicles to be quickly recharged and utilized in situations where a longer-range vehicle could have simply continued driving.

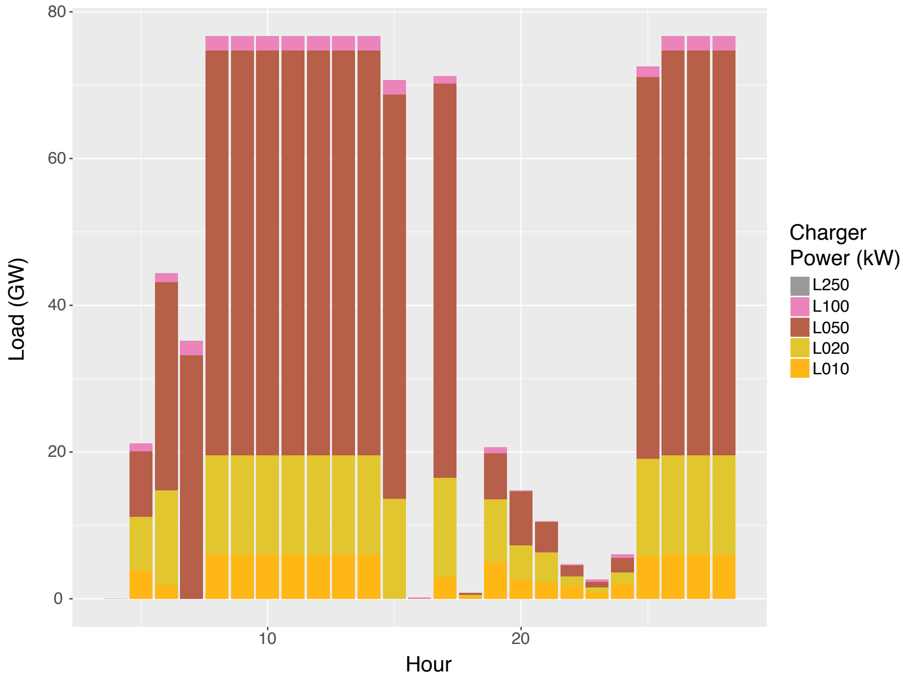

Figure 7.8: Charging profile of national fleet by charger power capacity.

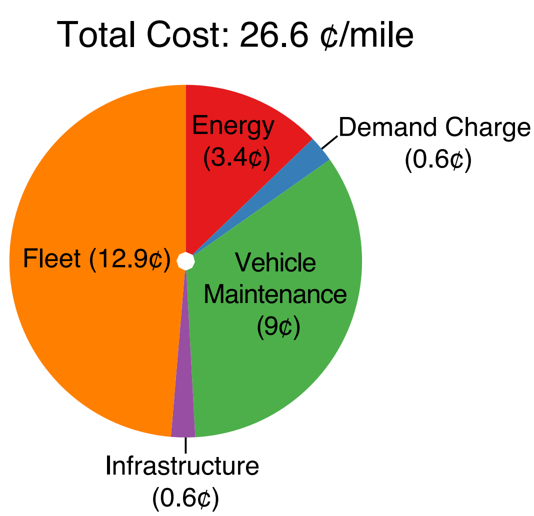

Figure 7.9: Cost per mile by cost category for the base scenario.

Price Shape

Finally, we explored the impact of the shape of daily electricity price profile. The scenarios are illustrated in Figure 7.4. The result of these different price scenarios on the aggregate

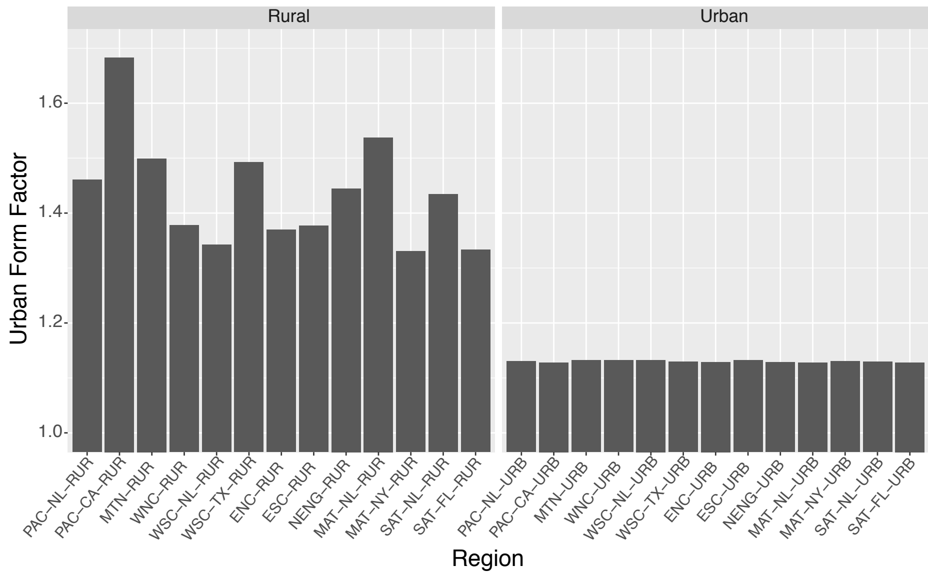

Figure 7.10: Urban form factor (μ_r) for each region in the base scenario.

