Integrated Modeling of Electric Vehicle Energy Demand and Regional Electricity Generation

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A Research Report from the National Center for Sustainable Transportation

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16. Abstract

This paper describes a model for developing highly resolved, time-of-day specific electric vehicle charging demand profiles from travel survey data. Since timing of vehicle charging is dependent on electric vehicle supply equipment (EVSE) availability, four EVSE scenarios are considered: 1) home only, 2) home and workplace only, 3) universal EVSE, and 4) a probabilistic scenario where EVSE availability varies by location. To illustrate the implications of differing demand profiles on power grid operation with high renewable generating capacity, the profiles are in a typical regional economic dispatch model. The results provide a valuable approach for understanding the interactions between vehicle electrification and renewable energy deployment while exploring an updated range of assumptions about EVSE availability and charging behaviors for New York and the six New England states. All scenarios result in increased peak demand and increased generation by non-renewable generating sources. This indicates that incentive mechanisms that influence charging decisions are necessary to attain lower emissions outcomes.

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EXECUTIVE SUMMARY

In order to reduce greenhouse gas emissions worldwide, a multitude of actions must be taken. Vehicle electrification is one of the primary mitigation methods widely recognized for the transportation sector. As a result, the relationship between vehicle electrification and renewable electrical energy deployment needs to be taken into consideration to ensure that increases in plug-in electric vehicle (PEV) penetration lead to minimized emissions from power generation. This report describes the development and application a model for developing highly resolved, time-of-day specific electric vehicle charging demand profiles from travel survey data for several alternative scenarios. The scenarios include alternative assumptions about EV adoption, charging preferences, and electric vehicle supply equipment (EVSE) availability. The model is applied in the combined region of New England and New York (7 states) using the data from the 2017 National Household Travel Survey (NHTS) assuming constant travel demand patterns and vehicle class by household.

Since timing of vehicle charging is dependent on charging choices as well as EVSE availability, four EVSE scenarios are considered: 1) home only, 2) home and workplace only, 3) universal EVSE, and 4) a probabilistic scenario where EVSE availability varies by location type. To illustrate the implications of differing demand profiles on electricity generation with high renewable generating capacity added to the region's existing infrastructure, a typical regional economic dispatch optimization model with dynamic wind and solar generation modeled across one year and adjusted in alignment with state-level renewable portfolio standard (RPS) targets is used to create 2030 generating portfolio.

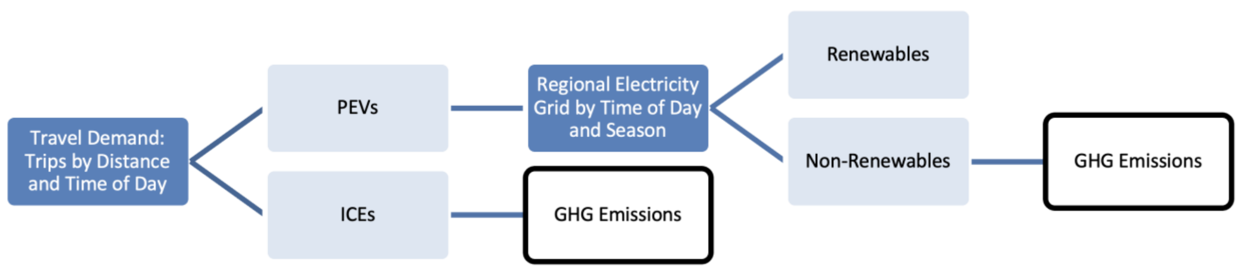
The model results provide a valuable approach for understanding the interactions between vehicle electrification and renewable electrical energy deployment while exploring a range of assumptions about EVSE availability and charging behaviors. Current generating capacity is shown to be more than adequate for 15% PEV penetration. However, all scenarios result in increased peak demand and increased generation by non-renewable generating sources. This indicates that incentive-based mechanisms that influence charging decisions are necessary to attain lower emissions outcomes.

It is crucial that PEV charging demand profiles be based on real-world travel data. As PEV technology improves, travel behaviors will change in response. Future studies will require expanded data collection, over the traditional one-day travel survey, to capture more accurate depictions of driver behaviors.

