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List of Acronyms

AFDC	Alternative Fuels Data Center
BEV	battery electric vehicle
BEVxx	battery electric vehicle with a range of xx miles
DCFC	direct current fast charge
DOE	U.S. Department of Energy
EV	electric vehicle
EVI-Pro	Electric Vehicle Infrastructure Projection Tool
eVMT	electric vehicle miles traveled
EVSE	electric vehicle supply equipment
IHS	IHS Automotive (formerly Polk)
kW	kilowatt
L1	level 1 charger
L2	level 2 charger
MTS	Massachusetts Travel Survey
MUD	multiple-unit dwelling
NHTS	National Household Travel Survey
NREL	National Renewable Energy Laboratory
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
PHEVxx	plug-in hybrid electric vehicle with a range of xx miles
SUD	single-unit dwelling
VMT	vehicle miles travelled

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1 Introduction

This analysis of regional plug-in electric vehicle (PEV) infrastructure was conducted to provide guidance on charging infrastructure for PEVs to regional stakeholders through the U.S. Department of Energy's (DOE's) Vehicle Technologies Office.

1.1 Background and Study Objective

Given the complex issues associated with PEV charging and options in deploying charging infrastructure, there is interest in exploring scenarios of future charging infrastructure deployment to provide insight and guidance to national and regional stakeholders.

The complexity and cost of PEV charging infrastructure pose challenges to decision makers, including individuals, communities, and companies considering infrastructure installations. The value of PEVs to consumers and fleet operators can be increased with well-planned and cost-effective deployment of charging infrastructure. This will increase the number of miles driven electrically and accelerate PEV market penetration, increasing the shared value of charging networks to an expanding consumer base. Given these complexities and challenges, the objective of the present study is to provide additional insight into the role of charging infrastructure in accelerating PEV market growth.

To that end, existing studies on PEV infrastructure are summarized in a literature review. Next an analysis of current markets is conducted with a focus on correlations between PEV adoption and public charging availability. A forward looking case study is then conducted focused on supporting 300,000 PEVs by 2025 in Massachusetts. The report concludes with a discussion of potential methodology for estimating economic impacts of PEV infrastructure growth.

1.2 Literature Review

A literature review was conducted to assess state of the art techniques in the areas of estimating target EVSE densities for supporting PEV sales goals and siting individual charging stations to maximize utilization.

The Electric Power Research Institute (EPRI, 2014) established guidelines for PEV infrastructure planning using their Red Line/Blue Line model. This model applies a "benefits test" to estimate value of secondary (non-residential) charging events. Consumer vehicle travel is modeled using the 2009 National Household Travel Survey (NHTS). EPRI analysis finds secondary infrastructure requirements to be relatively low for the majority of consumers. Estimated need for direct current fast charging (DCFC) is especially low, on the order of 5 stations per 1,000 BEV100s. Multi-headed charging units are advocated as a means of increasing charger utilization and decreasing total infrastructure requirements.

Xi et al. (2013) used a linear integer program to simulate the number of level 1 (L1) and level 2 (L2) charging stations required at work and public locations, aiming to maximize either the number of electric vehicles (EVs) charged or the energy throughput from the chargers, assuming a budget constraint. Using 2010 Mid-Ohio Regional Planning Commission dataset along with an EV adoption probability, they predicted EV travel flows in Central Ohio as well as the number, type, and location of charging stations.

Zhang et al. (2013) modeled different L1 and L2 charging scenarios for both plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), assuming that EV users' charging behavior aims to minimize their cost. The input data were obtained from the 2009 NHTS for California (20,295 vehicles covering 83,500 trips), while time-of-use electricity rates from Pacific Gas and Electric were used. They showed that for PHEVs, charging time strategies reduce operating cost more significantly than charging availability (location). A 60-mile-range BEV would achieve 88% of its trips with 3.3-kilowatt (kW) home charging only and 96% with a combination of home, work, and public charging in the proportions of 80%, 9%, and 11%, respectively.

Dong et al. (2014) proposed an activity-based assessment for driving and charging behavior using genetic algorithm-based optimization. Varying budget constraints yields different proportions of each charger type (L1, L2, and DCFC). Their analysis of 2006 Puget Sound Regional Council household travel data showed that while very few trips exceed the typical BEV range, daily vehicle miles travelled (VMT) exceed it more often. Optimally located public chargers could effectively reduce range-constrained days and trips for BEV drivers. With no work or public charging, 10% of trips and 20% of VMT are missed. With a budget of $2,000 per EV to fund 150 L1 and 350 L2 chargers, missed trips are reduced to 2.5% and missed VMT to 12%.

Zhang et al. (2015) optimized direct current fast charging station allocation and temporal utilization to maximize electric VMT (eVMT) through a set-cover problem. A minimum of 290 charging locations were estimated based on analysis of the 2000 California Household Travel Survey. This network is shown to provide good coverage with 98% BEV trip feasibility covering 92% of VMT. Different charging scenarios were investigated: random and late charging will increase the grid demand in the afternoon, while early, cheap, and reserve strategies evenly distribute charging throughout the day. A charger reservation system can dramatically reduce the wait time and utilize all the stations more evenly.

Ahn and Yeo (2015) derived optimal public DCFC density by minimizing the total cost (the sum of additional trip cost, cost of delay time, and the installation and operating cost of charging stations) for a given unit area. The model was applied to study EV taxis (22-kW-hour battery, 90-mi. range) in Daejeon, South Korea, and generated a charging station density map of this urban area. An optimal allocation of density of 112 DCFC stations for 955 EVs was recommended.

Chen et al. (2013) developed a mixed-integer optimization program considering budget constraints (which limit the total number of charging stations to be deployed) and avoiding resource clustering (by specifying minimum station spacing). The data from the 2006 Puget Sound Regional Council Household Activity Survey were used to identify parking location by traffic analysis zone. Parking duration was then regressed to zone attributes (e.g., population and job density, parking prices, transit access, etc.) and trip attributes (work, shopping, recreation, etc.). The forecasted parking demand provided input to the mixed-integer optimization program, which strategically locates 80 public charging stations across 900 traffic analysis zones in the Seattle, Washington, region.

Guo and Zhao (2015) applied a Fuzzy-TOPSIS-based Multi-Criteria Decision Making (MCDM) method to the problem of electric vehicle supply equipment (EVSE) siting in Beijing. They first determined environmental, economic, and social criteria pertaining to EVSE and assigned weights to each subcriterion based on expert opinions. Fuzzy set theory was used to build a fuzzy decision matrix, accounting for uncertainty and subjectivity of criterion weights. The TOPSIS method measured the relative performance of each alternative location, considering various conflicting criteria. It offers a robust decision making framework for sustainable siting of EVSE.

Vazifeh et al. (2015) analyzed the movement patterns of individuals through cellphone data over a span of 4 months. Their data-driven optimization framework aimed to minimize the total distance travelled by drivers from the end of their intended trip to the closest available DCFC station. They built an energy demand model for EVs based on individual trip trajectories and an assumption for EV adoption rates. Two set cover algorithms, Chvatal's greedy approach and a Genetic Algorithm (GA) meta-heuristic search, were employed to approximate near-optimal DCFC locations in the Boston, Massachusetts, metropolitan area.

Yi and Bauer (2016) formulated an optimal energy-aware charging infrastructure placement framework. The population per ZIP code in South Bend, Indiana, and Chicago, Illinois, were used as inputs to a detailed EV energy consumption model based on their previous work. The route between each origin and destination was planned using Google maps accounting for routing, elevation, driving cycles, and environmental information. The multi-objective decision model located charging stations to maximize the number of reachable households under an energy constraint while minimizing the overall transportation energy consumption of charging actions.

Maia et al. (2015) proposed a holistic, human-centered design approach to EVSE infrastructure planning. They applied design thinking to create a list of objectives for EVSE planning: visibility, convenience, branding, reliability, affordability, operating cost, initial cost, financial competitiveness, displacement of gas vehicles, and reduced energy use. The relative importance of these objectives was shown to evolve as the EV market matures. Geographic information system analysis was used to map candidate EVSE locations in Vancouver, British Columbia, Canada. The target locations were refined to best satisfy the above criteria.

1.3 Methodology Dimensions

While the reviewed studies investigate distinct elements of PEV charging infrastructure, often with specific geographic focus, the problem is generally defined along the following dimensions.

Location and power level of chargers: While many studies focus on publically accessible charging stations, it is common to see a focus either on destination charging at L1/L2 stations or mid-trip charging at DCFC stations.

Vehicle type and electric range: Each of the studies considers a finite combination of one or more vehicle types (PHEV/BEV) and electric ranges.

Travel patterns: Light-duty consumer travel patterns are established in each study using household travel surveys, outputs of a travel demand model, or telematics data from mobile devices.

Geography: Most studies consider a very specific region at the city or state level. National studies tend to focus less on geography and more on distributions of travel distance, destination type, and dwell times.

Charging behavior: Clearly the literature is most diverse in its treatment of consumer charging behavior. Methodologies range from simplified economic models of charging behavior at the individual level to complex optimization routines seeking to minimize various objective functions. This is likely the most fertile area for further research as validation using real-world data on charging behavior becomes available.

Modeled outputs: PEV infrastructure research has focused on efficient allocation of limited resources for station siting and/or requirements assessment to support a given number of PEVs.

Modeling in Section 3 of this report aims to build on existing literature by employing a methodology that considers all combinations of charging locations and power levels, a mix of PHEVs and BEVs with several electric ranges, real-world travel from survey data, and a state-level geographic focus. Consumer charging behavior is modeled as being economically efficient at the household level with special attention paid to residents of multi-unit dwellings (MUDs). Outputs include a requirements assessment for total number of charging plugs required to support a given PEV market. Additional results include consumer participation rates for distinct combinations of charger location and power level, simulated charging load profiles, consumer eVMT benefits, and charging station utilization rates.

Before discussing this study's modeling approach in more detail, a summary of existing data on PEV and EVSE markets is provided in Section 2.

2 Current State of the Market (through 2015)

Data used in this study were taken from the Alternative Fuels Data Center (AFDC) (DOE 2016) station locator and IHS Automotive (IHS) Vehicle Registration Database (previously R.L. Polk). EVSE and PEV counts are aggregated at the county level, resulting in 2,496 county-level samples used in the analysis with at least one public charging station and at least one PEV registration.

2.1 Aggregate EVSE and PEV Counts

Figure 1 shows the locations of 12,609 publically available charging stations indexed in the AFDC station locator database (through 2015) (DOE 2016). The average station in the database provides 2.5 charging plugs with 80.0% of plugs classified as providing L2 power, 10.5% are classified as DCFC, and 9.5% of plugs classified as L1 power.

