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Modeling plug-in electric vehicle charging demand with BEAM

The framework for behavior energy autonomy mobility

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1. Abstract

This report 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 preliminary 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.

2. Introduction and Context

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.

3. Methodology

3.1. 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.

3.2. 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.

3.2.1. 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 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 [1].

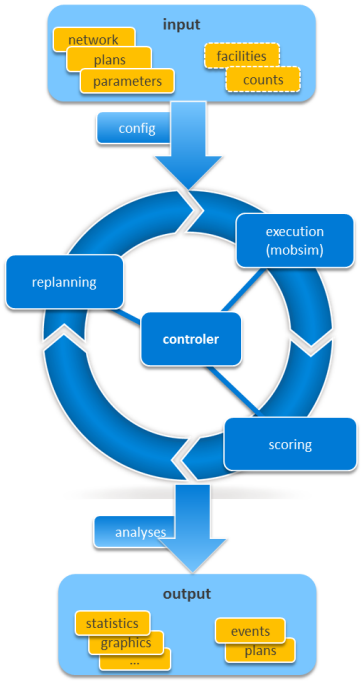

Figure 1: Process flow of the MATSim iterative simulation loop.

3.2.2. BEAM Extension to MATSim

BEAM leverages MATSim and extends some of its existing contributions related to plug-in electric vehicles (PEVs) [2] [3]. 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 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.

3.2.2.1. 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 1.

Table 1: Vehicle attributes in BEAM.

Attribute	Description
Vehicle Name	E.g. the make/model or generic vehicle class.
Electric Energy Consumption Model	See Section 3.2.2.2.
Petroleum Energy Consumption Model	For PHEVs. See Section 3.2.2.2.
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.

3.2.2.2. 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 [4] is shown in Figure 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.

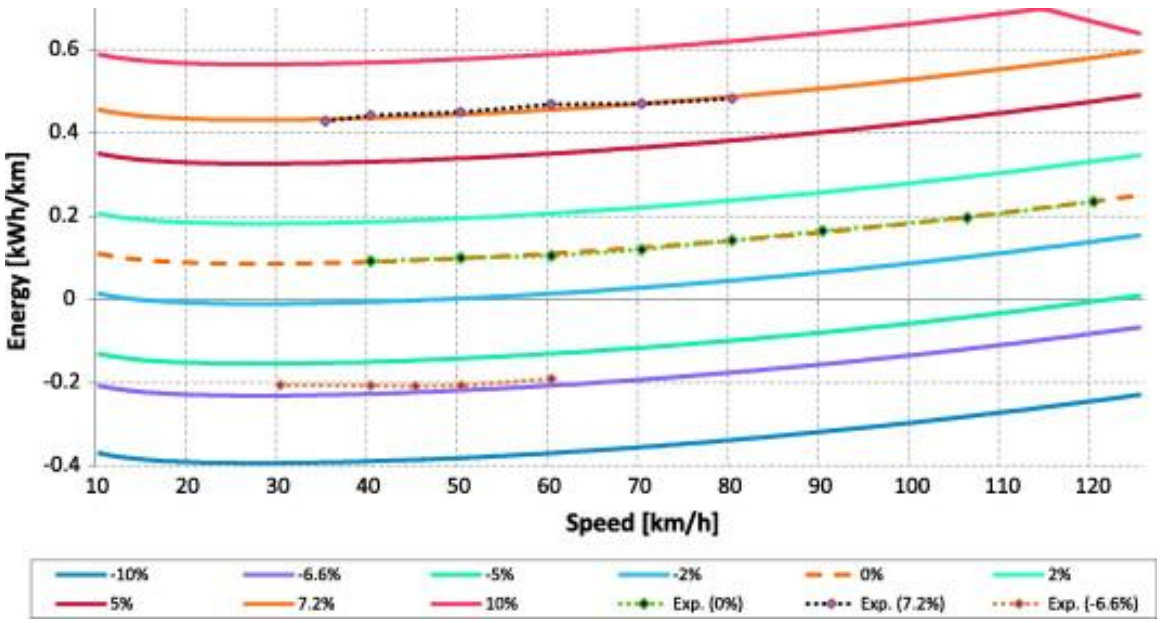

Figure 2: Figure reprinted from [4]: "Energy consumption per unit of distance required to maintain a constant speed for several degrees of inclination and experimental runs (Exp.) for 0%, 7.2% and −6.6%."

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.

3.2.2.3. 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 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).

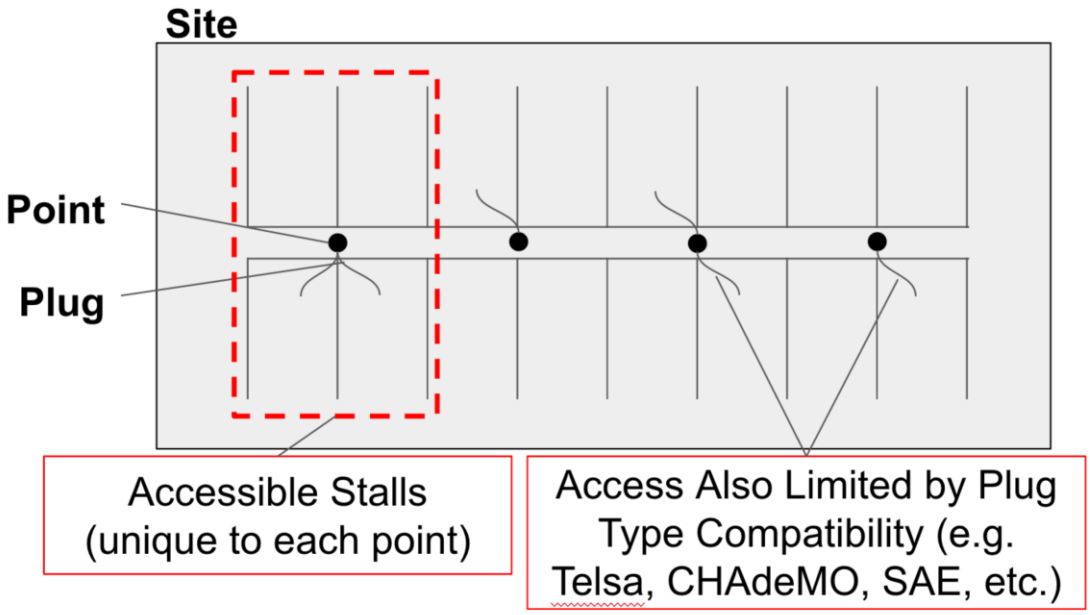

Figure 3: In BEAM, charging sites have multiple charging points which are accessible to limited parking spaces and can have multiple charging plugs of various types.