Highlights

- Travel survey data is used to create time-of-day and stop-based electric vehicle electricity demand
- Regional wind and solar generation is modelled across one-year
- Generating capacity is more than adequate for 15% plug-in electric vehicle penetration in New York and New England
- Incentive mechanisms to alter charging behavior are needed
- Implementation of widespread workplace charging facilities is recommended

Graphical Abstract



1. Introduction

Within the transportation sector, vehicle electrification is widely cited as a primary mitigation strategy for realizing the large magnitude of GHG reductions needed globe-wide (Audoly et al., 2018; IPCC, 2014; McCollum et al., 2014; Morrison et al., 2015; Pleßmann and Blechinger, 2017). Numerous studies have demonstrated significant GHG reductions from vehicle electrification and the magnitude of these GHG benefits increase as the GHG intensity of electricity generation falls (Moro and Lonza, 2018; Samaras and Meisterling, 2008). This paper contributes a time-specific modeling method using charging demand profiles that reflect the travel and charging behaviors of plug-in electric vehicle (PEV) owners to accurately evaluate and plan for the impact of vehicle charging on overall emissions.

Our first research objective is to develop a PEV-charging demand model (PEV-CDM) that uses time-of-day specific charging demand from travel survey data that is consistent with real-world driving patterns and basic consumer vehicle preferences. Our approach builds on two key assumptions. First, that travel patterns are dependent on a spatial distribution of origins and destinations that changes relatively slowly, and therefore that near-future driving patterns will be broadly similar to current driving patterns. Second, that drivers are unlikely to significantly alter their travel patterns to accommodate technological differences between internal combustion engine vehicles (ICEVs) and PEVs; this means that the driving patterns of future PEV drivers can be approximated by examining current ICEV travel patterns when that travel is compatible with PEV electric ranges. Given these assumptions, travel survey data, such as that collected in the National Household Travel Survey (NHTS), can be converted to time-specific charging demand.

Our second research objective is to evaluate the implications of charging demand on power plant-level generating decisions, wind and solar utilization, and net GHG changes. To accomplish this goal, the PEV-CDM demand profiles are used as an input for a regional economic dispatch model that minimizes the cost of the power generation, subject to technical and regulatory constraints. This dispatch model operates on a set of power-generating facilities that includes significantly expanded wind and solar generation compliant with state-level 2030 Renewable Portfolio Standard (RPS) targets as of 2018. The combination of the PEV-CDM and the regional dispatch model demonstrates the impact of realistic PEV charging demand on wind and solar utilization, generating costs, and system-wide GHG emissions.

A study region consisting of New York and New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont) is used for two PEV penetration levels (5% and 15% of the vehicle fleet). Since the timing of vehicle charging is dependent on where charging infrastructure or electric vehicle supply equipment (EVSE) is available, four EVSE scenarios are considered: 1) home only, 2) home and workplace only, 3) a probabilistic scenario in which the likelihood of EVSE availability varies by location/stop type, and 4) universal EVSE availability. These combined EVSE/penetration scenarios result in eight charging profiles with differing total energy demand and temporal demand distributions. The model provides insight into the time-specific charging demand in New York and New England, as well as how charging demand timing is impacted by away-from-home charging opportunities that often occur during the daytime when solar generation is feasible.

This report begins by summarizing previous research on PEV adoption and charging behavior that informed the PEV-CDM in Section 2. Section 3 then describes the inputs to and operation of the PEV-CDM, as well as inputs and formulation of the regional economic dispatch model. The results of these models are presented in Section 4. Finally, the key findings and future research directions, including the need for research to evaluate alternative management strategies to affect charging behavior and thus optimize the combined potential of transportation and grid emissions minimization are presented in the Conclusions section.

2. Literature Review

Grid impacts occur across a range of spatial and temporal scales, from impacts on local distribution infrastructure (Hilshey et al., 2013) to system costs and power plant dispatch decisions (Dowds et al., 2013), and the impacts are regionally and temporally variable (Miller et al., 2020). One key research question is the degree to which vehicle charging facilitates or impedes the effective emissions-reducing integration of large amounts of variable renewable energy (wind and solar) into the power grid. Early research on the grid impacts of vehicle electrification concluded that delayed, overnight vehicle charging, coinciding with periods of low existing electricity demand, offered significant benefits for electric grid management (Parks et al., 2007). However, the rapid deployment of solar generation has resulted in substantial changes in the net load throughout the day, resulting in idle generating capacity during daytime hours and increasing the rate at which fossil-fueled power plants need to ramp up through the late afternoon and evening. Over the long term, vehicle-grid integration (VGI), in which charging load can be scheduled or managed to reduce the cost of grid operations, or more advanced vehicle-to-grid (V2G) interactions which allow for bidirectional electricity flow, offer the potential to create significant synergies between PEVs and wind and solar generation (Lund and Kempton, 2008; Niesten and Alkemade, 2016).

