Modeling Plug-in Electric Vehicle Charging Demand with BEAM:

the framework for Behavior Energy Autonomy and Mobility

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Contents

Introduction

- The benefits of 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 of plug-in electric vehicles (PEV) 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.
- 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.

Methodology

- Agent-Based Integrated Systems Modeling
  - Agent-based models are conceptually simple.
  - Individual actions of agents can be defined with a combination of technical familiarity and common sense.
  - The emergent outcomes of agent-based models are complex.
  - Through the process of interpreting the emergent outcomes, agent-based models can inspire insight into system dynamics that challenge intuition and preconceived notions.

Methodology

- The BEAM Framework
  - BEAM is an extension of MATSim.
  - MATSim – Multi-Agent Transportation Simulation which features:
    - High fidelity simulations: explicitly representing individuals and their interactions with detailed models of infrastructure
    - Captures the emergent outcomes of self-interested participants in a market
    - Agents maximize personal utility through iterative execution of the mobility simulation, followed by scoring of the each agent’s experience and then replanning their day to improve the score

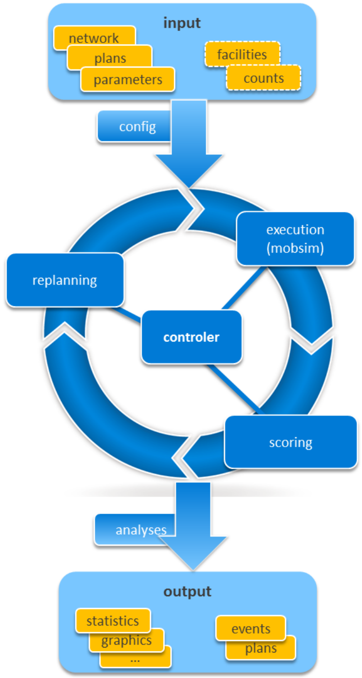


Figure 1: Process flow of the MATSim iterative simulation loop.

Methodology

- The BEAM Framework (cont.)
  - BEAM extension to MATSim.
    - PEVs are now represented in MATSim, including key vehicle characteristics and energy consumption models
    - Utility associated with charging is combined with MATSim utility for mobility
    - Charging infrastructure is explicitly modeled including physical access to plugs from parking spaces and queuing systems to manage order of sessions
    - Agents are modeled as finite state machines, model actions are dispatched as events in a discrete event simulation engine

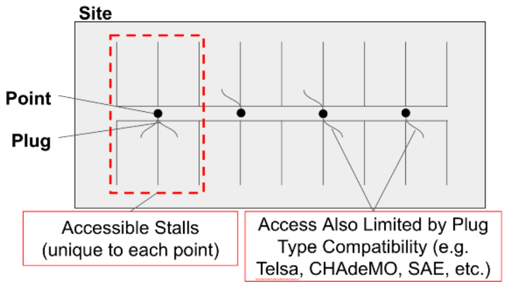


Figure 3: In BEAM, charging sites have multiple charging points which are accessible to limited parking spaces and can have multiple charging plugs of various types.

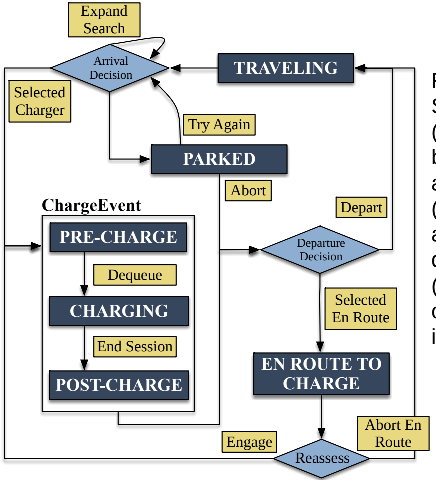


Figure 4: States (dark blue), actions (yellow), and decisions (light blue) of agents in BEAM.

Methodology

- The BEAM Framework (cont.)
  - BEAM extension to MATSim.
    - A flexible framework for modeling the decision on whether to charge at a given location is used to simulate alternative choice models including an “always charge” heuristic, a simple random decision, and a nested logit discrete choice model
    - The nested logit choice model includes a detailed utility function that balances the tradeoffs between time, expense, and convenience of choice alternatives

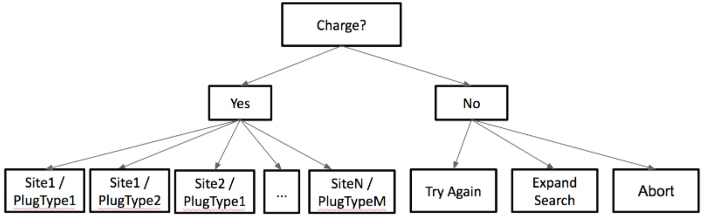


Figure 5: Structure of the arrival decision model in BEAM for deciding what site/level charger to select or – if charging is not chosen – what adaptation strategy to elect.