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.

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.

3.2.2.4. 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

Figure 4: States (dark blue), actions (yellow), and decisions (light blue) of agents in BEAM. 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.

3.2.2.5. 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. Some actions (such as "dequeue" and "end session") are scheduled by the charging infrastructure though they ultimately lead to actions by the agents. Table 2 provides a brief description of the logical flow associated with the actions and decisions in Figure 4.

A typical path through the states in diagram in Figure 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.

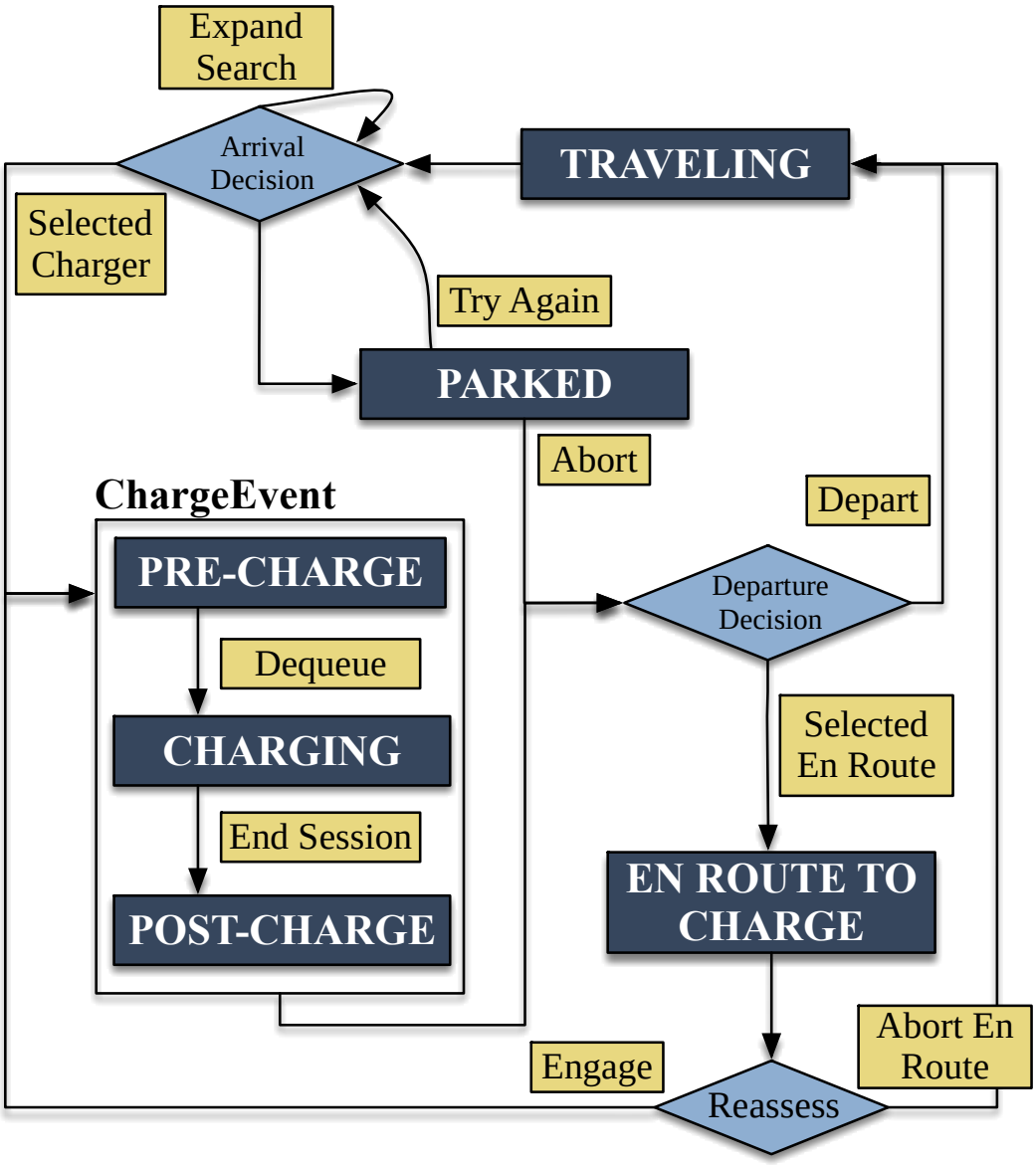

Figure 4: States (dark blue), actions (yellow), and decisions (light blue) of agents in BEAM.

Table 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 to *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 3.2.2.4). 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 3.2.2.4). 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.

3.2.2.6. 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 3.2.2 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 capacities, 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 and Table 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. To date, three decision models have been implemented in BEAM, which are described in Table 3.

Table 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 3.2.2.7.

3.2.2.7. 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 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 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.

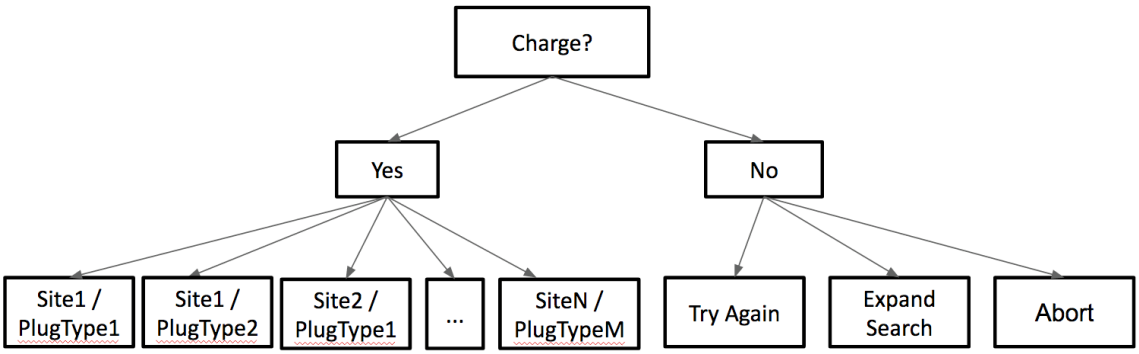

Figure 5: Structure of the arrival decision model in BEAM for deciding what site/level charger to select or – if charging is not chosen – what adaptation strategy to elect.

The nested logit model specification from [5] 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 $N_m$within that nest, is expressed as a multinomial logit formulation, i.e.:

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

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:

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

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 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. The coefficient values in Table 4 are the result of the calibration process described below in Section 5.2.

3.2.2.8. Charge/Discharge Control

As described in Section 3.2.2.3, 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: 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. 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.

4.1. 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.

4.2. Urban Mobility

Based on work by [6] and [1], 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 ~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 [7] 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.