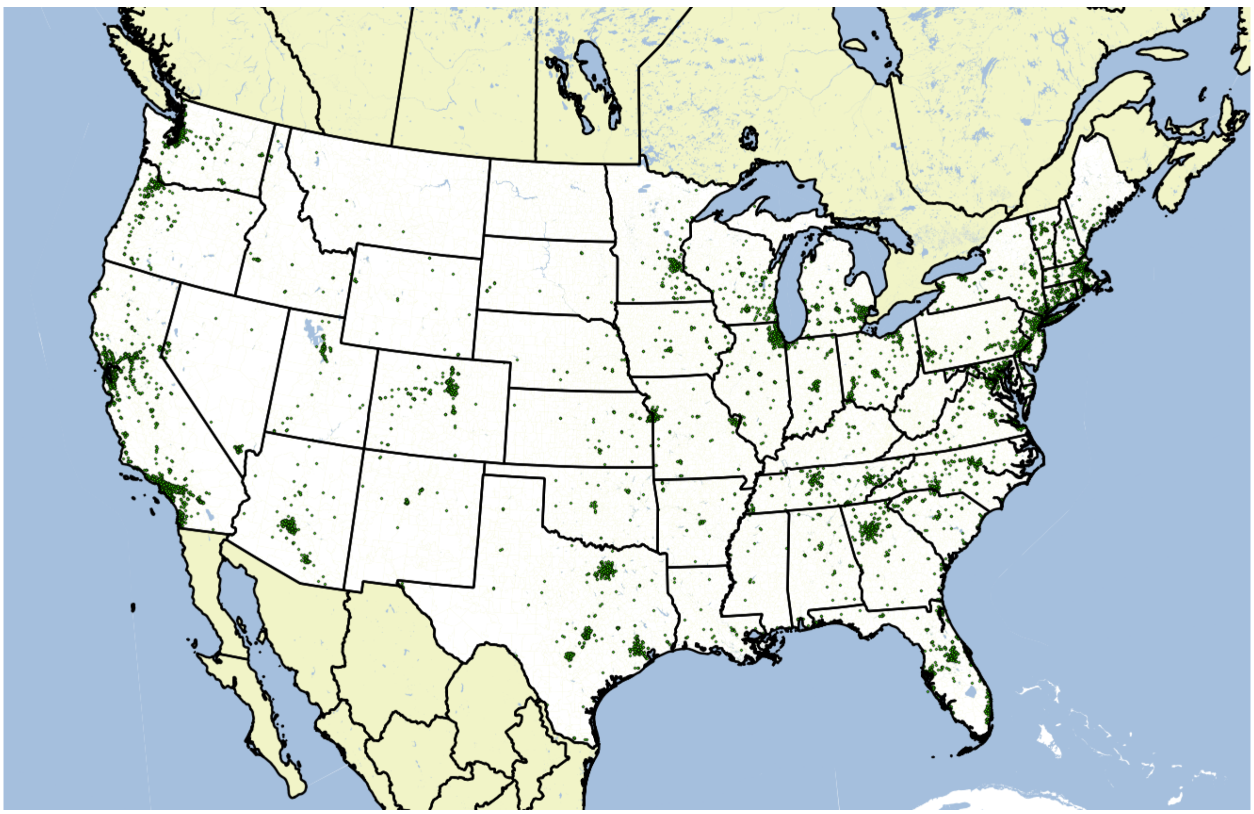

Figure 1. U.S. public charging station locations through 2015 (DOE 2016)

Figure 2 provides a density map of PEV registrations derived from the IHS database (rendered at ZIP code resolution). The IHS database shows a total of 388,427 PEVs registered with a 50/50 split between BEVs and PHEVs through 2015. The two most prominent vehicles in the database are Nissan Leafs (84,369; 21.7%) and Chevrolet Volts (84,300; 21.7%).

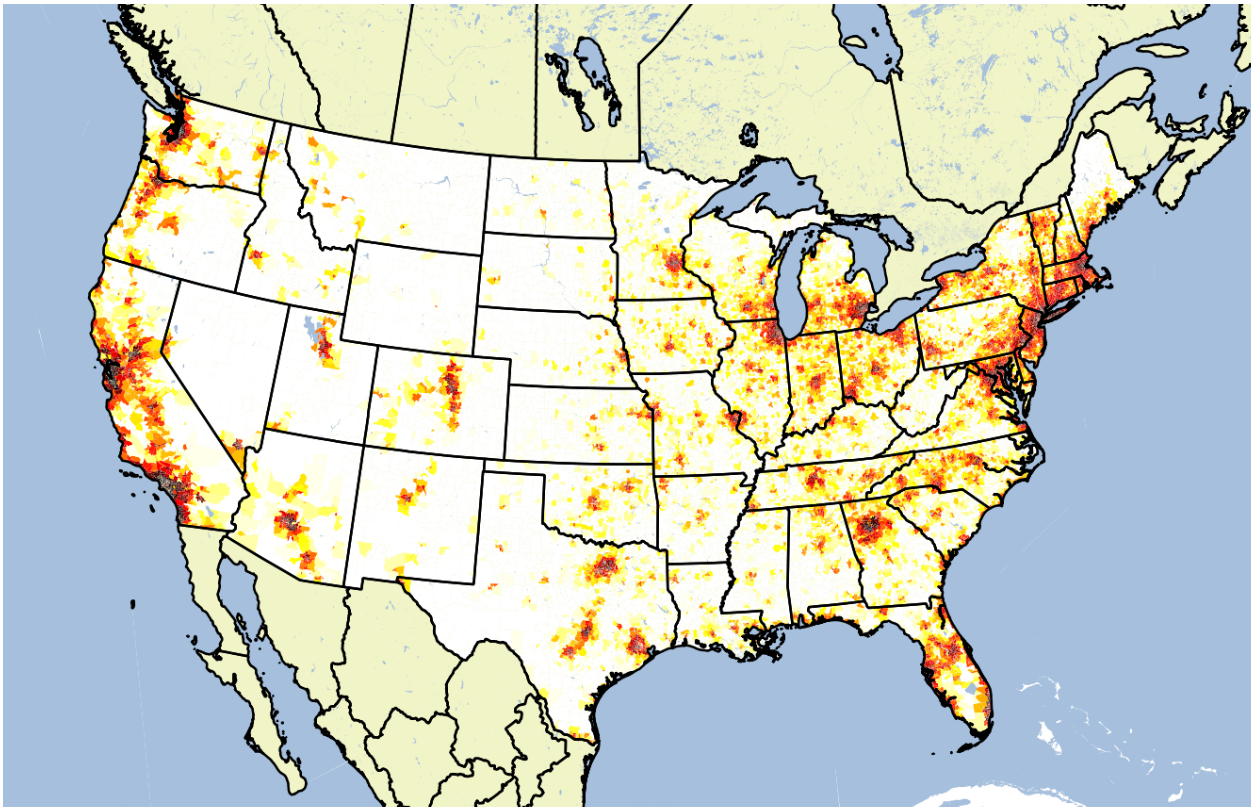

Figure 2. ZIP code density of registered PEVs through 2015 (via IHS)

2.2 Simplified EVSE/PEV Correlations

PEV registration and station location data are overlaid to examine correlation (Figure 3). The linear trend line reveals a relatively strong correlation ($R^2 = 0.8365$) between the number of EVSE plugs and PEV registrations at the county level (excluding counties with fewer than 10 charge plugs or PEVs). The average U.S. County currently provides 43 public plugs for every 1,000 PEVs. Note that the linear trend line is visually distorted in the log-log plot.

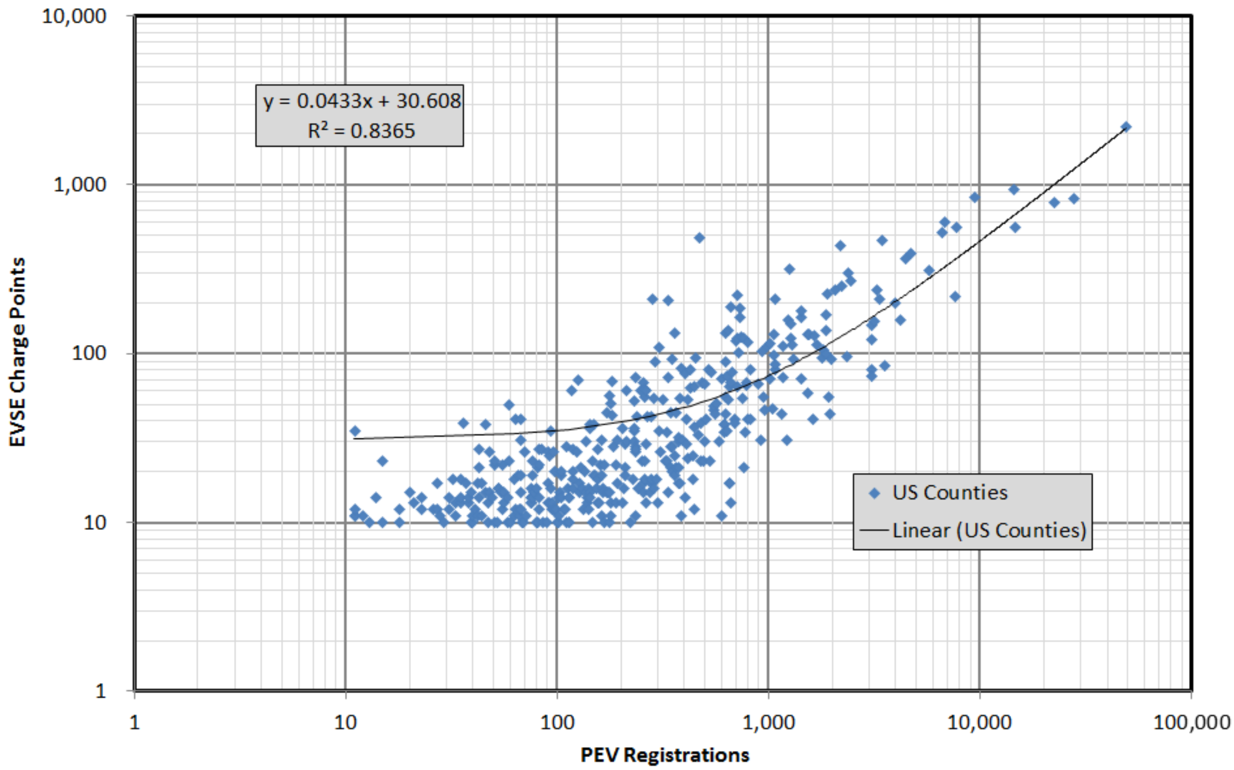

Figure 3. Existing EVSE and PEV counts by U.S. County through 2015

While the average U.S. County currently provides 43 public charge points per 1,000 PEVs, it is important to highlight regional differences in this ratio. Figure 4 shows counties with relatively high and low densities of public charging stations.