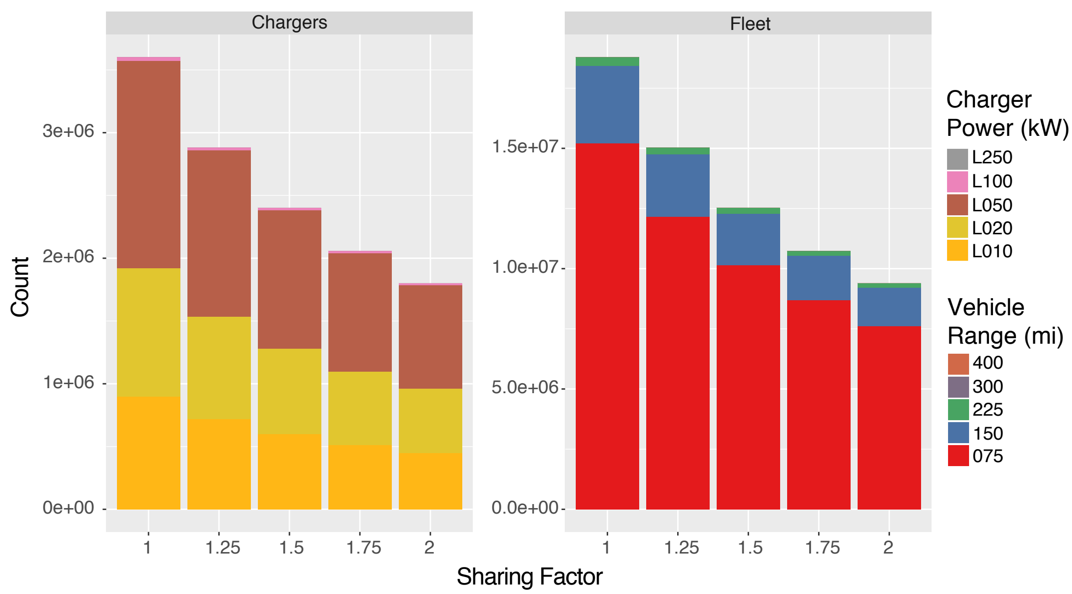

Figure 7.11: National charging infrastructure (left) and fleet composition (right) requirements for varying assumptions on sharing factor σ_d (x-axis).

charging profile are shown in Figure 7.13.

Across all scenarios, the charging profile in the first half of the day is almost identical but varies in instructive ways in the second half of the day, after the 4pm mobility peak. In the flat pricing scenario, charging never returns to the maximum during the rest of the day,