As discussed in Sovacool et al. (2017), however, in addition to technical challenges, consumer behavioral preferences also present significant challenges that must be addressed before VGI is widely adopted. In this context, it is important to understand the interactions between unmanaged vehicle charging and renewable energy generation. Modeling unmanaged charging requires detailed data on when and how far vehicles are traveling; where, when, and how long vehicles are stopped and able to charge; and their energy demand when they do charge. While there is a growing body of empirical charging data (Smart and Salisbury, 2015), the utility of these datasets for understanding future charging demand from a growing cohort of PEV owners is limited, since they are often derived from early adopters driving PEVs with relatively limited range in the context of more limited publicly available charging infrastructure (also referred to as electric vehicle supply equipment or EVSE). Consequently, modeled PEV charging demand profiles that can capture broader travel patterns and EVSE charging availability scenarios are needed to understand the interaction between PEV charging and high levels of wind and solar generation.

The magnitude and timing of PEV charging demand depend both on who adopts PEV technology and on the decisions that these PEV owners make about when to charge their vehicles. Since PEV adoption rates are unlikely to be uniform, and because adoption rates are likely to be correlated with travel behavior patterns – when, how far, and for what purpose vehicles are driven – understanding the predictors of PEV adoption is crucial for developing reasonable charging demand profiles. Travel behavior determines when and where vehicles are parked and potentially able to charge, as well as how much energy they require for charging. Each time a PEV is parked at a location with EVSE, the PEV operator faces a charging decision. In some cases, immediate future travel will necessitate charging the vehicle during a particular stop, but often the decision to charge or not will hinge solely on the operator's discretion. Thus, understanding decision-making with regard to discretionary charging events is also essential to reasonably model the timing of PEV charging demand. Relevant literature on PEV adoption to date and the limited prior research on existing charging behavior are summarized below.

2.1. PEV Adoption

Given the current gap between PEV adoption and PEV adoption targets, it is highly likely that policy interventions will need to play a significant role in promoting PEV sales. Looking at PEV sales in Canada, Axsen and Wolinetz conclude that aggressive PEV mandates are achievable (Axsen and Wolinetz, 2018). Hardman et al. reviewed 35 different studies on the influence of purchase incentives on PEV adoption and found incentives generally effective, especially when applied at the time of purchase with value-added tax or purchase tax exemptions (Hardman et al., 2017). Prior research has generally shown interest in PEVs is positively correlated with income, education, full-time employment, multi-car households, and male gender, and negatively correlated with age. Many of the variables have also been shown to be correlated with travel behavior patterns and annual vehicle miles of travel (VMT) (Leard et al., 2019; Martin et al., 2016; McGuckin and Fucci, 2018). Awareness and higher density of publicly available EVSE is also associated with a higher interest in PEVs. An overview of these relationships is provided in Table 1 and several studies on PEV adoption are described individually below. More detailed summaries of demographic predictors of PEV adoption can additionally be found in Hardman et al. (2016), Javid and Nejat (2017), and Nazari et al. (2019).

Table 1. Predictors of Interest in PEVs

Variable	Impact on interest in/adoption of PEVs	Studies
Age	Age is inversely correlated with PEV interest	(Carley et al., 2013; Hidrue et al., 2011; Lane et al., 2018)
	PEV interest highest in middle age	(Axsen et al., 2016; Plötz et al., 2014)
Education	Education is positively correlated with PEV interest	(Axsen et al., 2016; Carley et al., 2013; Helveston et al., 2015; Hidrue et al., 2011; Javid and Nejat, 2017)
EVSE	Awareness/availability of publicly available EVSE is positively correlated with PEV interest	(Javid and Nejat, 2017; Lane et al., 2018; Narassimhan and Johnson, 2018; Sierzchula et al., 2014)
	EVSE increases interest in PHEVs but not BEVs	(Nazari et al., 2019)
Gender	PEV interest is higher among men than women	(Axsen et al., 2016; Carley et al., 2013; Helveston et al., 2015; Hidrue et al., 2011; Plötz et al., 2014)
Income	PEV interest increases with household income	(Axsen et al., 2016; Javid and Nejat, 2017; Lee et al., 2019)
Vehicle ownership	Multi-vehicle ownership/high ratio of vehicles to drivers increases PEV interest	(Carley et al., 2013; Nazari et al., 2019)
	Ownership of hybrid/alternative fuel vehicles is positively associated with PEV interest	(Axsen et al., 2016; Lane et al., 2018)