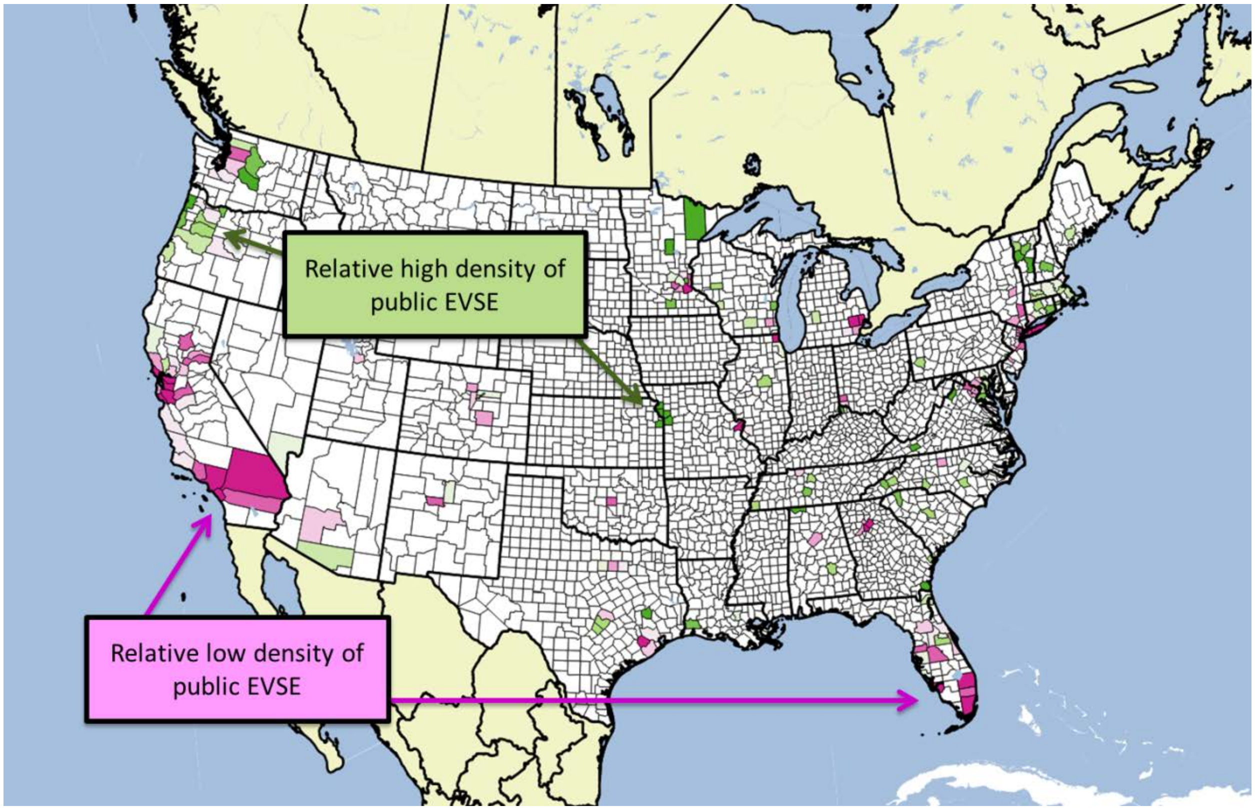

Figure 4. Counties with relatively high and low densities of public EVSE

2.3 Normalized EVSE/PEV Correlations

In addition to IHS and AFDC data on PEV registrations and public EVSE installations, variables from the American Community Survey are used to normalize the data for factors known to influence PEV market growth, such as income, education level, and housing type. The American Community Survey is a survey that provides vital information about jobs, education, employment, housing, daily commute to work information, and a host of other information. The information can be obtained at the county or at the ZIP Code Tabulation Area from the Census Bureau's FactFinder (United States Census Bureau 2016).

Two scenarios are considered for the normalized EVSE/PEV correlations. In the first scenario, the predictor variable is assumed to be the actual number of PEVs at the county level, whereas in the second scenario the predictor variable is assumed to be the number of PEVs per 10,000 people. In each scenario, five models were run. The first model considers all of the 2,496 valid county-level samples for the ordinary least squares regression model. The subsequent versions consider only the top 500, 200, 100, and 50 counties in PEV registrations.

The first task involves selecting the independent variables that will adequately capture the variance in the dataset. Too many will lead to over fitting, and too few will provide an inaccurate estimate. Independent variables in this analysis include charging ports, MUD housing units, household income, education level, and state incentives. These variables are selected based on experimentation with various combinations of variables from the AFDC, IHS, and American Community Survey datasets. All variables are normalized to have zero mean and unit variance.

Statewide incentives for PEVs and EVSE installations are directly included in the analysis from the AFDC (DOE 2016). Financial incentives for PEV purchase and EVSE installations are included in the model. All other incentives—such as high occupancy vehicle / high occupancy toll lanes exemption, parking exemptions, emission test waivers, registration tax waivers, vehicle-to-grid credits, and PEV-specific charging rates—are qualitatively scored and weighed based on their availability. While it is acknowledged that some manufactures have introduced new PEV models regionally in phases (as opposed to simultaneously introducing new PEV models nationally) no attempt is made to normalize for this effect.

Table 1 presents the regression model results with the output variable being the total number of PEVs at the county level (including only the top 100 counties in terms of PEV registrations). Total number of charging ports in a county and percent of households classified as MUD have the highest significance levels in this model with quantity of public charging stations positively correlated with PEV registrations and MUD households negatively correlated with PEV registrations. Results for the other county groupings were similar in terms of coefficient signs and significance levels.

Table 1. Regression Model Results: Top 100 Counties (absolute version)

Y= Absolute Number of PEVs	Coeff.	Std.	t	Pr(>|t|)	Signif.
Absolute Number of Ports	0.9925	0.0552	17.9710	< 2e-16	***
% of Housing Units that are MUDs	-0.4152	0.0941	-4.4140	0.0000	***
Household Estimate of Mean Income	0.1257	0.0777	1.6170	0.1090	
Population 25 to 64 years - Bachelor’s degree or higher	0.0416	0.0652	0.6390	0.5250	
Financial Incentives for PEVs	0.1408	0.1215	1.1590	0.2490	
Financial Incentives for EVSEs	0.0939	0.1436	0.6540	0.5150	
Qualitative Score of Other Incentives	0.1763	0.1317	1.3380	0.1840	
Multiple R-squared	0.9372				
Adjusted R-squared	0.9324				

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 2 summarizes the results when the output variable is assumed to be PEVs per 10,000 people (again, including only the top 100 counties in terms of PEV registrations). The same set of independent variables is used. Relative to the model used to estimate absolute PEV registrations, the per capita model places increased significance on household income, education level, and financial PEV purchase incentives. Results for the other county groupings were similar in terms of coefficient signs and significance levels. Coefficient signs remain consistent between both the absolute and per capita models.

Table 2. Regression Model Results: Top 100 Counties (per capita version)

Y= Number of PEVs per Capita (10k)	Coeff.	Std.	t	Pr(>|t|)	Sig
Number of Ports per 10K	2.3957	0.2468	9.7060	0.0000	***
% of Housing Units that are MUDs	-0.5667	0.1421	-3.9890	0.0001	***
Household Estimate of Mean Income	0.6036	0.1213	4.9740	0.0000	***
Population 25 to 64 years - Bachelor's degree or higher	0.1237	0.0591	2.0930	0.0391	*
Financial Incentives for PEVs	0.3327	0.1843	1.8050	0.0743	.
Financial Incentives for EVSEs	0.2026	0.2235	0.9070	0.3669	
Qualitative Score of Other Incentives	0.2787	0.2010	1.3870	0.1688	
Multiple R-squared	0.7942				
Adjusted R-squared	0.7787				

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Figure 5 compares the R^2 values for all models and scenarios. We see that the absolute model provides stronger correlation across all county samples (which is intuitive given the strong correlation previously observed between absolute EVSE and PEV counts). Correlations in both models become stronger as the county sample size is reduced (particularly in the per-capita model), likely indicating a smaller degree of variability in independent variables when zeroing in on the most successful PEV markets.

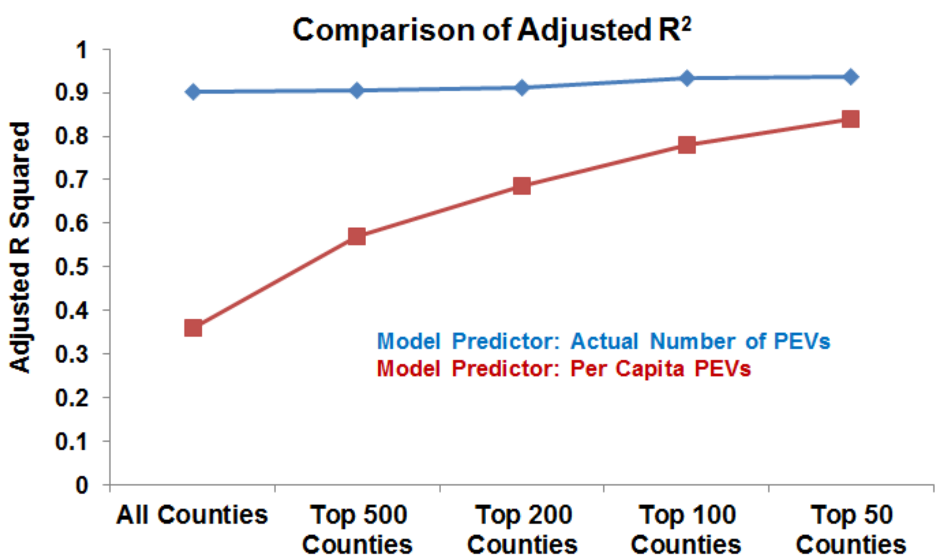

Figure 5. Comparison of R^2 values for different models

For visualization purposes, Figure 6 compares the model-predicted number of PEVs (from the absolute model) with the actual number of PEVs for the top 100 counties.

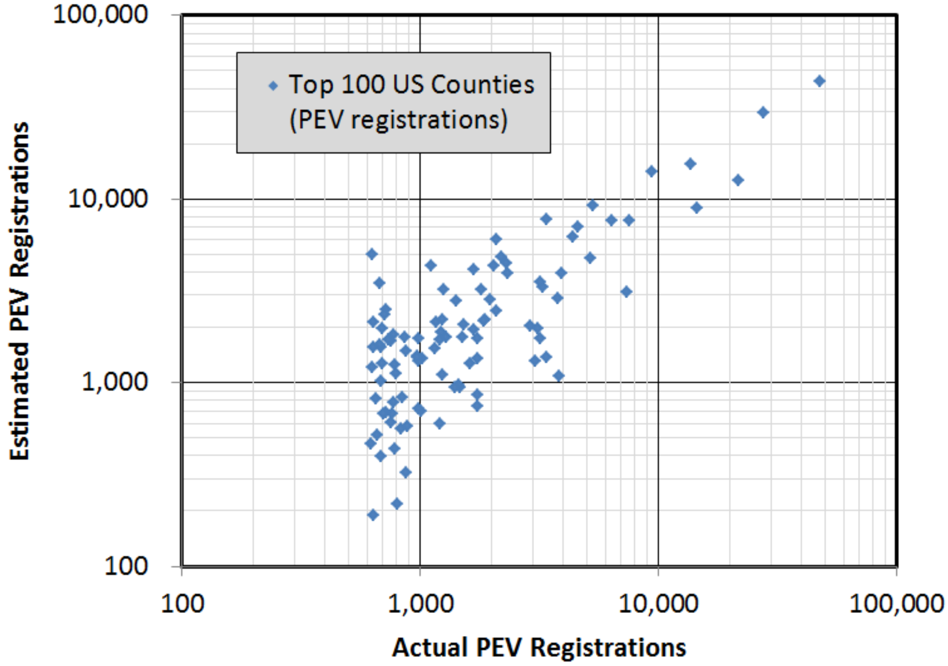

Figure 6. Agreement between actual PEV registrations and model-estimated PEV registrations

3 Regional Requirements Analysis

In addition to present day market data on PEV adoption and public EVSE installations, we would like to be able to estimate future requirements for public EVSE under various PEV adoption scenarios (as was previously discussed in Section 1). This section will review the National Renewable Energy Laboratory's (NREL's) development of the Electric Vehicle Infrastructure Projection Tool (EVI-Pro), a model to estimate future requirements for charging infrastructure. EVI-Pro will be applied to a case study of Massachusetts to estimate requirements for meeting the state's zero emission vehicle (ZEV) goals for 2025.