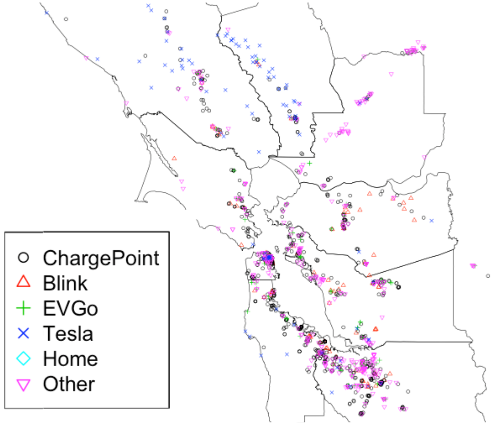
Table 4: Excerpt of the utility function attributes and coefficients in the calibrated nested logit model in BEAM.

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
...	...	...	...	...

Model Application

- Model is applied to the San Francisco Bay Area
- Mobility data are derived from the Metropolitan Transportation Commission's activity-based travel demand model
- PEV ownership is based on California Clean Vehicle Rebate Project data
- Charging infrastructure is derived from the U.S. DOE Alternative Fuels Data Center

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



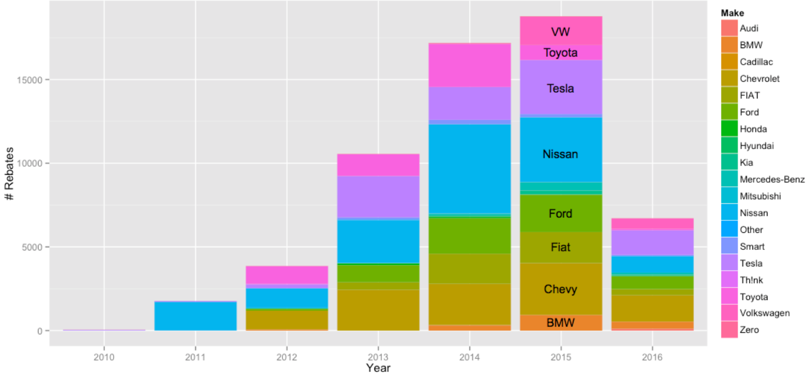


Figure 6: Rebates claimed in the San Francisco Bay Area as mid-2016 by vehicle make and year (data from California Clean Vehicle Rebate Project).

Model Application

- Observed charger utilization is developed by sampling from public APIs of charger availability online.

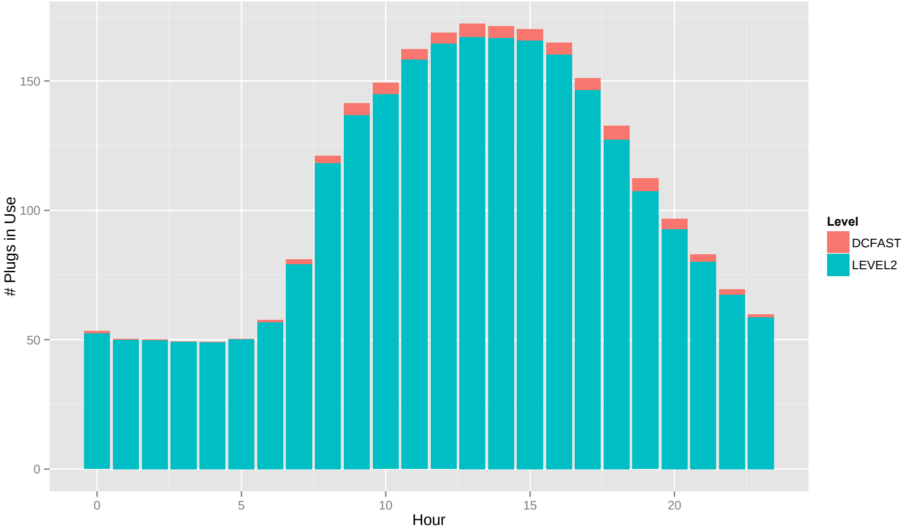


Figure 8: Observed utilization of chargers on a weekday aggregated across San Francisco Bay Area.