4.3. 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 [8] (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 6.

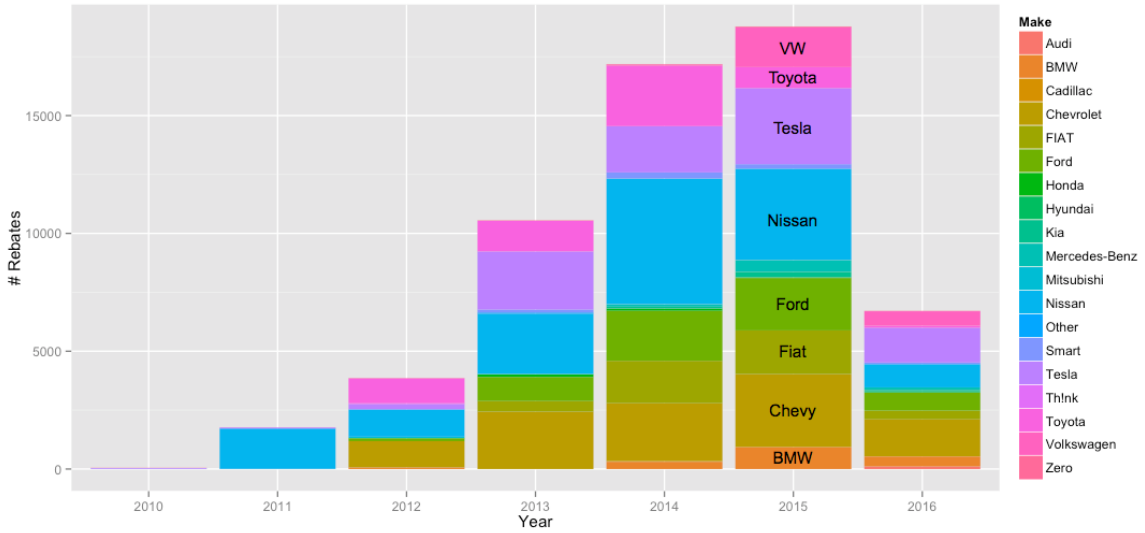

Figure 6: Rebates claimed in the San Francisco Bay Area as mid-2016 by vehicle make and year (data from California Clean Vehicle Rebate Project).

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 [9], which can be used with BEAM.

The vehicle attributes are summarized in Table 5. The source for these data were a combination of resources from OEM model specifications and the U.S. DOE fuel economy website [10]. The electric energy consumption models for all PEVS are based on the work of [4]. 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 5.

Table 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	

4.4. 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 6 and Table 7 list attributes and market penetration of charger types and network operators. Figure 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 [11], 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 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 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

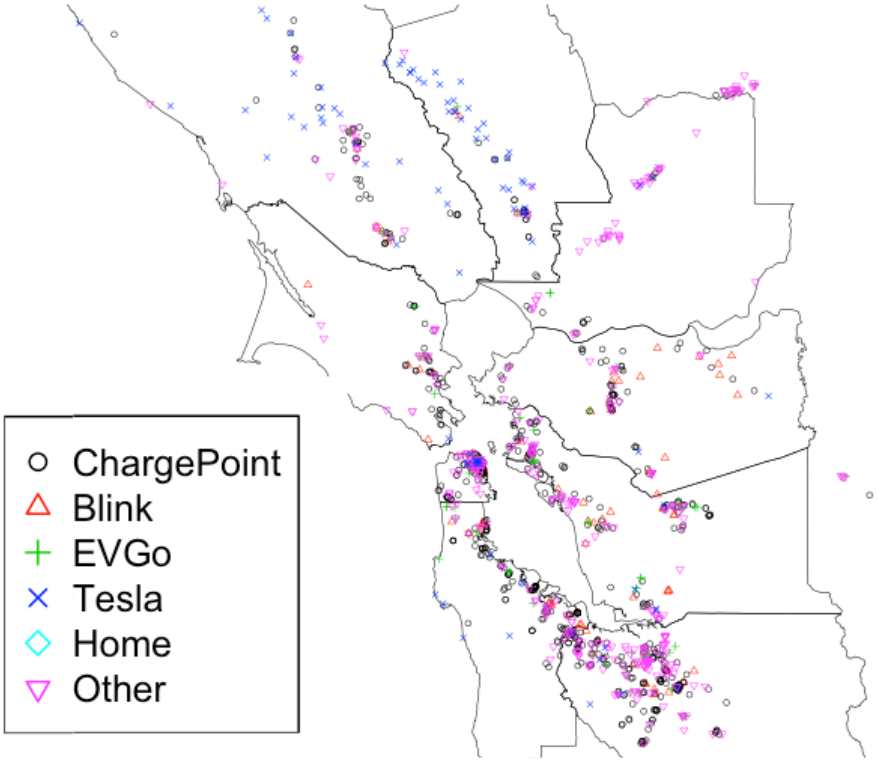

Figure 7: Charging Infrastructure in the San Francisco Bay Area as of mid-2016 according to data from the Alternative Fuels Data Center.

4.5. 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 8 and Figure 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 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.

5. Results and Analysis

5.1. 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 10 and Figure 11, we show the temporal distribution of trip departures in the mobility data disaggregated by activity type. In Figure 10, the activity types refer to the activity being completed at the time of departure while in Figure 11 the types refer to the destination activity. In Figure 12 we show the distribution of travel distances in the Bay Area application, both by individual trip and by total travel distance each day.