3.1 EVI-Pro Methodology

In collaboration with the California Energy Commission, NREL is developing EVI-Pro to estimate regional requirements for charging infrastructure to support consumer adoption of light-duty PEVs. EVI-Pro uses PEV market projections and real-world travel data from mass market consumers to estimate future requirements for home, workplace, and public charging. The goals of the model include: anticipating spatial/temporal consumer demand for charging while capturing variations with respect to residents of single-unit dwellings (SUDS) and MUDs, weekday/weekend travel behavior, and regional differences in travel behavior and vehicle adoption. A graphical representation of the model is presented in Figure 7.

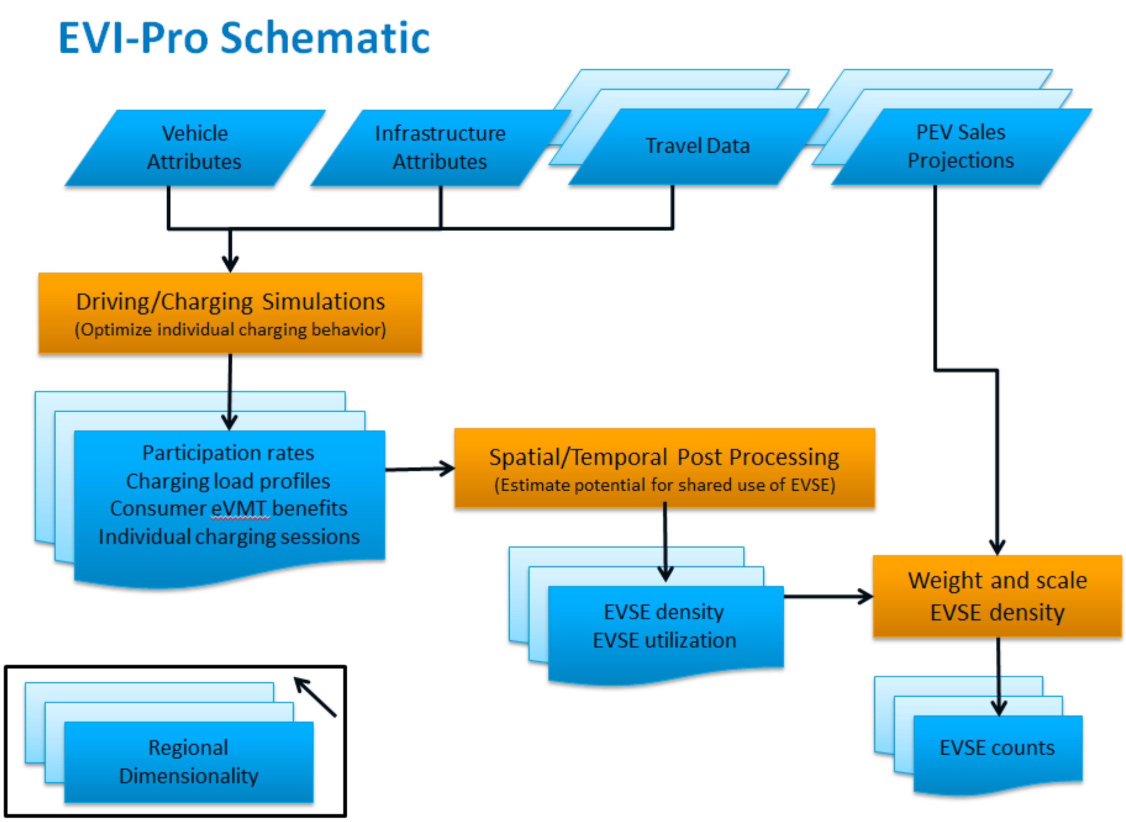

Figure 7. EVI-Pro model structure

The fundamental assumption in EVI-Pro is that consumers prefer charging scenarios that enable them to complete all of their existing travel while minimizing operating cost. To define which charging scenarios consumers will elect, individual travel days from regional household travel surveys are simulated in the model. An example travel day is shown in Table 3.

Table 3. Example Single-Day Travel Profile

Start Time	Miles	Destination	Dwell Hours
8:15 a.m.	4.3	Work	3.3
12:05 p.m.	4.3	Home	1.1
1:28 p.m.	0.6	Public	0.2
1:48 p.m.	4.5	Work	2.8
4:50 p.m.	13.8	Public	3.7
9:10 p.m.	14.6	Home	10.5

Each travel day is simulated multiple times for each potential combination of charging behavior (e.g., L1-Home, L2-Home, L1-Home plus L1-Work, etc.). A matrix of all potential charging options is shown in Table 4. While there is growing interest in the deployment of high power DCFC stations (up to 350kW), this analysis takes the conservative approach of modeling DCFC using the current 50kW standard. Future studies may be conducted using EVI-Pro to investigate effects of DCFC power level.

Table 4. Potential Charging Options Available to Consumers in EVI-Pro

Location	Level	Power	Comment
Home	L1	1.4 kW	
	L2	3.6 kW	BEVs simulated with higher L2 power to enable full overnight charge
Work	L1	1.4 kW	
	L2	6.2 kW	PHEV on-board charger limits max power to 3.6 kW in model
Public	L1	1.4 kW	
	L2	6.2 kW	PHEV on-board charger limits max power to 3.6 kW in model
	DCFC	50 kW	BEVs only

For the example travel day shown in Table 3, the simulated consumer preference in a BEV100 would be for L1-Home charging (this assumes flat electricity rates through the day and lowest cost electricity at the home location). Battery state of charge for this cost-optimal simulation is shown in Figure 8. Note that for BEVs, a range tolerance of 20 miles is implemented, meaning that any charging scenario where remaining range drops below 20 miles is discarded from the list of available options.

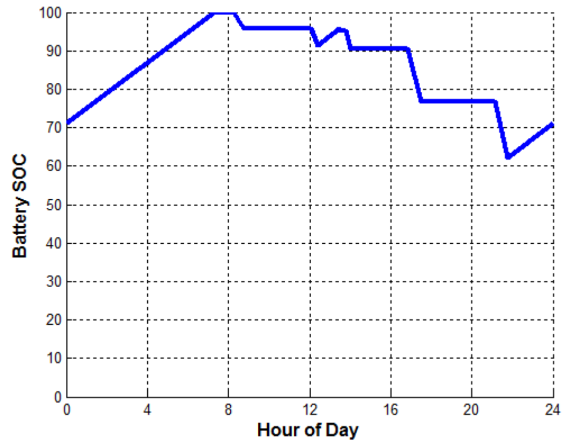

Figure 8. Simulated battery state of charge (SOC) for a BEV100 with L1-Home charging subjected to the example travel profile shown in Table 3

This optimization routine is repeated for all travel days in a given survey and for all vehicle types under consideration (PHEV20, 40, 60 and BEV100, 200, 300 in this study).

3.2 Massachusetts Case Study

To illustrate EVI-Pro capabilities, the model is applied to a case study of Massachusetts. Massachusetts was selected based on its participation in the Multi-State ZEV Action Plan and it's representation of the large vehicle market in the Northeastern U.S.

3.2.1 Massachusetts EVSE and PEVs Counts (through 2015)

As of 2015, IHS data show 6,535 PEVs registered in Massachusetts. Relative to the United States at large, we find the BEV/PHEV split preferenced towards PHEVs in Massachusetts; this observed preference is manifested with Massachusetts having lower registrations of Nissan Leafs and higher registrations of Toyota Plug-In Prius vehicles (again, relative to the national average; see Figure 9).

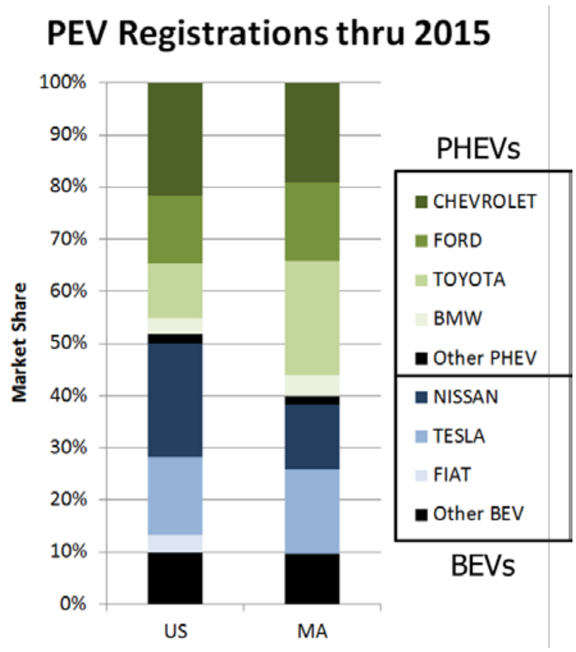

Figure 9. PEV market share for the United States and Massachusetts

PEV registration densities (by ZIP code) from IHS are overlaid with public EVSE locations from the AFDC station locator in Figure 10 (DOE 2016). Table 5 summarizes PEV registrations and public EVSE installations through 2015. Relative to the national average, we find that Massachusetts currently exhibits a high EVSE density (152 public plugs per 1,000 PEVs in Massachusetts versus a national average of 43 public plugs per 1,000 PEVs).

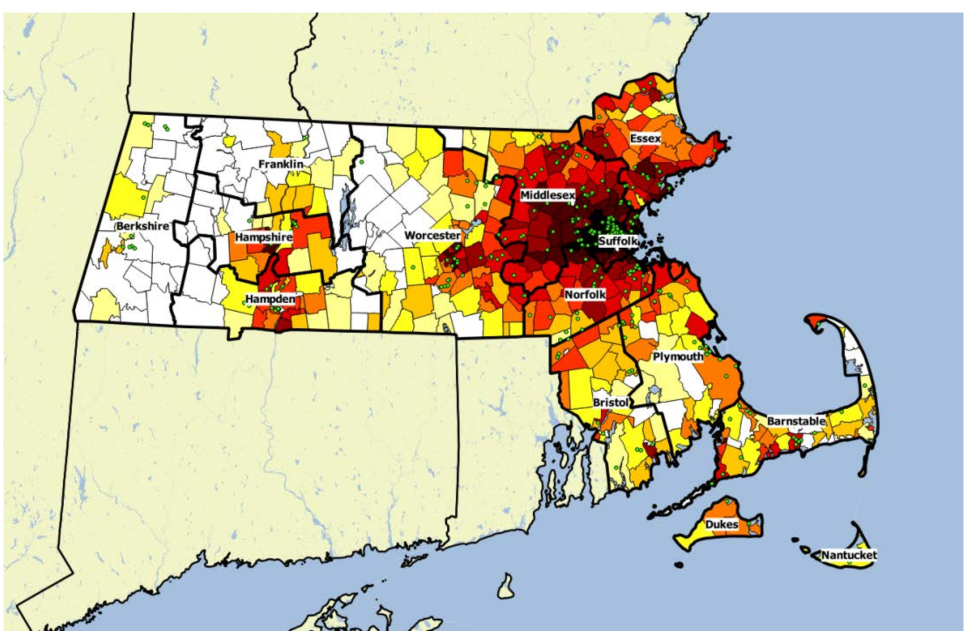

Figure 10. PEV registration density (by ZIP code) with existing public EVSE through 2015. County boundaries and labels are provided as reference.