Two studies looked at vehicle purchase decisions in the 2012 California Household Travel Survey (CHTS) (Javid and Nejat, 2017; Nazari et al., 2019). These studies differ from many other studies related to PEV purchase decisions in that they use revealed preference data from historical vehicle purchases, rather than analysis of stated preference data. Just over 400 households of PEV owners are included in this dataset (Javid and Nejat, 2017). Logistic regression by Javid and Nejat on the decision to purchase a PEV rather than ICEV found that the likelihood of PEV adoption increased with household income, the highest level of education in the household, per capita EVSE availability, and regional retail gasoline prices. Notably, the analysis found no significant relationship to gender and minimal impact of age, trip duration, and household size (Javid and Nejat, 2017). Nazari et al. conducted a nested logit modeling to further break down vehicle choice among battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs) and hybrid electric vehicles (HEVs), and internal combustion engine vehicles (ICEVs) (Nazari et al., 2019). In addition to income and education, their analysis concluded that PEV adopters tend to live in close proximity to level-2 charging stations and tended not to live in apartments (Nazari et al., 2019). Somewhat counterintuitively, census tract EVSE density was positively correlated with PHEV adoption, but not with BEV adoption. These studies indicate that spatial analysis and location (as used here) will be important components of integrated transportation and electricity grid modeling.

A U.S. survey in 2008-2009 found that PEV orientation increased with education and interest in smaller vehicles and decreased with age, but did not find a relationship to income or number of household vehicles (Hidrue et al., 2011). A 2012 survey of adults in the United States found demographic variables, including gender (greater interest among males) and education (greater interest with higher education), correlated with interest in alternative fuel vehicles (Carley et al., 2013). A survey of 1,080 drivers in the United States in 2013 was designed specifically to distinguish between interest in two types of PEVs: PHEVs and BEVs (Lane et al., 2018). The authors concluded that interest in PHEVs appeared to be based on practical factors such as lower fuel costs, subsidies for PEVs, and specific vehicle design features, as these buyers were primarily selecting between PHEV and ICEV options. In contrast, interest in PEVs was more closely aligned with perceived environmental benefits and less on financial considerations. BEVs were less appealing to respondents who relied heavily on their vehicle, potentially reflecting range anxiety (Lane et al., 2018). Among early adopters in Germany, Plotz et al. found a higher affinity for PEVs among men, individuals in multi-person households, and full-time workers, and that PEV adopters were less likely to live in larger cities (Plötz et al., 2014). A Norwegian study also found that higher incomes and proximity to major cities were significantly related to BEV sales (Mersky et al., 2016). Hardman et al. (2016) defined low- and high-end EV adopters. High-end adopters were willing to pay a higher BEV premium and included a higher proportion of female adopters than the low-end group. Additionally, high-end adopters were older, more educated, and had higher incomes, although both groups had higher incomes and car ownership rates than the population of the United States as a whole.

Projecting future PEV adoption based on these past studies should be approached with some caution, as the characteristics that define early adopters of a technology will become less distinguishing as the technology becomes widespread. In an attempt to understand this transition, Axsen et al. surveyed consumers in British Columbia, Canada to study the differences between PEV "Pioneers", Potential Early Mainstream buyers, and Potential Late Mainstream buyers (Axsen et al., 2016). Within the survey sample, respondents that already owned a PEV as of the 2015 study date were termed Pioneers while respondents who owned an ICEV but expressed an interest in PEVs were termed Potential Early Mainstream adopters. Respondents who did not express an interest in PEVs were termed Potential Late Mainstream adopters. The authors found that awareness of PEV technology was very low among both groups of potential mainstream adopters and that the Potential Early Mainstream respondents showed higher interest in PHEVs over BEVs, while the Pioneers showed a preference for BEVs (Axsen et al., 2016). As in other studies, the Pioneers were more likely to have higher income and education, be middle-aged and male, and live in multi-vehicle households. In contrast, Potential Early and Late Mainstream adopters did not differ from one another in terms of age, income, education, or gender and more closely resembled the Canadian population as a whole. This supports the expectation that as PEV adoption becomes more widespread, PEV owners will more closely resemble the general population.