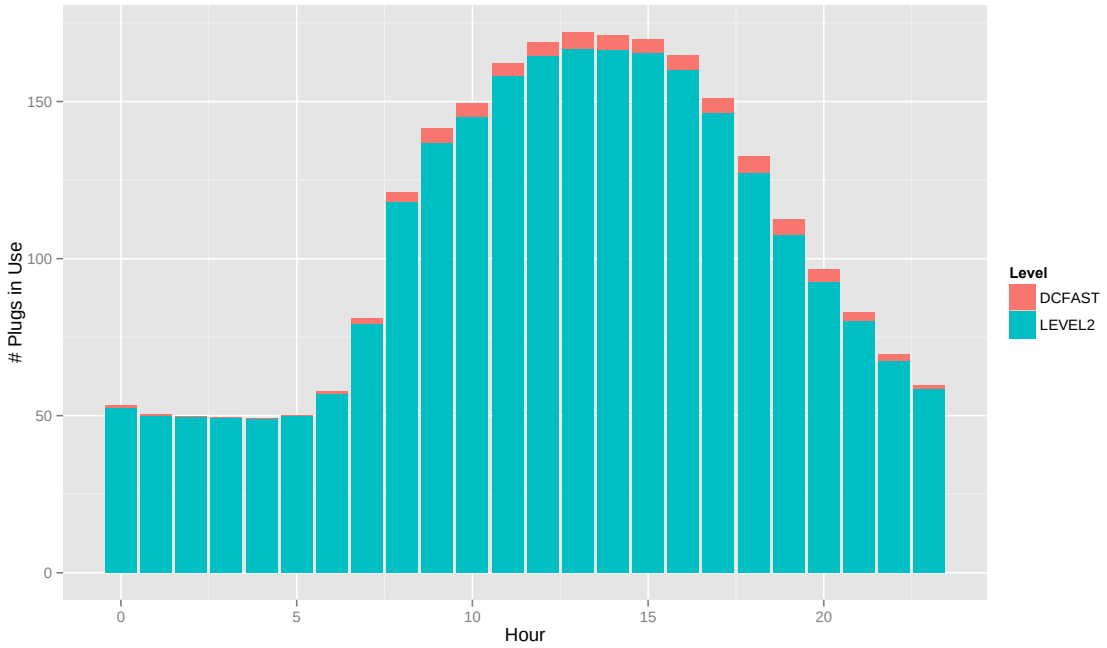

Figure 8: Observed utilization of chargers on a weekday aggregated across San Francisco Bay Area.

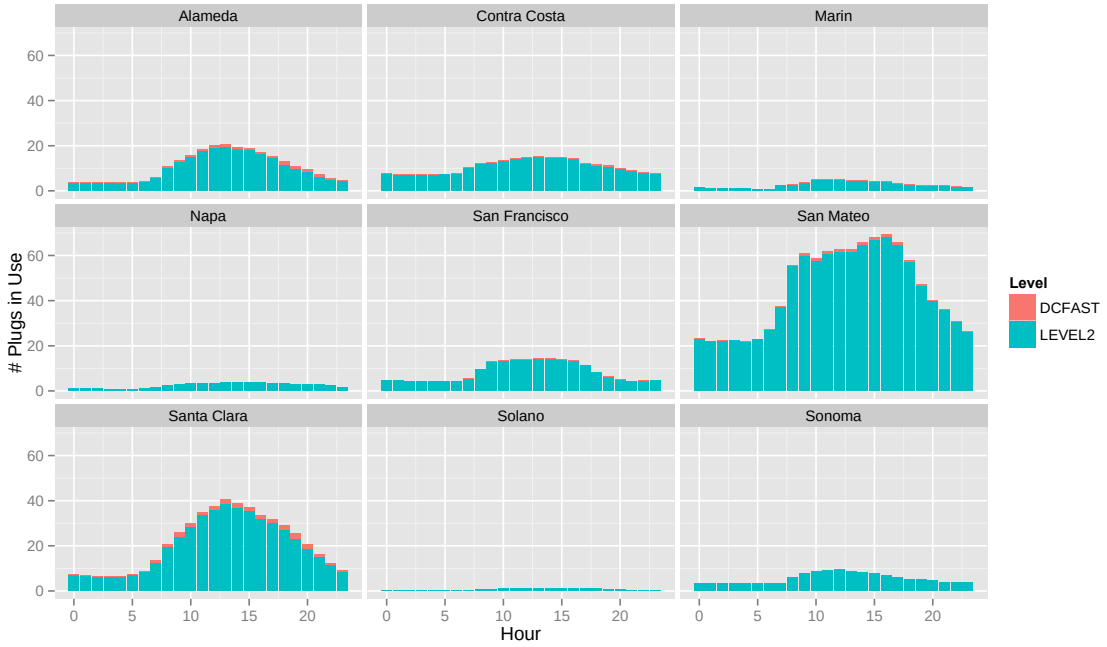

Figure 9: Observed utilization of chargers on a weekday by county across San Francisco Bay Area.

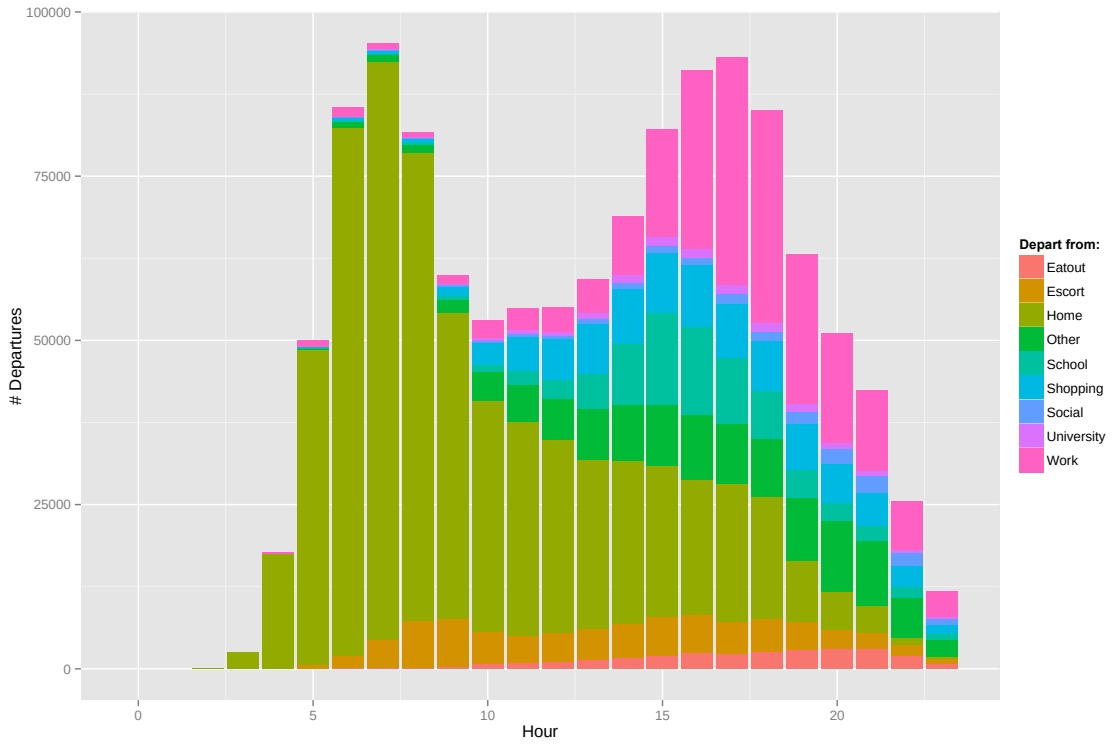

Figure 10: Departure times in San Francisco Bay Area application of BEAM by type of activity from which the agent is leaving.