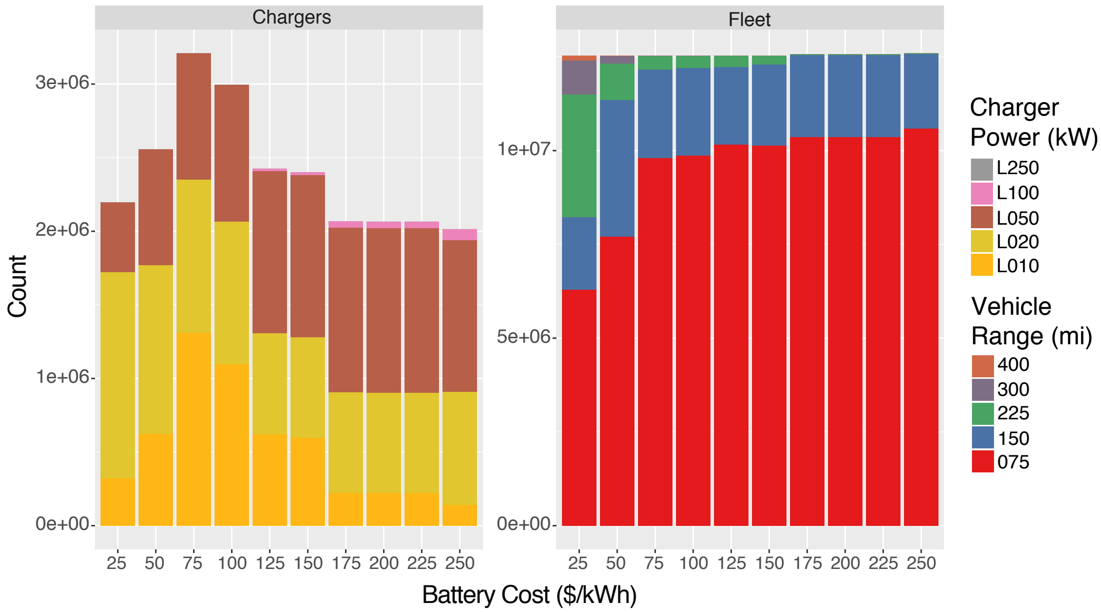

Figure 7.12: National charging infrastructure (left) and fleet composition (right) requirements for varying assumptions on battery cost (x-axis).

indicating that there is no binding constraint on when the vehicles charge in the absence of price variation. These two results support the general conclusion that across all scenarios, charging in the first half of the day is largely dispatched to supply mobility and charging in the second half of the day is largely dispatched to minimize energy costs. For the remaining price scenarios, the price-responsive charging follows common sense patterns, avoiding the highest cost hours in favor of the lowest cost.

7.5 Conclusion

We have formulated a quadratically constrained, quadratic programming problem designed to model the requirements of SAEVs at a national scale. We treat the size of the SAEV fleet and the necessary charging infrastructure as decision variables, allowing for heterogeneous vehicle ranges and charger levels. The model minimizes operational costs by choice of the timing of fleet recharging while requiring that mobility demand be served and energy conservation be maintained. Planning costs are simultaneously minimized by amortizing the cost of the fleet and charging infrastructure to a daily time period.

In our base scenario solution, we find that all mobility in the United States currently served by 276 million personally owned vehicles could be served by 12.5 million SAEVs at a cost of $0.27/vehicle-mile. The energy requirements for this fleet would be 1142 GWh/day (8.5% of 2017 U.S. electricity demand) and the peak charging load 76.7 GW (11% of U.S. power peak).