Overall, the PEV adoption literature shows a relatively consistent set of socio-demographic factors that are linked to interest in PEVs. These factors are also correlated within the transportation planning literature with differences in travel behavior patterns, and therefore in the amount of energy that is required for charging and the time of charging opportunities. While, as discussed by Axsen, the socio-demographic distinctiveness of PEV drivers is likely to diminish as PEVs become more common, it is an important consideration for near-term modeling efforts and the design of future charging systems.

2.2. PEV Charging Behavior

Decision making about PEV charging varies across individuals, reflecting differing travel patterns, variable access to EVSE, and differing levels of risk aversion about battery depletion. Early work using empirical vehicle data and user surveys indicates that the desire to charge increases as the battery state of charge (SOC) decreases and that many drivers (especially BEV drivers) do not wait until the SOC is low to begin charging. This research also shows that home and work charging account for the vast majority of charging events. It is important to remember that PEV battery capacity and publicly available EVSE locations have both increased significantly in recent years. Consequently, the charging decisions captured in these existing studies, made by drivers with shorter-range PEVs and fewer EVSE options, may not be fully reflective of current and future charging behavior.

One of the largest empirical PEV charging datasets was collected and analyzed by the Idaho National Laboratory (INL) as part of the U.S. Department of Energy's ChargePoint America and EV Project initiatives (Smart and Salisbury, 2015). These initiatives collected data from 8,000 privately owned PEVs (Nissan Leaf BEVs and Chevrolet Volt PHEVs) from 2011 through 2013. All told, these vehicles drove 125 million miles and completed 6 million charging events. Participants were recruited to share their vehicle usage and charging data in exchange for the installation of Level-2 EVSE (240-volt) at their residences. Volt drivers frequently fully depleted their batteries before charging and averaged 1.5 charging events per day. Leaf drivers frequently recharged with significant remaining battery capacity and averaged 1.1 charging events per day. The home was the dominant charging location for both Leaf (84% of charging events) and Volt owners (87% of charging events), with most owners utilizing overnight, home charging on a near-daily basis. Drivers tended to utilize only a few away-from-home charging locations, with workplace charging the predominant source of non-home charging. Access to workplace charging increased the average annual eVMT for both Volt and Leaf drivers. Looking at data from public charging stations, the INL team found that highly utilized EVSE tended to be located at stop types with longer parking durations (including shopping malls, commuter lots, and downtown parking lots), suggesting that drivers may not find it worthwhile to plug in their vehicles for shorter stops.

Several studies have found that driver charge decisions are sensitive to battery SOC and that drivers often charge at a relatively high SOC rather than waiting until the battery is mostly depleted. Results from the U.S. Department of Energy's (DOE) EV Project showed that fewer than 12% of charging events started with a battery SOC below 30% (Smart and Schey, 2012). Franke and Krems (2013) used travel and charging diaries recorded by 79 BEV operators in Germany to assess how drivers appraised the relationship between their travel needs and remaining electric range to make charging decisions, which they termed the "user-battery interaction style". Two-thirds of users started charging events with an average battery SOC greater than 40%, compared to approximately 10% of users who started charging events with a SOC of less than 20%. Drivers charged an average of 3.1 times per week. Sun et al. (Sun et al., 2015) used data collected from 234 private BEVs in Japan between 2011 and 2013 to explore the factors that influence the timing of charging at home after the last trip of the day. The authors used a multinomial discrete choice model to assess the likelihood that drivers would charge immediately upon returning home, charge overnight (defined as after 11:00 PM), charge during another time period or not charge at all. The model included battery SOC and numerous future travel variables. The likelihood of all types of charging events increased as SOC decreased and as the next day's VMT increased. Latinopoulos et al. (2017) analyzed a small survey of BEV drivers in the UK and Ireland to explore the role of range anxiety on travel and charging decisions. They found that a subset of drivers chose to charge at a higher SOC to reduce the perceived risk of running out of battery, while others would only charge if the remaining SOC was inadequate for their next trip. A small survey of potential PEV owners found willingness to pay for charging increased as SOC diminished and as charging speeds increased (Latinopoulos et al., 2017).