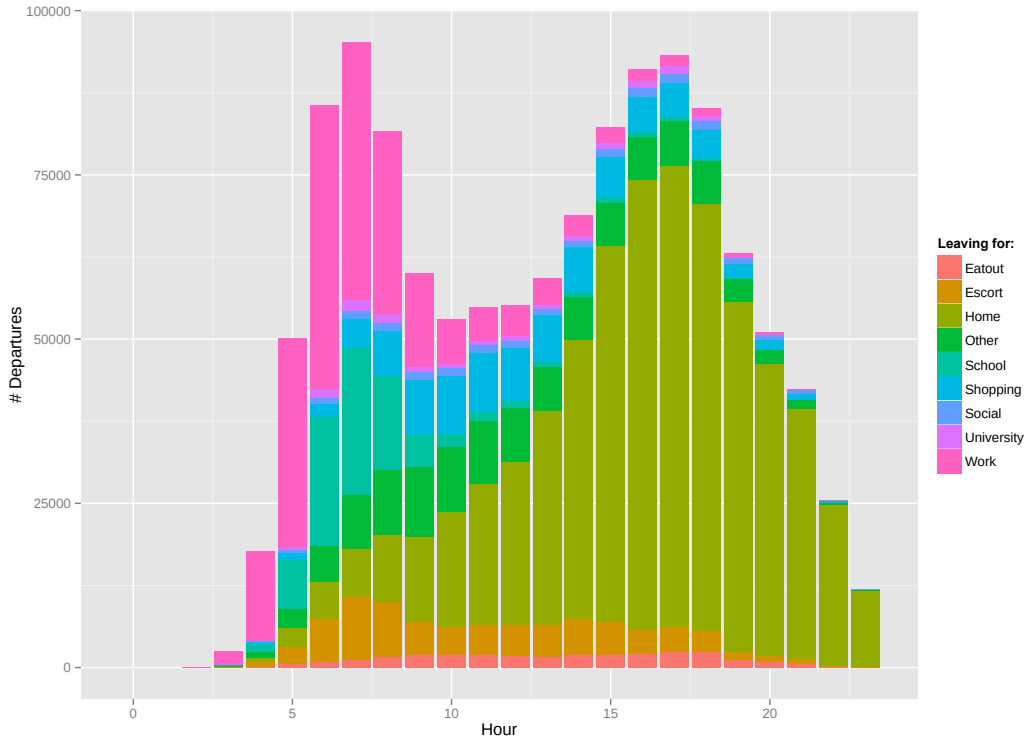

Figure 11: Departure times in San Francisco Bay Area application of BEAM by type of activity to which the agent is going.

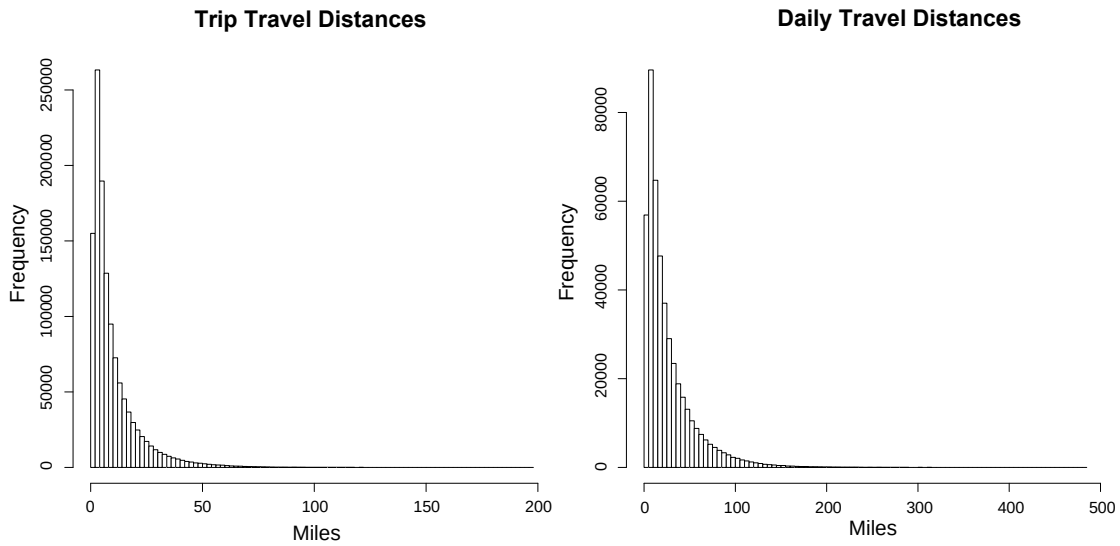

Figure 12: Distribution of travel distances in Bay Area application of BEAM.

5.2. 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 choice modeling in the literature. We took advantage of the work of [12] [13] and [14] to choose an initial set of parameter values that approximate the tradeoffs between the attributes of the chargers and agents in Table 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 [12], 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 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 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).

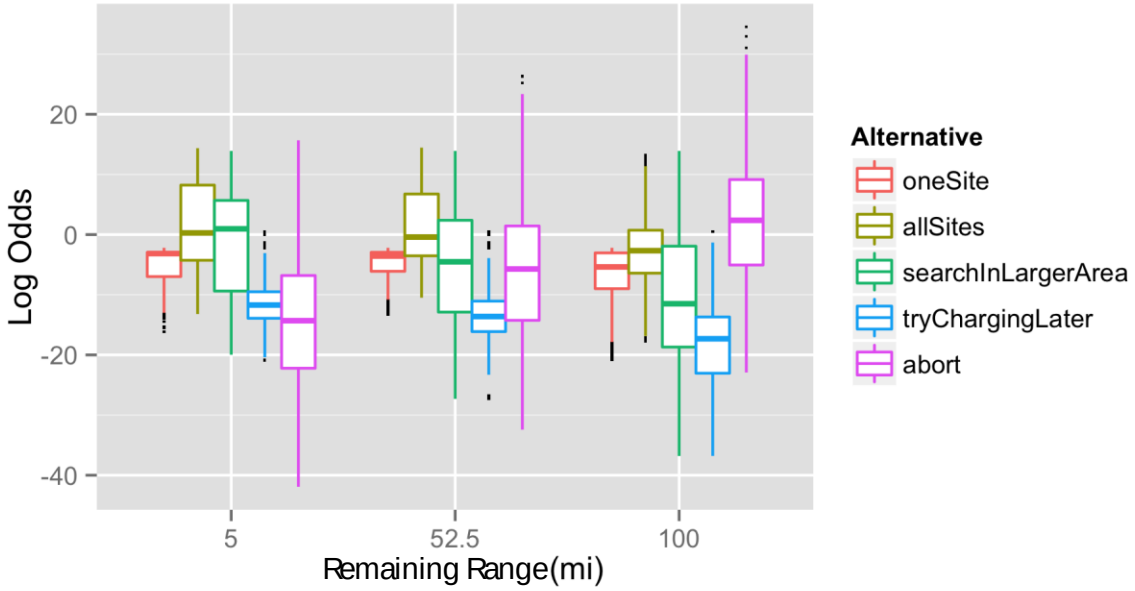

Figure 13: Log odds of five alternatives from a nested logit model with preliminary parameters across a wide range of charger and situational attributes. The situational attribute "remaining range" is varied along the x-axis. The box plots represent the distribution of log odds computed as all other model attributes are varied.