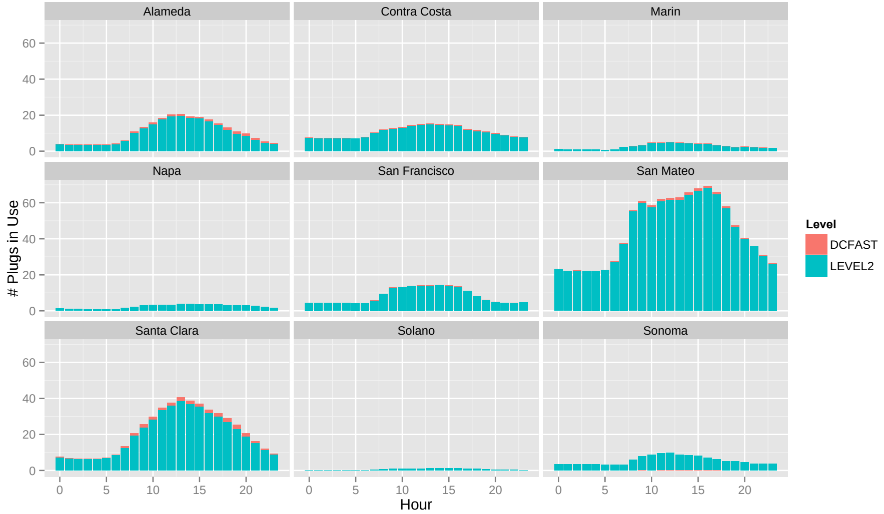


Figure 9: Observed utilization of chargers on a weekday by county across San Francisco Bay Area.

Results and Analysis

- PEV Trip Demand

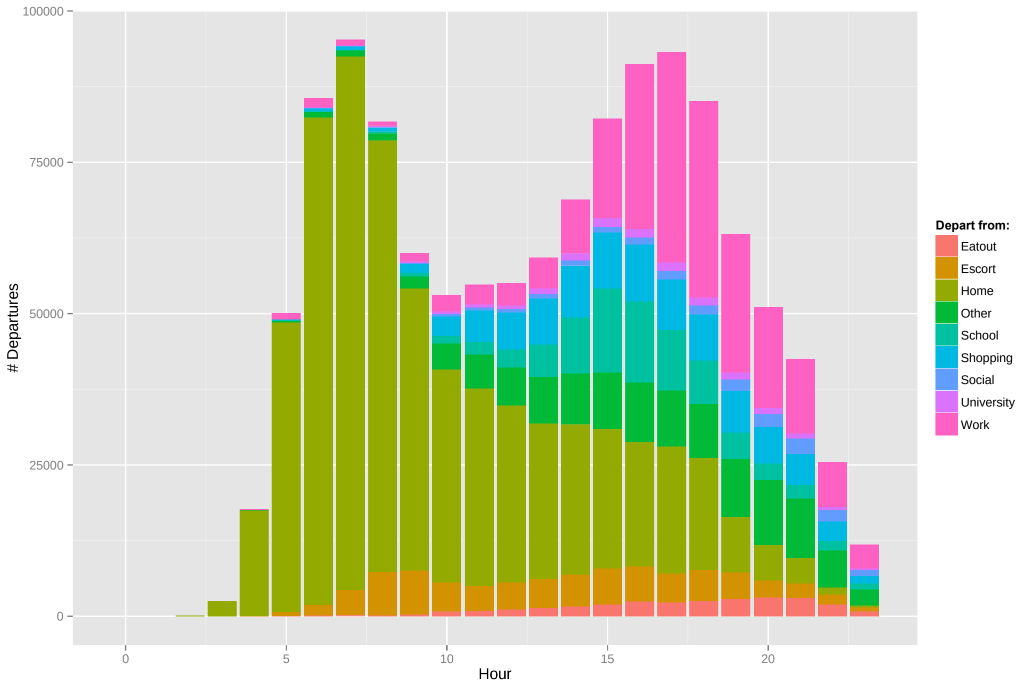
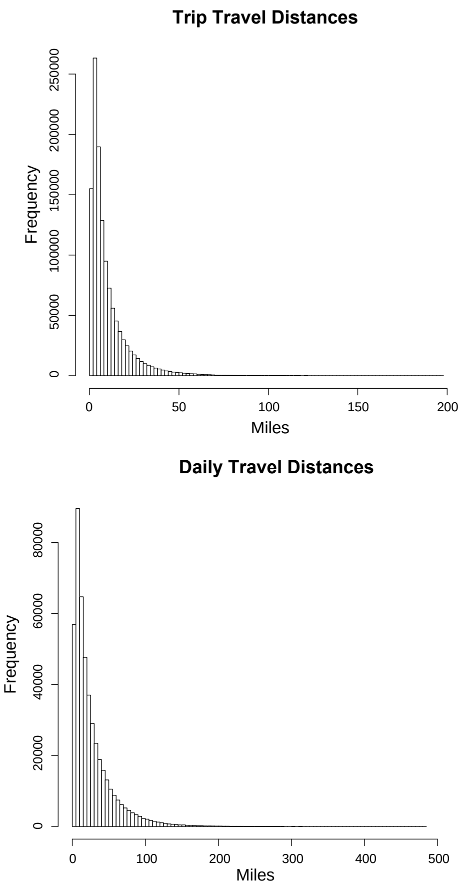