Table 5. Summary of Massachusetts EVSE and PEV Counts by County through 2015

County	Charge Points	PEVs	EVSE per 1,000 PEVs
Barnstable County	43	181	238
Berkshire County	22	82	268
Bristol County	28	236	119
Dukes County	3	60	50
Essex County	66	657	100
Franklin County	10	86	116
Hampden County	34	213	160
Hampshire County	40	267	150
Middlesex County	300	2,366	127
Nantucket County	10	13	769
Norfolk County	123	759	162
Plymouth County	53	318	167
Suffolk County	189	665	284
Worcester County	75	632	119
State Total	996	6,535	152

Of the 996 public charge points in Massachusetts (AFDC) through 2015, we find a similar distribution to the national average in terms of power levels with 5.7% L1, 87.1% L2, and 7.1% DCFC.

3.2.2 2011 Massachusetts Travel Survey

The 2011 Massachusetts Travel Survey (MTS), which was conducted by the Massachusetts Department of Transportation, was a single-day survey that included collecting data from 20,177 vehicles from 12,462 households, for a total of 83,518 driving trips across all 14 Massachusetts counties. A density map of vehicle trip counts by ZIP code is shown in Figure 11.

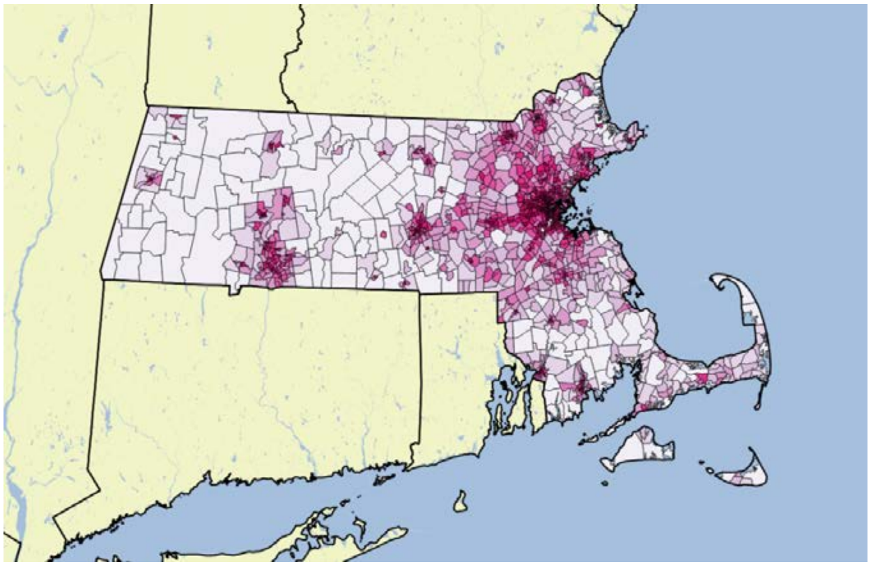

Figure 11. 2011 MTS vehicle trip density by ZIP code

The 2011 MTS was spatially and demographically stratified to produce a representative sample of household travel behavior in Massachusetts. A sample share comparison between census population and 2011 MTS surveyed households is shown in Figure 12.

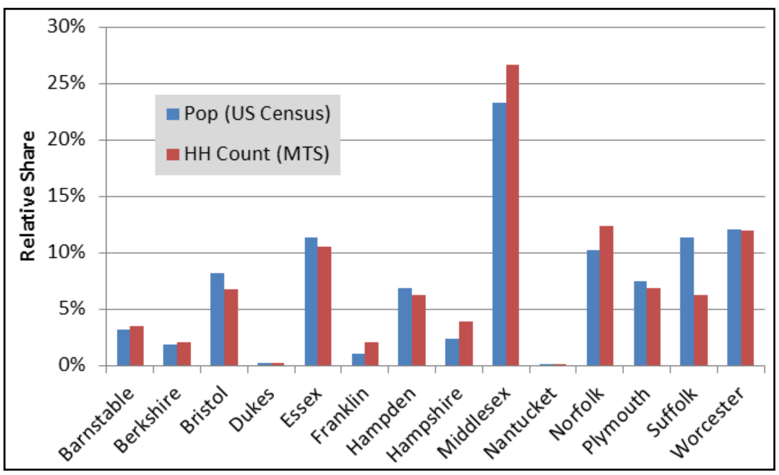

Figure 12. Massachusetts sample share: US Census (population) compared to 2011 MTS (surveyed households)

Daily VMT is calculated for all vehicles in the 2011 MTS and plotted as a cumulative distribution in Figure 13 (with the equivalent distribution from the 2009 NHTS). The Massachusetts sample features a very similar daily VMT distribution to the national sample, both in terms of average daily VMT (MTS = 34.9 mi and NHTS = 36.7 mi) and median daily VMT (MTS = 23.3 mi and NHTS = 23.1 mi). Further inspection of the 2011 MTS reveals typical vehicle use profiles (see Figure 14 for MTS distributions of vehicle trip start times and trips per vehicle-day).

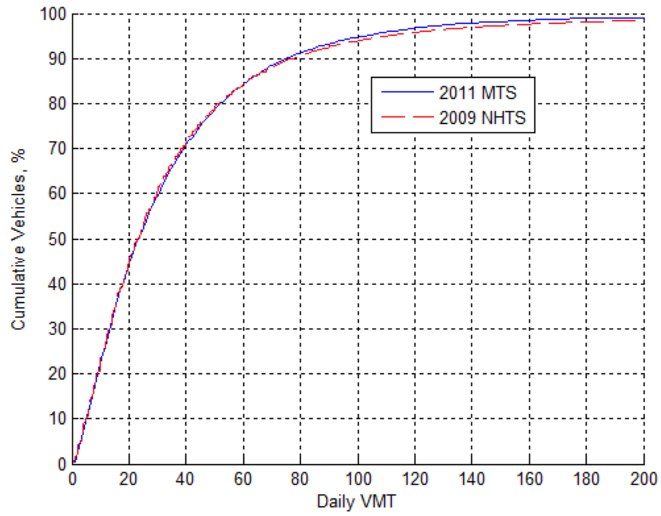

Figure 13. Daily VMT comparison of 2011 MTS and 2009 NHTS data

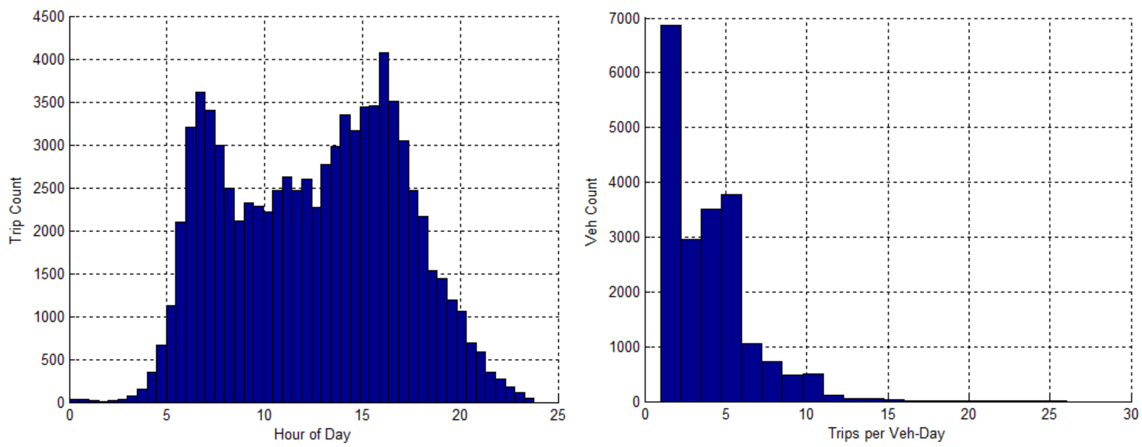

Figure 14. 2011 MTS distributions of vehicle trip start times (left) and trips per vehicle-day (right)

Of particular interest to the study of PEV charging is the duration of time spent dwelling at specific destinations. Figure 15 presents cumulative distributions of the time spent by MTS vehicles in each of four classifications: 1) driving, 2) parked at home, 3) parked at work, and 4) parked in public (public destinations defined as all non-home, non-work locations).

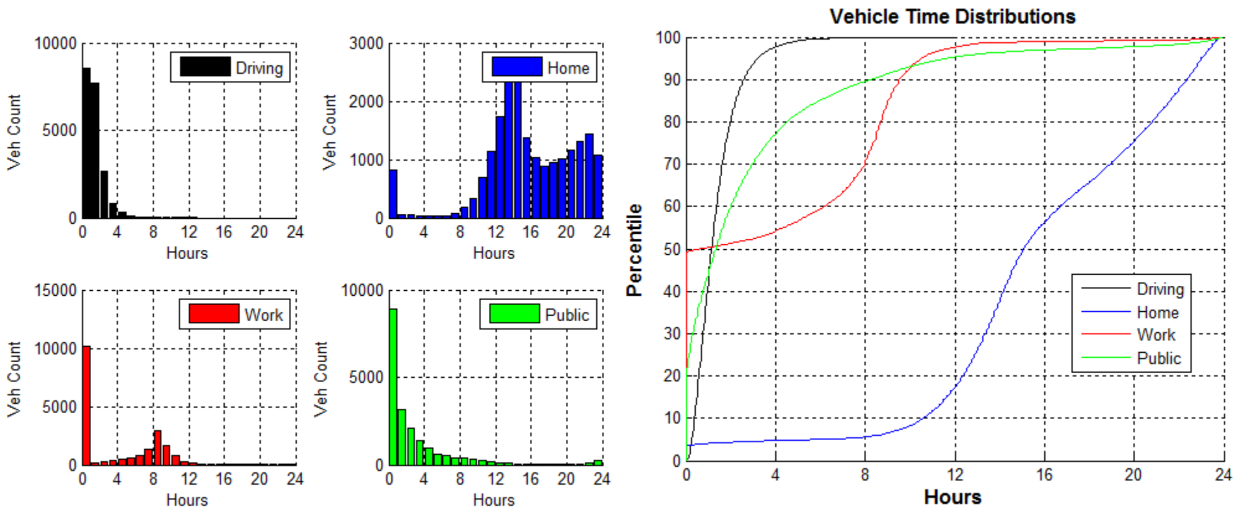

Figure 15. 2011 MTS vehicle time distributions

From the MTS data, we see the average vehicle spent 1.4 hours driving, 15.6 hours parked at home, 4.1 hours parked at work (8.4 hours parked at work for those vehicles making at least one work trip on their survey day), and 3.0 hours parked at a public locations. While the average result of this analysis is intuitive, it is important to highlight the significant shares of vehicles in the study with atypical behavior patterns. For instance, 10% of vehicles in the survey spent more than 2.5 hours driving, 6% of vehicles spent less than 9 hours parked at home, and 10% of vehicles spent more than 8 hours at public locations. Recognizing that a large segment of the vehicle fleet operates with atypical travel patterns on any given day is an important step in the design of charging infrastructure networks robust enough to support mass market adoption of PEVs.

3.2.3 EVI-Pro Simulations

3.2.3.1 Simulated Consumer Charging Behavior

EVI-Pro was run using data from the 2011 MTS with the assumption that consumers have access to home charging and prefer to do the majority of charging at their home locations. Alternate scenarios, including those with an absence of home EVSE for residents of MUDs, can be explored in future work. The resulting consumer selections for workplace and public charging access are shown in Tables 6 and 7.