5.2.1. Aggregated Comparison of Simulated and Observed Charging Profiles

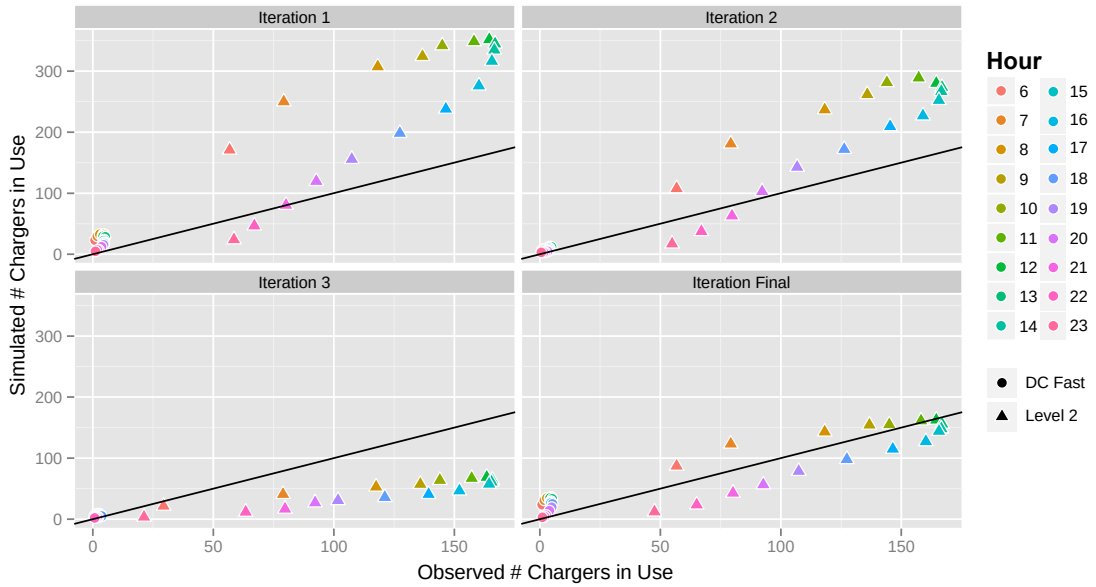

Figure 14: Simulated vs. observed charger utilization for four sets of parameter values in the nested logit decision model in BEAM. Each point represents a comparison of the number of public chargers in use by charger level and hour according to BEAM outputs versus observed from charging networks in the Bay Area in mid-2016.

The four parameter sets shown in Figure 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). 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 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.

5.2.2. Spatially Distributed Comparison of Simulated and Observed Charging Profiles

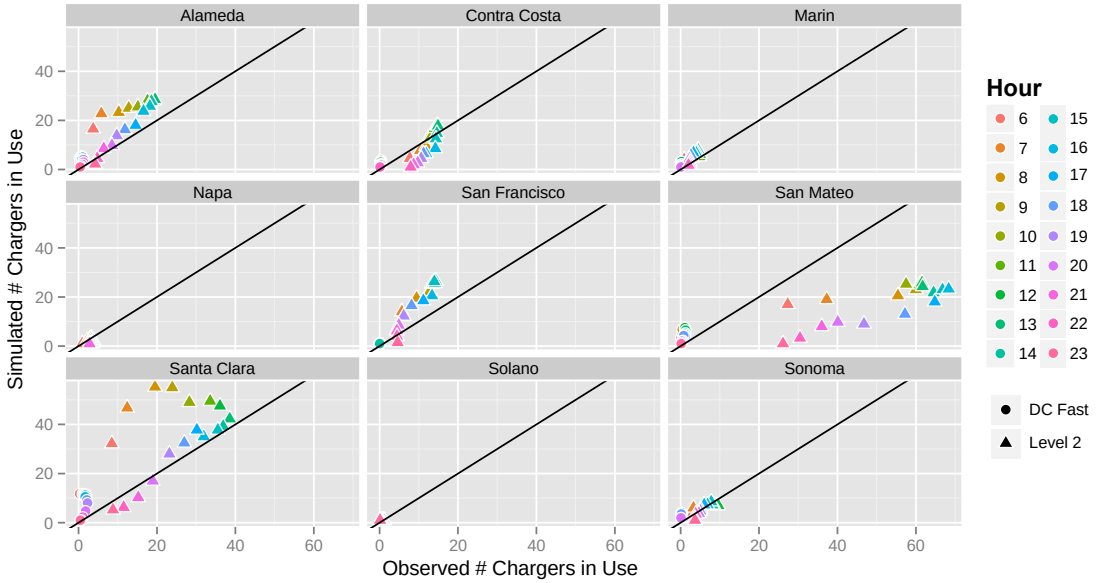

Figure 15: Simulated vs. observed charger utilization for the preliminary calibrated nested logit decision model by county in BEAM. Each point represents a comparison of the number of public chargers in use by charger level and hour according to BEAM outputs versus observed from charging networks in the Bay Area in mid-2016.

5.3. PEV Charging Behavior

Based on the models of decision-making described in Section 3.2.2.6, Table 3, including the preliminarily calibrated nested choice model, we conducted some preliminary analysis with BEAM to illustrate the value of simulating regional mobility and charging behavior with such a detailed, agent-based, spatially explicit approach.

5.3.1. 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 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.