Figure 10: Departure times in San Francisco Bay Area application of BEAM by type of activity from which the agent is leaving.

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



Results and Analysis

- Preliminary Model Calibration and Validation
  - Gross probabilities of the choice alternatives were initially based on literature review and on the judgment of our modeling team
  - Then we engaged in an empirical calibration of the Bay Area BEAM model by comparing simulated charging profiles to observed patterns

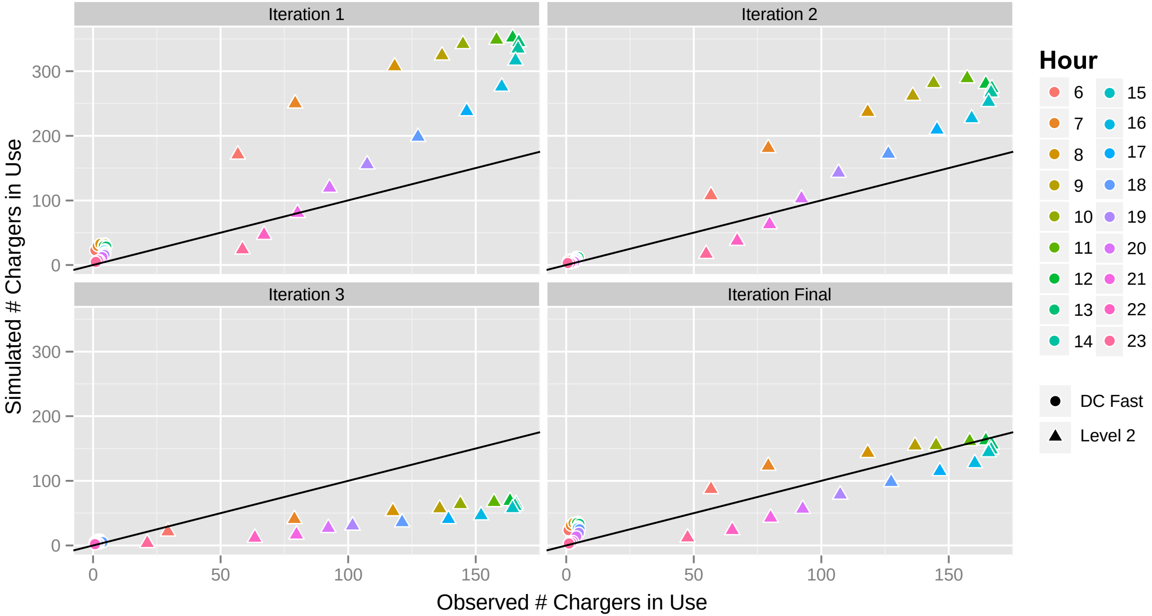


Figure 14: Simulated vs. observed charger utilization for four sets of parameter values in the nested logit decision model in BEAM. Each point represents a comparison of the number of public chargers in use by charger level and hour according to BEAM outputs versus observed from charging networks in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

Results and Analysis

- Impact of Constrained Infrastructure on Charging Profiles
  - One common modeling simplification is to ignore the fact that charging infrastructure in the public sphere is constrained
  - We tested the impact of this simplifying assumption
  - There is a dramatic difference in the charging profile of the agents when infrastructure is abundant versus constrained
  - CONCLUSION: 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.