Table 6. Percent of Simulated Consumers Selecting Workplace Charging as a Component of Their Individual Travel Day Charging Behavior (by Vehicle Type)

	PHEV20	PHEV40	PHEV60	BEV100	BEV200	BEV300
None	69.5%	83.0%	89.6%	91.8%	93.5%	93.7%
Work Level 1	29.1%	15.1%	8.4%	7.2%	5.9%	5.7%
Work Level 2	1.4%	1.9%	2.1%	1.0%	0.6%	0.5%

Table 7. Percent of Simulated Consumers Selecting Public Charging as a Component of Their Individual Travel Day Charging Behavior (by Vehicle Type)

	PHEV20	PHEV40	PHEV60	BEV100	BEV200	BEV300
None	70.8%	84.5%	90.2%	93.6%	95.8%	96.2%
Public Level 1	2.0%	1.1%	0.8%	0.4%	0.4%	0.3%
Public Level 2	27.1%	14.4%	9.1%	5.2%	3.5%	3.4%
Public DCFC	0.0%	0.0%	0.0%	0.8%	0.3%	0.1%

Across all scenarios we see the majority of simulated consumers requesting no access to workplace or public EVSE and performing all charging at their home location. The average workplace dwell time for commuters of 8.4 hours enables L1 charging to be sufficient for most consumers requesting access to workplace charging. Alternatively, we find the majority of consumers seeking access to public charging requesting either L2 or DCFC power levels to enable sufficient charge transfer given the average 3.0-hour public dwell times. Across all scenarios, we find reliance on workplace and public charging decreases as vehicle electric range increases.

These results assume that consumers can perform the majority of charging at their home location where electricity is presumably the cheapest. As with the sensitivity around availability of home charging for residents of MUDs, alternate scenarios (including access to free workplace charging) can be run in future studies and have the potential to dramatically impact results.

3.2.3.2 Consumer Benefits of Workplace and Public Charging

Figure 16 presents fleet-wide eVMT benefits enabled by increased consumer access to workplace and public charging. Consumer access to workplace charging can be seen to increase fleet-wide eVMT by 3 to 12 percentage points with public charging access providing an additional 5 to 12 percentage point improvement in eVMT (vehicle type specific with greatest benefits for the PEVs with the shortest electric range).

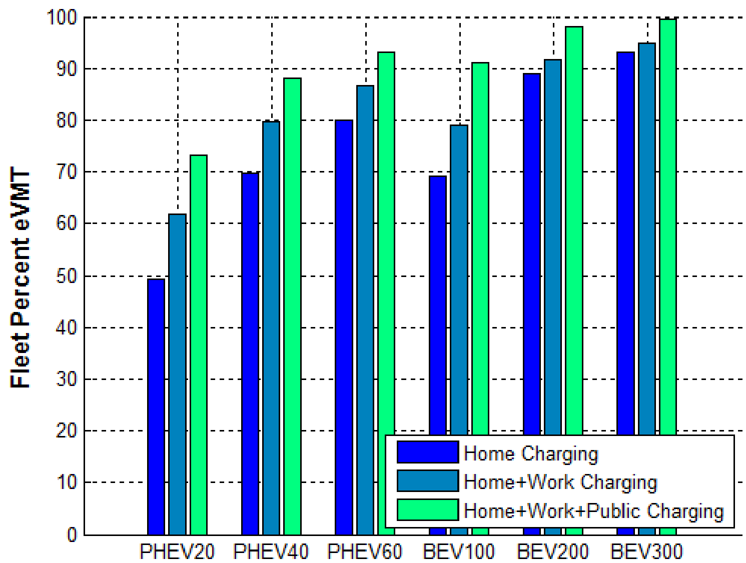

Figure 16. Fleet average percent eVMT based on EVI-Pro simulation of the 2011 MTS under various infrastructure scenarios

3.2.3.3 Simulated Charging Load Profiles

The resultant normalized, aggregate charging load profiles from EVI-Pro simulation of the 2011 MTS are shown in Figure 17 for all vehicle types. Aggregate charging loads at home locations are shown to peak roughly between 4 p.m. and 10 p.m. (depending on vehicle type) coinciding with the end of individual household travel days. Aggregate charging loads at work locations are shown to peak roughly between 7 a.m. and 2 p.m. (most notably for the PHEV20), coinciding with the arrival of individual consumers arriving at work. Aggregate charging loads at public locations are relatively consistent during the day hours (8 a.m. to 8 p.m.).

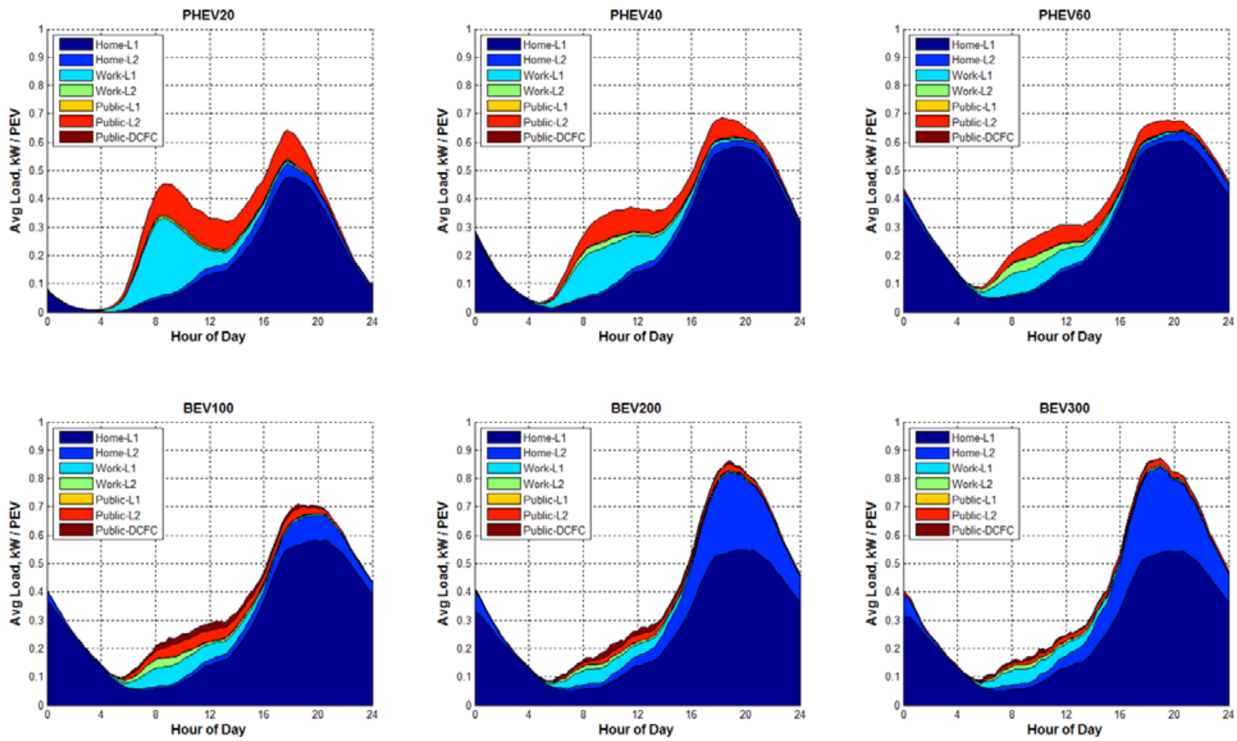

Figure 17. Normalized, aggregate charging load profiles from EVI-Pro simulation of the 2011 MTS by time of day, location type, and vehicle type

3.2.3.4 Spatial Aggregation of Simulated Charging Events

In addition to simulation results in the temporal dimension, a wealth of detailed spatial data is generated from EVI-Pro simulation of the 2011 MTS. Figure 18 shows an example map from the Boston metropolitan area, including markers for vehicle destinations visited in the travel survey (green markers), destinations that coincide with simulated consumer charging events (red markers), and consolidated charging locations representing hypothetical public charging stations. Locations of simulated charging events are consolidated using 0.1-mile buffers (10-mile buffers for DCFC stations). After spatial consolidation, the temporal results are reviewed to determine the maximum number of charging plugs necessary at each station.

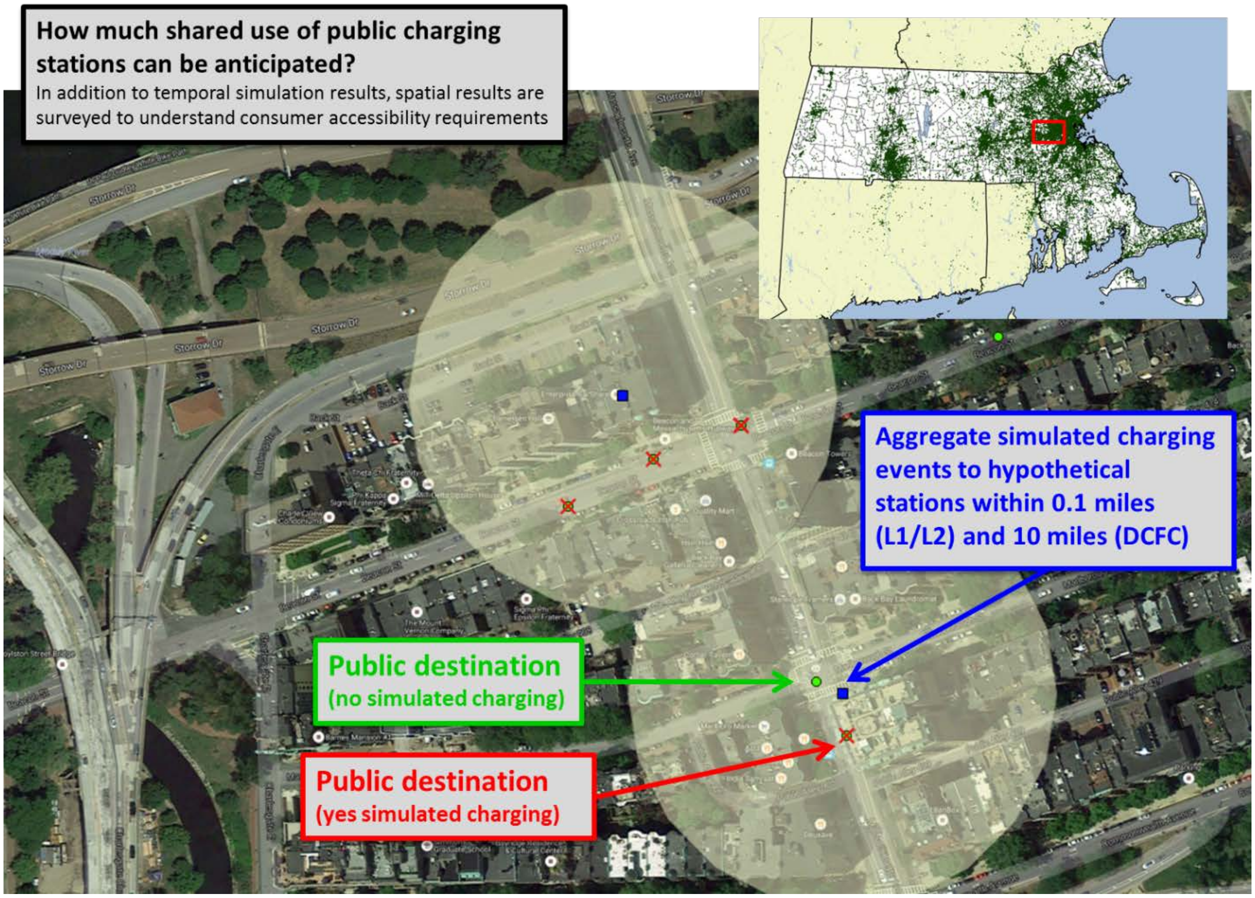

Figure 18. Example map from the Boston metropolitan area showing travel destinations overlaid with simulation results (satellite imagery credit: © 2009 Google, Map Data © 2009 Tele Atlas)

3.2.3.5 Estimated Requirements for PEV Charging Stations

Analysis of spatial and temporal results of simulated consumer charging behavior enables derivation of density requirements for public charging infrastructure (estimated public plugs per 1,000 PEVs). A range of density values is displayed in Figure 19 to convey scenarios that are relatively conservative or aggressive with regard to infrastructure planning. The conservative scenario is sized to exactly meet consumer peak power demands (neglecting spatial coverage) while the aggressive scenario is sized to fully satisfy spatial/temporal simulation results (based on available travel data).