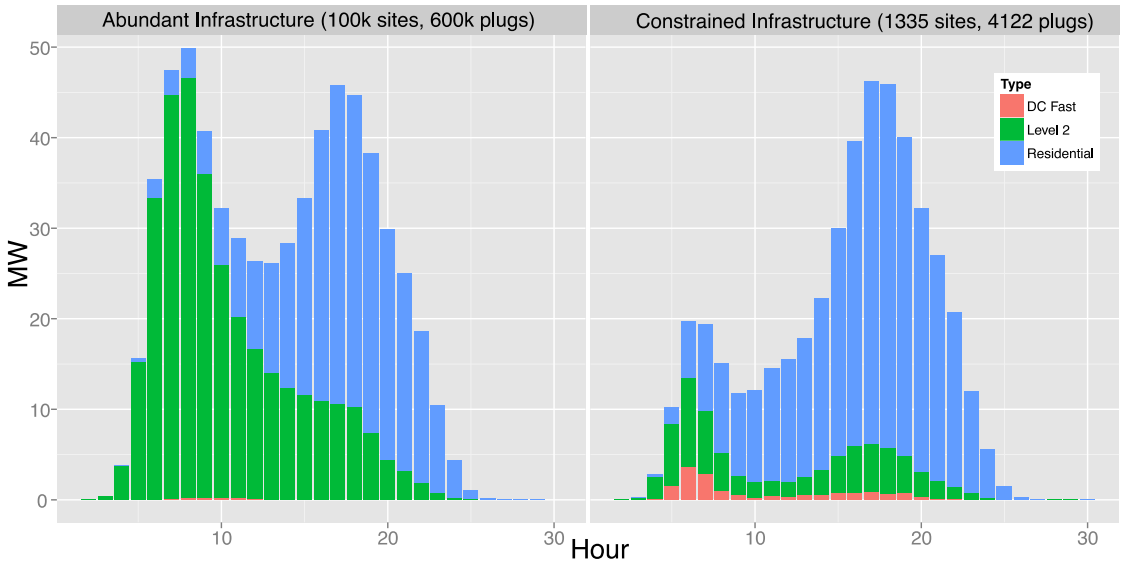

Figure 16: Instantaneous charging demand for PEVs in the Bay Area under a scenario with abundant and constrained charging infrastructure. Demand is disaggregated by charger type (Level 2, DC Fast, or residential). The charging decision model used is "Always Charge on Arrival."

5.3.2. 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 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 17 were produced from the same model run as the "constrained" scenario in Figure 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 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.

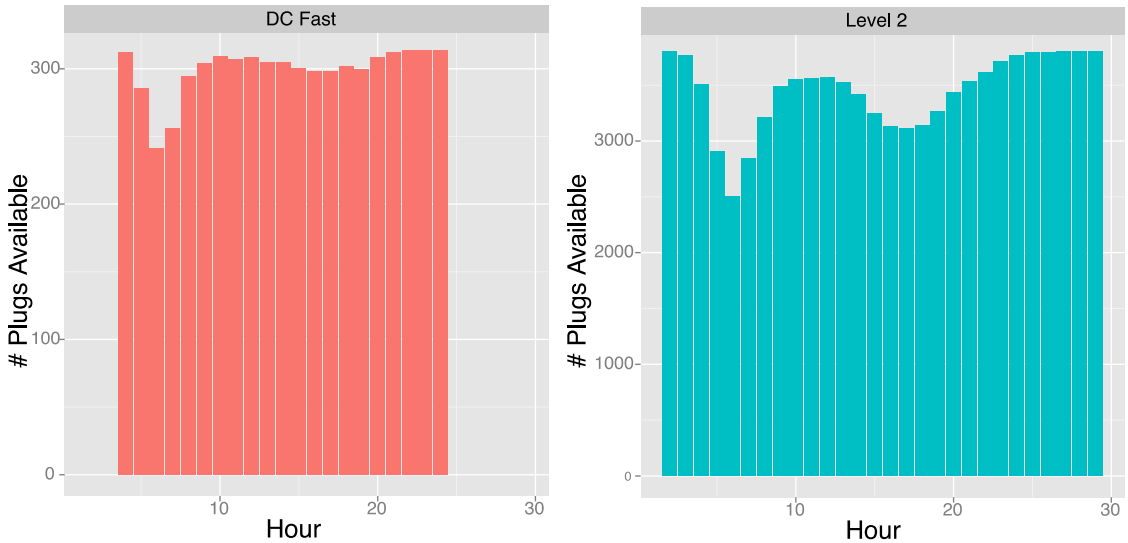

Figure 17: Plug availability for the baseline Bay Area BEAM scenario with the "Always Charge on Arrival" decision model. Here, availability is defined as plugs that are not actively charging any vehicle and are accessible by empty parking spaces, though they could be plugged into a vehicle.

5.3.3. Impact of Alternative Models of Charging Decisions on Charging Profiles

Finally, in Figure 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 6.3, 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.

6. Remaining Research Gaps

6.1. 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

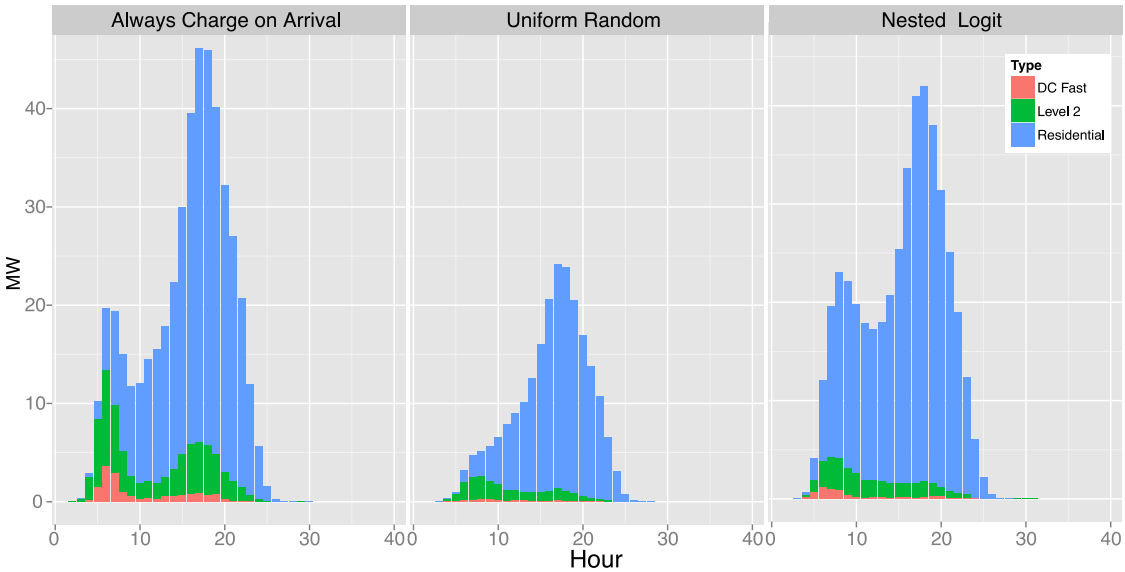

Figure 18: Instantaneous charging demand for PEVs in the Bay Area under the baseline infrastructure scenario and three different models of charging decisions. Demand is disaggregated by charger type (Level 2, DC Fast, or residential).

defined.