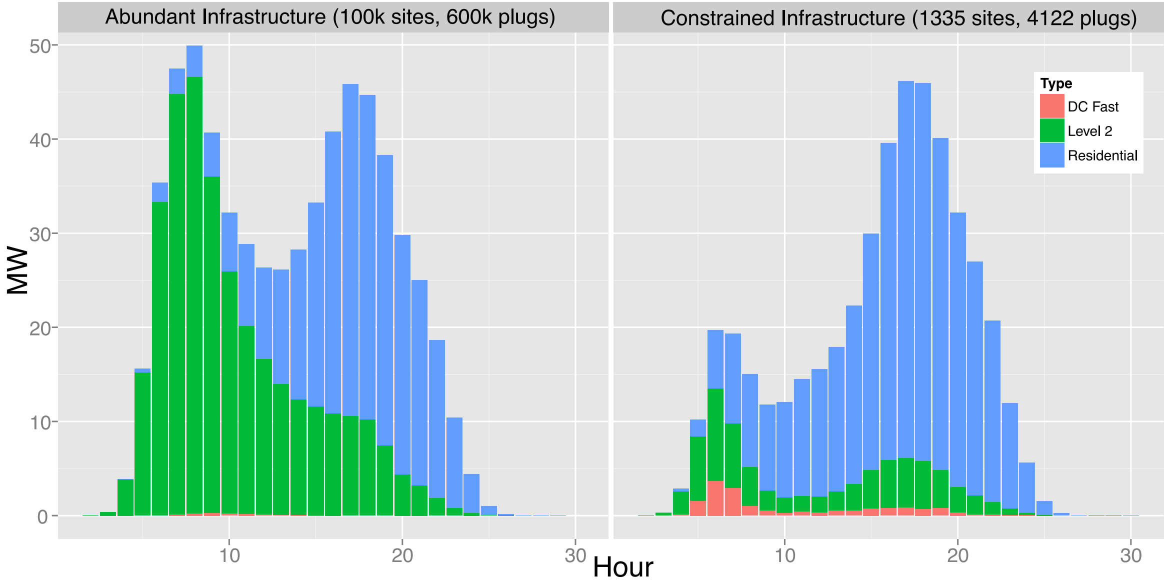


Figure 16: Instantaneous charging demand for PEVs in the Bay Area under a scenario with abundant and constrained charging infrastructure. Demand is disaggregated by charger type (Level 2, DC Fast, or residential). The charging decision model used is “Always Charge on Arrival.”

Results and Analysis

- Impact of Spatially Dispersed Charging Infrastructure on Charging Profiles
  - A common modeling simplification is to ignore spatial dimensions.
  - But under constrained charging conditions and an “Always Charge on Arrival” choice strategy, we see that many plugs remain available.
  - These plugs are not in use despite the fact that our previous analysis established that there is unfulfilled demand for charging.
  - CONCLUSION: chargers are spatially sparse and are only cover a fraction of the sites within 2 km of agent activities.