Here we see the greatest requirements for public infrastructure come from public L2 stations with a range of 10 to 340 public plugs estimated per 1,000 PEV (dependent on vehicle type and level of conservativeness). Results show lesser requirements for numbers of L1 and DCFC stations, and reliance on publicly available infrastructure decreases as vehicle electric range increases.

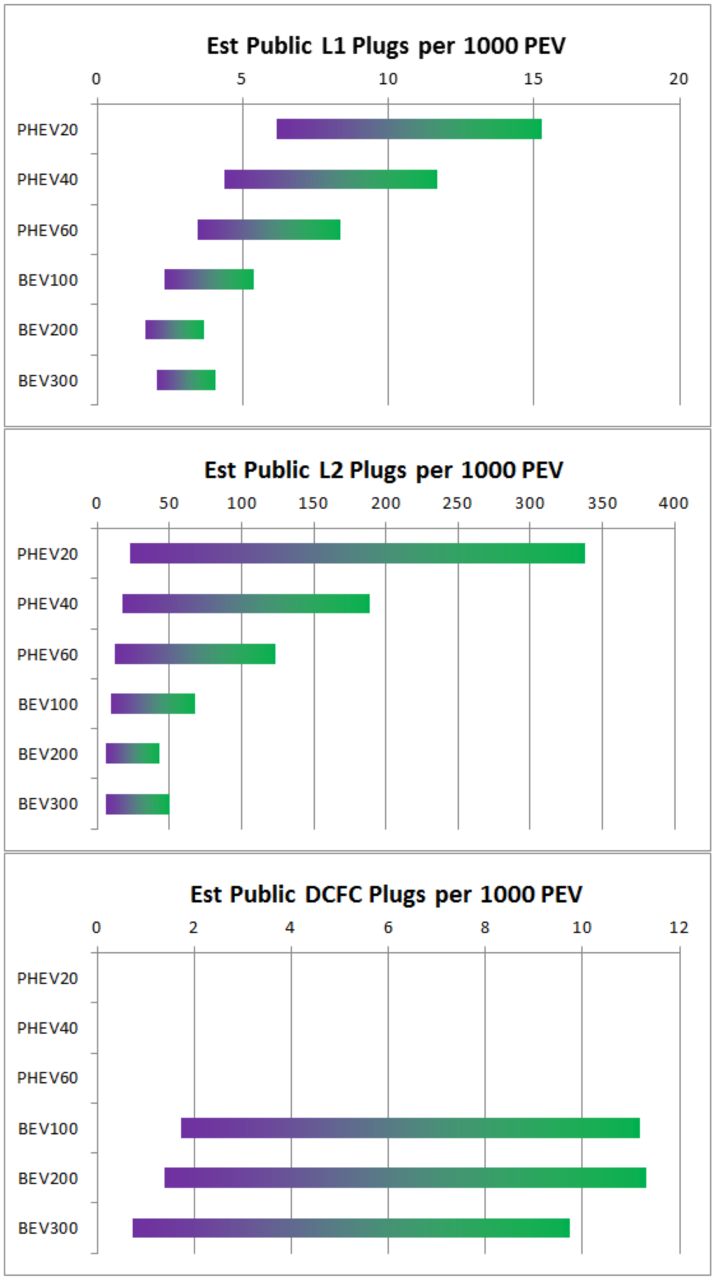

Figure 19. Estimated number of public plugs per 1,000 PEVs by vehicle type and EVSE power level

To arrive at an absolute estimate of number of plugs for Massachusetts, we revisit the multi-state ZEV Action Plan. The Massachusetts contribution to this plan targets 300,000 PEVs to be on the road by 2025. A hypothetical growth trajectory for Massachusetts to meet this goal is shown in Figure 20 (represents 57% annual growth in PEV sales).

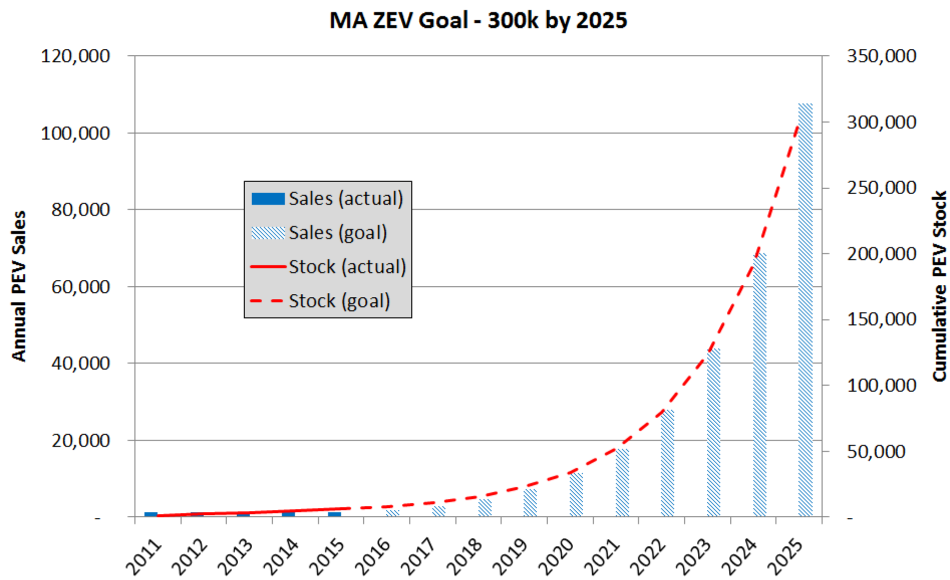

Figure 20. Hypothetical growth trajectory for Massachusetts to meet the 2025 goal of 300,000 PEVs

The 2025 goal of 300,000 PEVs is distributed by county using projections from the Massachusetts Executive Office of Energy and Environmental Affairs and by housing type using vehicle stock information from the 2011 MTS (see Figure 21). This distribution results in 20% of PEVs being allocated to residents of MUDs and 80% to residents of SUDs. PEVs are uniformly distributed within each county using the six BEV and PHEV types simulated in EVI-Pro.

County	SUD	MUD
Barnstable County	2.2%	0.2%
Berkshire County	1.4%	0.2%
Bristol County	2.5%	0.8%
Dukes County	0.8%	0.0%
Essex County	10.3%	2.3%
Franklin County	0.9%	0.2%
Hampden County	4.8%	1.0%
Hampshire County	4.1%	0.8%
Middlesex County	28.5%	7.4%
Nantucket County	0.3%	0.0%
Norfolk County	9.0%	1.8%
Plymouth County	4.8%	0.6%
Suffolk County	2.2%	3.1%
Worcester County	7.9%	1.7%

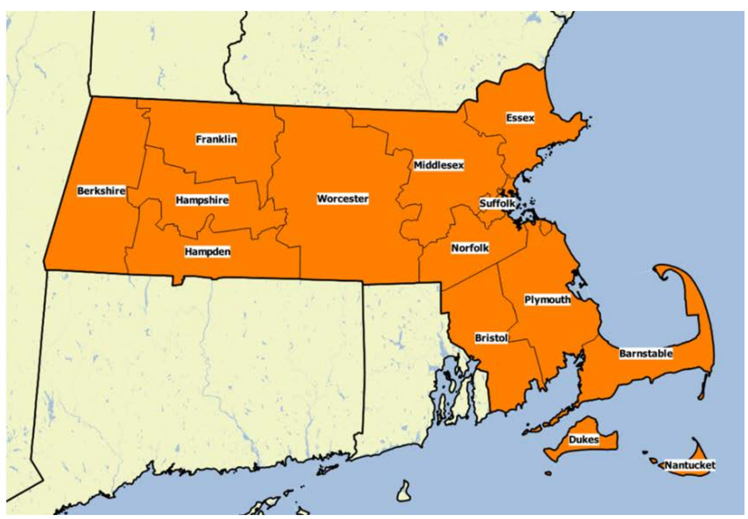

Figure 21. Projected distribution of PEVs across Massachusetts in 2025

EVSE density and PEV sales projections are combined to generate estimates of absolute requirements for workplace and public charging infrastructure in Massachusetts to support the 2025 ZEV goal of 300,000 vehicles. The results, shown in Figure 22, indicate 37,413 to 45,270 workplace plugs (predominantly L1 plugs) and 4,935 to 44,645 public plugs (predominantly L2). These results correspond to 125 to 151 workplace plugs per 1,000 PEVs and 17 to 149 public plugs per 1,000 PEVs. Public plug count estimates are broken out by county in Figure 23.

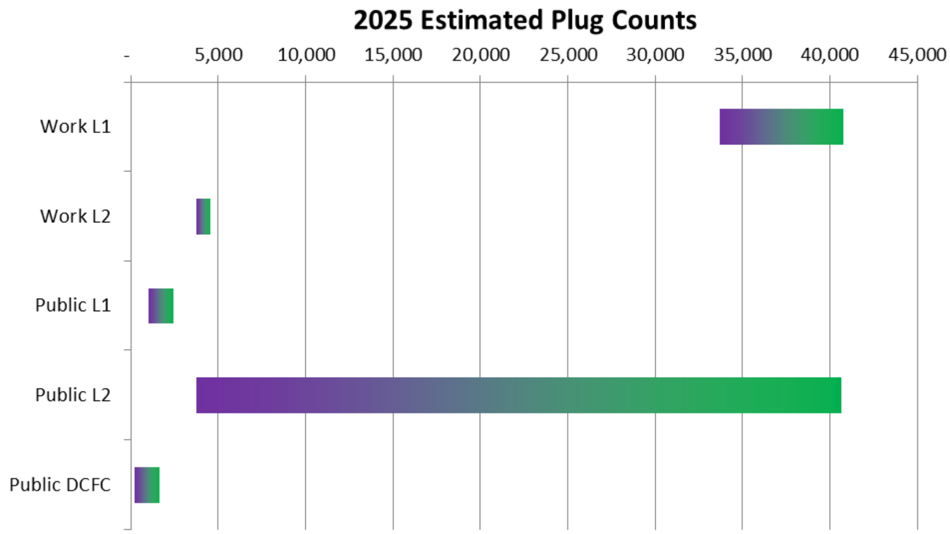

Figure 22. Estimated workplace and public plug counts required to support 300,000 PEVs in Massachusetts