6.2. Additional Calibration Work

As described in Section 5.2, 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 4.3, 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 [11] or through data licensing with OEMs.

6.3. 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.

6.3.1. The Computational Challenge

As explored in [15] and [16], 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.

6.3.2. 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 [17], 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 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 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 20, we show the spatial distribution of charger need (in red) and the corresponding result of sampling 500 charging sites from the spatial distribution.

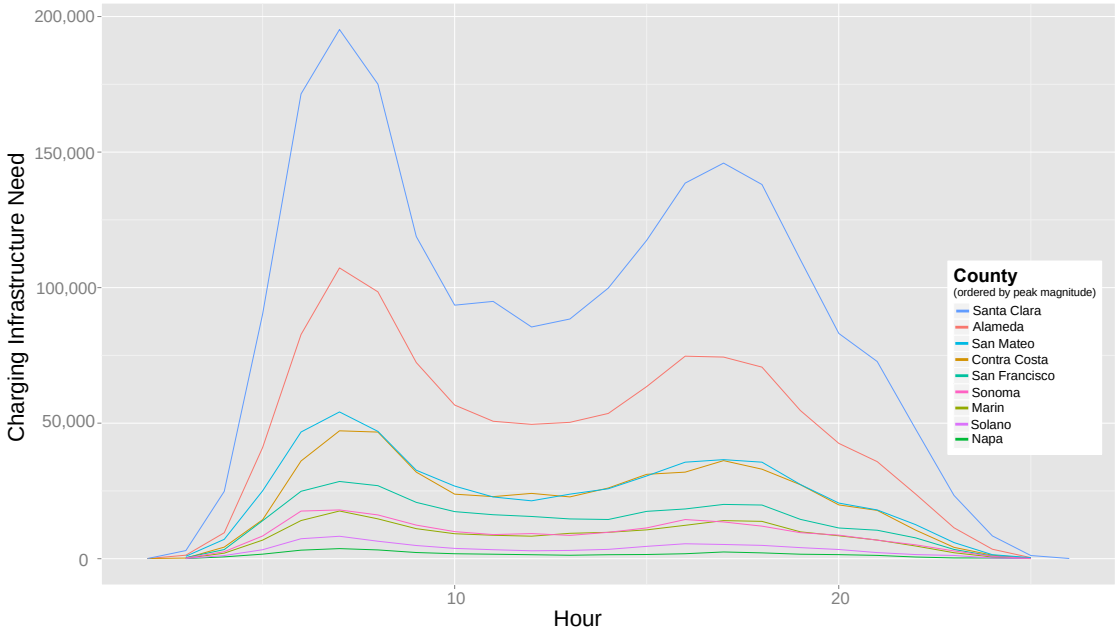

Figure 19: Charging infrastructure need by hour of day and county.

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

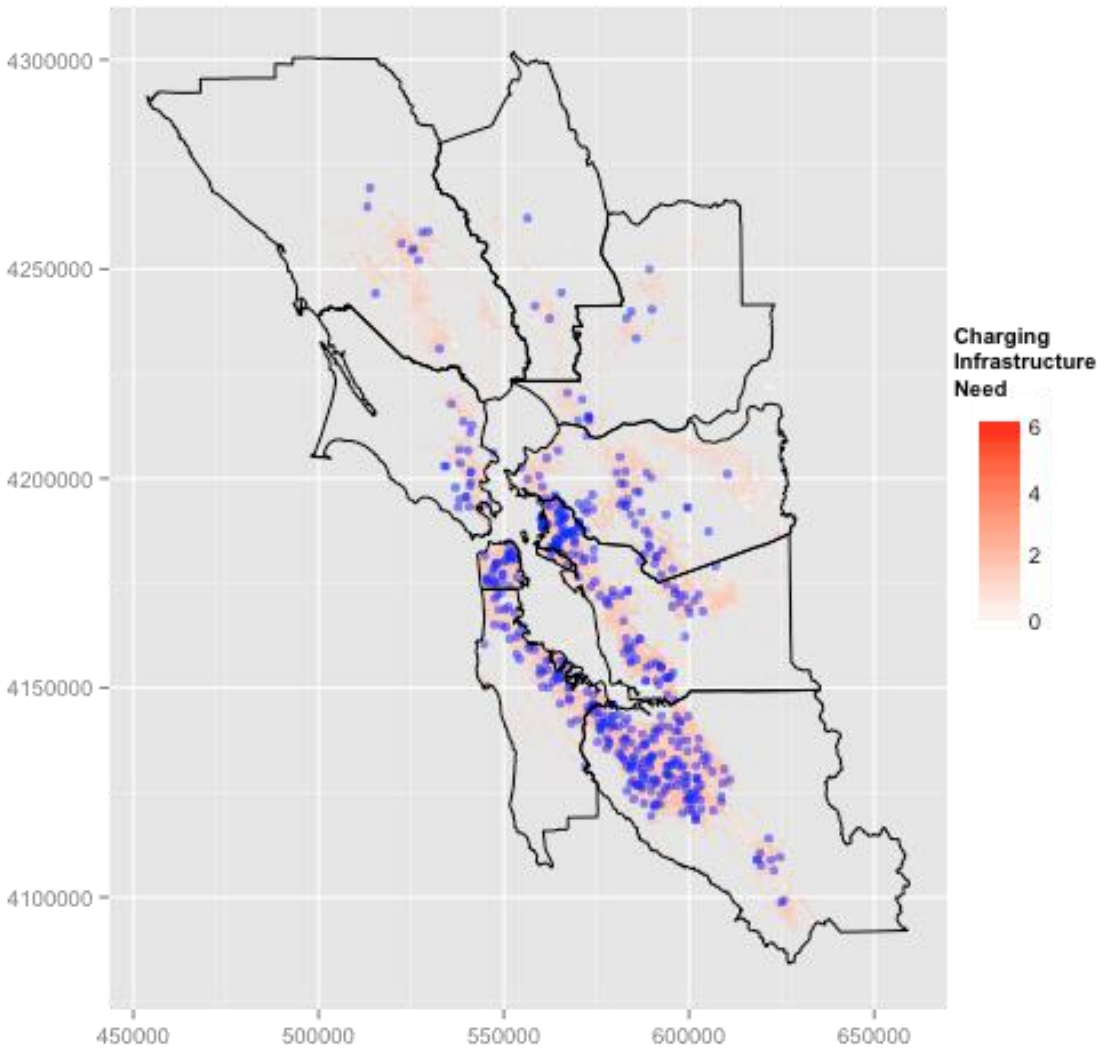

Figure 20: Example of siting 500 charging sites (blue circles) in road network by sampling from a probability distribution based on link by link infrastructure need.

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.

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