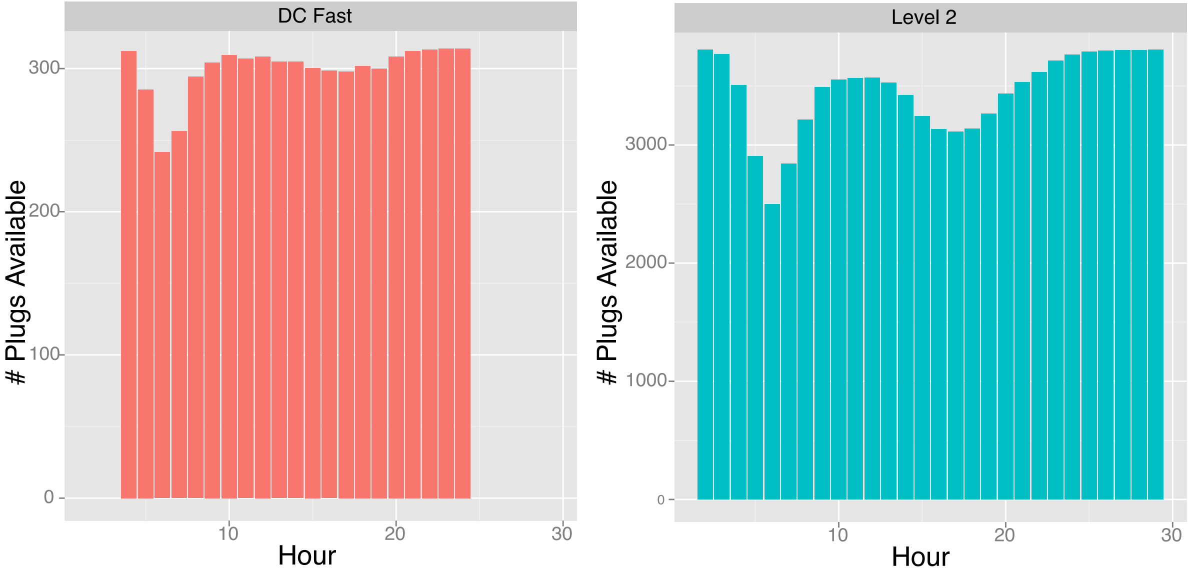


Figure 17: Plug availability for the baseline Bay Area BEAM scenario with the “Always Charge on Arrival” decision model. Here, availability is defined as plugs that are not actively charging any vehicle and are accessible by empty parking spaces, though they could be plugged into a vehicle.

Results and Analysis

- Impact of Alternative Models of Charging Decisions on Charging Profiles
  - There is a clear difference in the charging profile of the agents when different choice models are used
  - CONCLUSION: modeling driver behavior is critical to reproducing observed charging profiles.

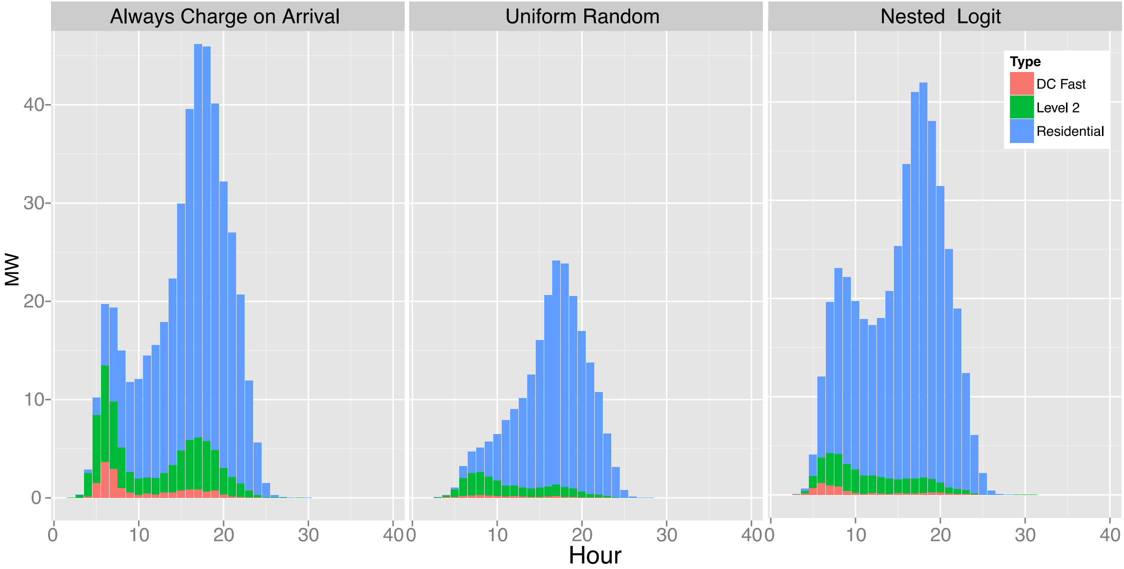


Figure 18: Instantaneous charging demand for PEVs in the Bay Area under the baseline infrastructure scenario and three different models of charging decisions. Demand is disaggregated by charger type (Level 2, DC Fast, or residential).

Remaining Research Gaps

- Develop a method of incorporating this work into the BaSce analysis
  - Once BEAM is integrated with the PLEXOS production cost model, it can be used to refine estimates of the benefits and costs that accrue to the power system in the BaSce analysis
- Additional Calibration Work
  - Using improved sources of data, LBNL could re-calibrate the nested logit choice model using more sophisticated calibration algorithms
- Apply Newly Conceived Charging Infrastructure Siting Methodology
  - The utility functions evaluated by agents throughout the simulation provide an ideal and novel metric for infrastructure adequacy in space and time. Based on these data, a metric for need can be derived and used to spatially distribute new chargers in proportion to their need.

Conclusions

- 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
- Spatially explicit modeling of charging infrastructure is critical due to the relatively sparse distribution of chargers in urban networks
- Drivers balance tradeoffs with regards to time, cost, convenience, and range anxiety when deciding about whether to charge
- Simulating discrete choices improves modeling accuracy and can provide a useful metric for siting new charging infrastructure

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