Charging behavior is, of course, influenced by EVSE availability, as the opportunity to charge is dependent on the presence of EVSE. Hardman et al. wrote a comprehensive review of consumer preferences and interactions with EV charging infrastructure in 2018 that found charging occurred primarily at four stop types: home, work, shopping centers/other public locations, and along long-distance travel corridors (Hardman et al., 2018). They report that home charging accounts for the majority (50-80%) of all charging events for PEVs, while the workplace is the next most frequent charging location. In general, the authors found BEV owners were more likely to utilize away-from-home charging opportunities than PHEV owners. Kim et al. (2016) utilized four years of transaction data from publicly available EVSE in the Netherlands to assess the frequency and regularity with which drivers utilized public charging stations. A latent class hazard model classified PEV users as either routine chargers, who exhibited consistent public EVSE usage patterns, or erratic chargers, who utilized public EVSE more randomly. Only 33% of PEV drivers exhibited routine usage of public EVSE. A large survey conducted in 2016-17 collected a seven-day charging history from 7,979 PEV owners in California that included information about charging locations (home, work, public), charging level (Level 1, Level 2, DC Fast), and charging cost (Lee et al., 2020). Respondents were classified based on their charging behavior (e.g., home-only chargers, home-and-work chargers, or work-and-public chargers). More than half of the sample (53%) consisted of home-only chargers, while home-and-work chargers constituted 16% of the sample, and chargers who utilized home and public charging stations composed 13% of the sample. Notably, 14% of the sample did not charge at home in the previous seven days. The authors found that women and older PEV owners showed a lower likelihood to use away-from-home charging infrastructure, while residents of multi-unit dwellings were more likely to charge at non-home locations. Drivers of older BEVs were more likely to be in the home-work charging group, perhaps reflecting the shorter range of these vehicles. In contrast, owners of PEVs with a range above 200 miles were less likely to use non-home charging locations, suggesting that longer-range PEVs may lessen the need and demand for public EVSE.

Existing research demonstrates a clear link between SOC and charging decisions but also indicates that charging decision-making varies among individuals, with some individuals charging more aggressively than others. EVSE availability, PEV range, and individual psychology all influence charging behavior. While still growing, the literature on charging probability by location was adequate to inform the charging probability component of the model simulations in this paper.

2.3. PEV Demand Simulation and Representation in Economic Dispatch Modeling

Many early grid impact studies made significant simplifying assumptions about vehicle charging behavior, e.g., that all charging occurs at home in the evening or off-peak (Ahmadi et al., 2015; Calnan et al., 2013; Foley et al., 2013), that all vehicles charge upon arrival as long as a stop has charging infrastructure and a 10-minute dwell time constraint is met (Vithayasrichareon et al., 2015), or that charging was limited to PHEVs (Andervazh and Javadi, 2017; Dowds et al., 2013; Vithayasrichareon et al., 2015). These initial studies are summarized in Gu et al. (2013) and Peng et al. (2012).

More recently, several studies have explored simulating PEV charging profiles based on real-world travel data, but their utilization in grid modeling has generally been limited to the study of optimized charging patterns. Summaries of the literature of PEV charging demand simulation based on household travel surveys are provided in Daina et al. (2017) and Pareschi et al. (2020). Pareschi et al. (2020) created simulated PEV charging profiles based on the Swiss Household Travel Survey. EVSE availability varies by stop type, and charging decisions are modeled stochastically as a function of SOC as is undertaken in this project. Parameterization of the charging behavior was calibrated against data from public PEV trials, including the U.S. DOE's EV Project initiative mentioned previously. The simulated PEV profiles reproduced the empirical charging data with a high degree of accuracy but were limited to a single day of charging. Miller et al. (2020) suggest that PEV demand profiles should account for regional and hourly variations in weekend and weekday vehicle travel and ambient temperature (which impacts electric drive efficiency) over a full 365-day period that captures the impact of seasonality in order to accurately model operating emissions. They utilized historical charging data from the EV Project to create a distribution of the share of total charging that takes place in each hour of the day and determined total energy demand using travel data from the 2009 NHTS. The GHG emissions from charging were calculated using historical emissions data from 2018 and 2019 and thus do not capture the interplay between charging demand and power plant dispatch decisions.