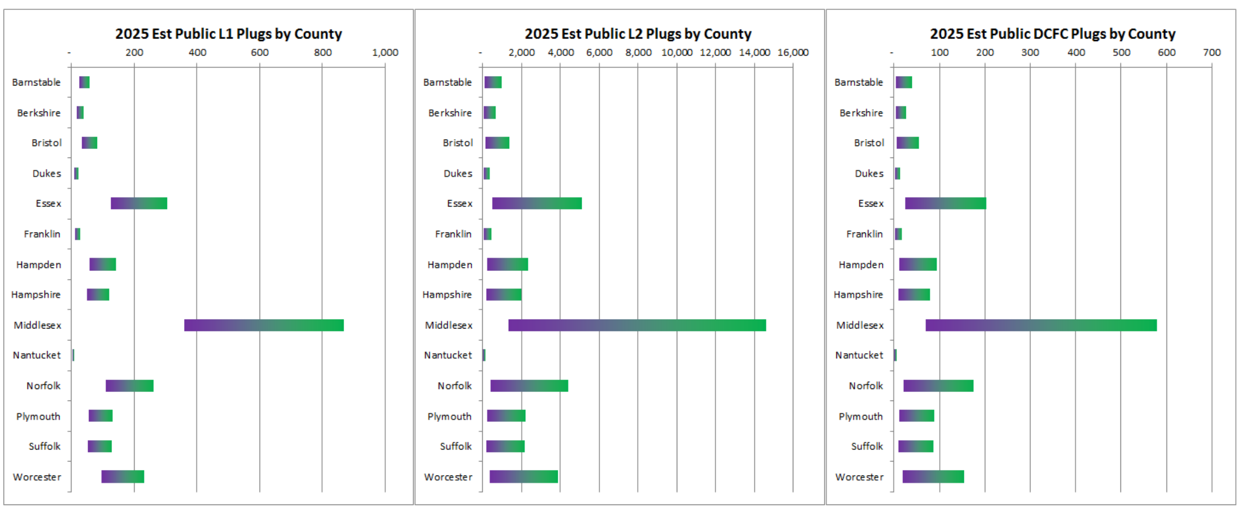

Figure 23. Estimated public plug counts required to support 300,000 PEVs in Massachusetts by county

It is worth noting the large bands of uncertainty placed around all station estimates in this analysis. Uncertainty in these estimates accounts for a number of factors, including:

- Vehicle sales projections
    - EVSE estimates in this analysis are designed around a 300,000 PEV scenario with equal splits among the six available electric ranges. Future PEV infrastructure requirements will be sensitive to the electric ranges that end up succeeding in the market.
- MUD access to home charging
    - This study makes an assumption that residents of MUDs will have reliable access to charging at their home location and will prefer to perform the majority of their charging at home. Access to EVSE at MUDs is far from a given and may require greater levels of workplace and public support to enable the Massachusetts sales goal (recall that 20% of PEVs were allocated to MUDs in this analysis). Alternate EVI-Pro results that do not assume reliable access to home EVSE at MUDs can be explored in future work.
- PHEV demand for public charging
    - PHEVs are simulated as having the greatest reliance on workplace and public charging in this analysis based on their limited electric range. This neglects the possibility that mass market consumers may be content using gasoline as a range extender on a regular basis (simulated consumers in EVI-Pro are diligent at maximizing eVMT via frequent charging).
- Shared use of public infrastructure
    - PEV infrastructure requirements in this analysis are based on simulation of a set of travel data including approximately 20,000 vehicles. Results from these simulations are extrapolated to a future scenario with 300,000 PEVs in Massachusetts. Consequently, this analysis likely underestimates the ability of consumers to have shared use of public EVSE in a high PEV density environment. The majority of hypothetical public stations in this analysis feature very low levels of utilization (see Section 3.2.3.6).
- Day-to-day travel variability
    - In addition to the limited sample size of the 2011 MTS (approximately 20,000 vehicles), the travel data only provide a single day of travel data for each individual vehicle. Personal travel is known to exhibit significant degrees of day-to-day variability based on longitudinal (long-duration) travel studies. Unfortunately, longitudinal travel data are difficult (and expensive) to obtain at large scales.
- Consumer tolerance for destination/station proximity
    - EVI-Pro makes an assumption that simulated charging events can be consolidated into hypothetical stations using a 0.1-mile buffer for L1 and L2 EVSE. This assumption implies that consumers have some proximity tolerance for the

distance between where they park (and charge) their vehicle and their desired destination. Adjusting this tolerance in the model is known to impact the resultant station densities.

3.2.3.6 Simulated Utilization of Public Charging Stations

It is important to note that not all public stations contribute equally to fleet eVMT improvements in EVI-Pro. Figure 24 shows simulated utilization of hypothetical public L1 and L2 stations in terms of unique charging sessions per day. Approximately 85% of hypothetical stations only provide a single charging session on the average simulated day. An additional 11% of hypothetical stations provide exactly two charging sessions on the average simulated day. Within the EVI-Pro simulation, it was relatively rare to identify public L1/L2 stations that provide more than two charging sessions per day. This result is driven by the relatively tight proximity tolerance of 0.1 mile enforced in the consolidation of simulated charging events into hypothetical public stations.

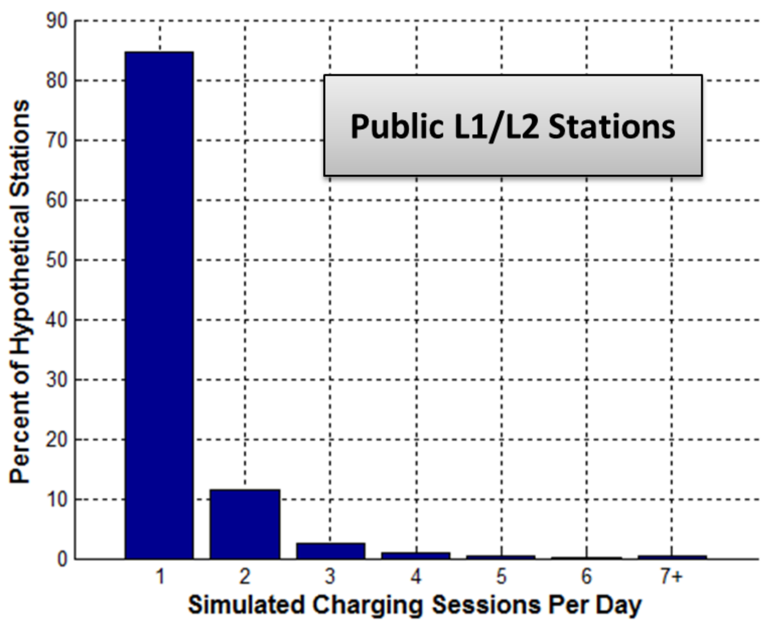

Figure 24. Simulated utilization of hypothetical public L1/L2 stations

Conversely, hypothetical DCFC stations experienced much higher levels of simulated utilization in EVI-Pro. Figure 25 shows simulated utilization of hypothetical public DCFC stations in terms of unique charging sessions per day. Here we find over 40% of hypothetical public DCFC stations enabling seven or more charging sessions per day. Again, this result is driven by the station proximity tolerance. Recall that for public DCFC stations, a destination proximity tolerance of 10 miles is employed. This tolerance allows simulated consumers to make dedicated stops at DCFC stations within a few miles of their eventual destination for 20–30 minute charging sessions.

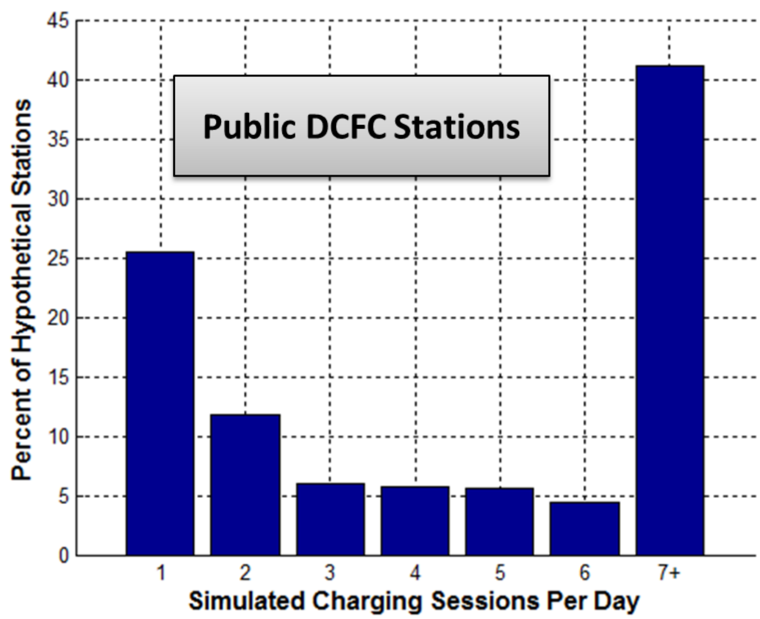

Figure 25. Simulated utilization of hypothetical public DCFC stations

4 Recommendations for Future Work

Future work in the area of regional planning for PEV charging infrastructure could be focused on two broad topic areas: 1) refinement/validation of EVI-Pro methodology and 2) co-simulation with other economic models for estimating impacts of investment in PEV charging infrastructure.

Significant validation work remains in order to develop further confidence in the infrastructure estimates generated by EVI-Pro. Validation activities could include additional regional case studies and comparison between existing charging station data and modeled outputs (such as total number of stations and station utilization). Several topics have also been identified in the area of model refinement, including:

- Incorporation of time of use rates and their effect on consumer charging behavior (particularly as it impacts end of day behavior at home).
- Consideration for mid-trip corridor charging on long-distance, inter-city travel.
- Identification of larger sample size datasets on consumer travel patterns, potentially including datasets from commercial mapping providers and simulated outputs of traffic demand models.
- Quantifying impacts of single- vs multi-day datasets on consumer travel, potentially using travel distances to pair simulated consumers with PEVs of appropriate electric range.

In the area of co-simulation with existing models, economic impacts and changes in jobs due to electric vehicle implementation can be estimated using tools such as the IMPLAN input-output (I-O) model. Based on the selection of vehicles and charging infrastructure, a set of expenditures for services and commodities such as vehicles, electricity, petroleum products, and chargers can be characterized. These values represent inputs into the IMPLAN model, which can be used to determine net changes. Net changes consider both increases and decreases in costs for items such as infrastructure, vehicles, petroleum, and electricity. Impacts are reported across four impact metrics:

- Employment is defined as the number of employees supported by an industry. This is not the same as full-time equivalence, which adjusts employment figures based on the number of part-time employees.
- Earnings are total compensation to workers and include all benefits such as retirement and health insurance.
- Output is a measure of total economic activity. It includes all sales and purchases. At a company level, it may be thought of as revenue.
- Gross domestic product is a measure of the value of production. It is an industry's sales less its purchases of inputs from other businesses. It includes payments to workers, tax payments, and property-type income such as profits.

Regions can use this information to better understand how PEVs and related infrastructure could affect their economy. Every region is unique, with different mixes of industries, different labor force characteristics, and different populations. The same scenario in two different regions could produce different results. State-level analysis would incorporate these differences and in doing so increase the relevance of the report to a larger potential audience.

This approach can be extended to multiple U.S. regions or local markets to estimate EVSE requirements and the resulting metrics for a given number of PEVs deployed. In addition to this capability, the EVI-Pro approach can also be modified to assess resulting EVSE costs, local electricity rates, premium required to recover upfront capital, electricity prices, electricity carbon intensities, and other factors. Moreover, when combined with a detailed spatial vehicle stock model, such as the Scenario Evaluation and Regionalization Analysis (SERA) model, the air quality improvements can also be included. Employing an air quality monetization tool, such as EPA's BENMap, in conjunction with a time-of-day electricity dispatch model, can allow for an approximation of public health benefits.

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