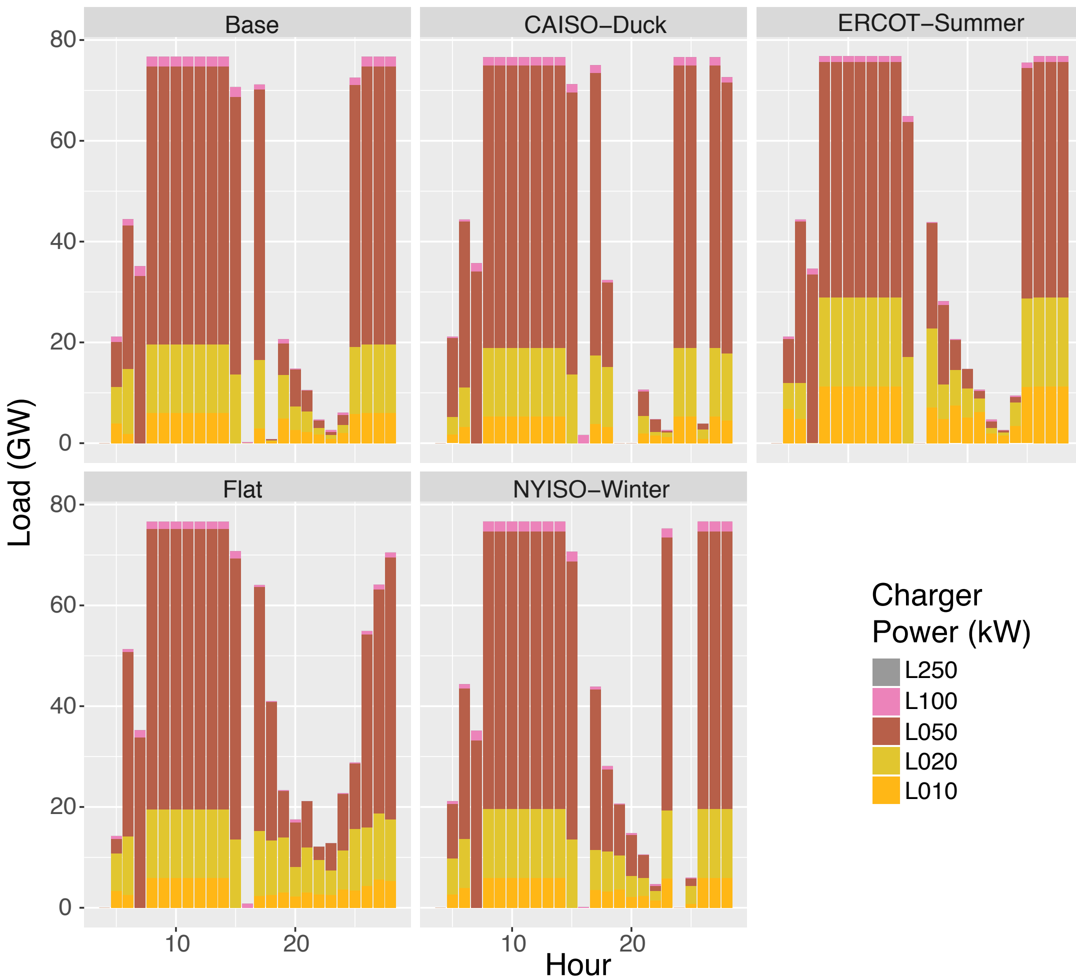

Figure 7.13: Resulting charging profile of national fleet by power capacity for various price assumptions.

The following tasks and model improvements remain for future research:

- Increase the number of days simulated to capture day to day and seasonal variability.
- Conduct further sensitivity analysis around regionally distinct pricing scenarios.
- Couple the model to a regional scale model of power generation, simultaneously minimize the cost of the mobility system with the cost of generating power.
- Add temporal overheads associated with charging and vehicle maintenance.
- Model heterogeneous battery lifetimes based on simulated cycling.
- Include other forms of transportation electrification (personally owned and medium/heavy duty vehicles).

- Investigate heterogeneous sharing and include in the model.
- Investigate variability of urban form factor by trip distance and time of day.
- Investigate variation in the peak electricity demand over different days or seasons.

Chapter 8

Conclusion

In this dissertation, I have presented six studies that advance our understanding of the technical and economic potential for vehicle grid integration based on a variety of methodological approaches that quantify the opportunity at multiple scales, across multiple geographies, and that cover scenarios with both personally owned PEVs and shared autonomous PEVs.

I have developed an approach to use an agent-based model of PEV mobility and charging demand to optimize the siting of charging infrastructure. In this work we found that optimal distribution of chargers requires different levels (rates of charging) and a spatial distribution that closely matches travel demand.

By developing a scheme to represent PEV load flexibility in a manner that respects the time-varying importance of future mobility needs, I have demonstrated the value of charging flexibility based on historical pricing data in California and New York.

I then explored the economic value of load flexibility by coupling two detailed models of the transportation and electric power system. I show that coordinated charging with large penetrations of PEVs can reduce the incremental operating cost of the electric system by 50%.

I also show that there could be a viable business case for fleets of autonomous PEVs to use vehicle-to-grid technology to serve electric loads during power outages.

Finally, I demonstrate that if all mobility currently served by light duty vehicles were instead served by shared, autonomous electric vehicles, then the vehicle sharing and the inherent load flexibility in the fleet operations would result in only a 8.5% increase in U.S. electricity demand and 11% increase in peak power consumption.

Future Areas of Research

The domain of vehicle grid integration is still relatively new, there are many areas of research that require additional attention.

There has been some research on traveler behavior with regard to PEV charging [41, 147]. These studies use stated or revealed preference techniques to assess traveler utility with respect to the attributes of their preferred charger in a given context. But there is still a gap in understanding how people value the temporal dimension of having energy in their battery. It is self-evident that travelers require a minimum range in their vehicle plus some margin of safety to accomplish their planned trips each day. What is not clear is the extent to which travelers value additional energy in their battery to accommodate unexpected trips or unexpected timing of trips. It might be the case that people value the security of a full battery so much that the value of supplying load flexibility to the power system is too marginal to incentive regular participation. After all, to make use of PEV load flexibility, a system would necessarily need to delay the delivery of energy to traveler's batteries, thereby introducing uncertainty and insecurity into the lives of the travelers.

Another area of research that is not well understood is the interaction between the transportation sector and the distribution grid. All of the analysis in this dissertation explores how PEV load flexibility could mitigate operational challenges on the wholesale power market. But PEV charging, especially fast charging, is likely to first cause expensive problems on the electric grid in the distribution system. These problems are highly localized and therefore difficult to analyze at a scale sufficient to make pervasive conclusions. But the technical and economic consequences of these issues will likely become a major focus of research and policy development over the next decade.

Related to distribution infrastructure is another emerging technical domain, electrification of medium and heavy duty vehicles in the transportation sector. Electric bus fleets are rapidly converting to PEVs and the production of heavy duty electric trucks could begin to ramp up in the next two years. These vehicles will require very high power charging infrastructure, necessitating major upgrades to distribution grid infrastructure and likely will be coupled with on-site distributed generation and energy storage resources to mitigate the very high but intermittent power demands.

Finally, while we cover the topic of autonomous electrified fleets of on-demand mobility, these mobility service markets are currently composed almost entirely of human drivers. There are challenges to properly incentivize drivers to use PEVs and to provision adequate charging infrastructure to minimize downtime.

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