Brady and O'Mahony created a stochastic simulation to generate PEV charging profiles based on GPS travel data collected during a BEV demonstration trial in Ireland (Brady and O'Mahony, 2016). The Bayesian charging demand model considers departure time from home; the number of journeys per day; total distance traveled per day; initial SOC; parking durations; charging availability; and whether owners charge after each journey, conditioned on the battery SOC, parking time, and journey number. The authors note that these profiles would be useful in grid integration and charging optimization analyses. Because the travel patterns used in the model were observed in low-range BEVs, it is unlikely that they capture the full range of travel that will be seen at higher PEV penetration levels. Hu et al. (2019) applied cumulative prospect theory, a behavioral science approach to describing decision-makers' level of risk aversion, to BEV charging behavior using NHTS travel data. None of the charging profiles described here are utilized for dispatch modeling or other grid impact analyses.

The grid impact studies that consider PEV charging demand in the context of high levels of renewable energy penetration generally assume that PEV charging is optimized at the system level (Coignard et al., 2018; Taljegard et al., 2019; Wang et al., 2020). Since public policy is advancing both renewable energy and PEV penetration and the feasibility and public acceptance of managed charging is not a given (Sovacool et al., 2017), joint consideration of renewable and unmanaged charging using high-quality simulated PEV charging demand as well as typical grid dispatch modeling as pursued here is warranted. The overall objective is to assess the extent to which managed charging will be needed to maximize renewable utilization and minimize emissions from power generation.

3. Methods and Data

3.1. Plug-in Electric Vehicle Charging Demand Model

The purpose of the PEV-CDM is to generate time-specific vehicle-charging profiles. The PEV-CDM operates on retabulated household travel survey data to create potential charging demand profiles that are consistent with real-world vehicle-based trips. The model calculates charging demand using the same temporal resolution as the input survey data. For this paper, electricity demand calculated for each minute is aggregated into hourly time steps, since this is the temporal resolution of the regional economic dispatch model. The PEV-CDM is set up so that altering assumptions about PEV adoption, charging preferences, and EVSE availability is straightforward. Thus, the model can be modified to evaluate a wide range of research questions related to PEV penetration, EVSE availability, and charging incentives.

As applied here, the PEV-CDM operates primarily on data from the 2016-2017 NHTS (Federal Highway Administration, 2017). Households that participated in the NHTS were asked to log all trips made by all household members on a single, assigned travel day. The dataset consists of four relational databases: a household table documenting attributes such as income and the number of vehicles owned; a person table documenting attributes of household members, including age, gender, and education; a vehicle table with vehicle class attributes and a primary driver designation; and a trip table documenting every trip that each person made on the travel day, including the travel mode and household vehicle used, when applicable. Data for the seven-state study region of New York and New England included 19,137 households and 34,479 household vehicles. The trip database captured 84,192 unique vehicle trips. The distribution of purposes for these trips is shown in Table 2. Average trip lengths, trip durations, and corresponding stop durations for vehicles making at least one trip on the travel day are shown in Table 3. Note that the number of stops in the dataset exceeds the number of trips because the vast majority of vehicles are stopped before the first trip and after the last trip on the travel day (in rare instances, vehicles either begin or end the day traveling). While the NHTS data has some limitations, most notably for this application that travel data are collected for only a single day, overall the data provide the most robust vehicle-travel dataset available for the study region. Use of the weights provided with the survey data for response bias are described below.

Table 2. Distribution of NHTS Trip Purposes (Destination-based)

Trip Purpose	Number of Trips	Share of Trips
Home	28,705	34%
Shopping	19,820	24%
Work	11,595	14%
Social/recreational	8,140	10%
Passenger drop-off	5,440	7%
Meals	5,304	6%
School/religious	2,132	3%
Medical	1,630	2%
Other	1,426	2%
Total	84,192	100%*

* The sum of individual lines exceeds 100% due to independent rounding

Table 3. NHTS Trip and Stop-length Summary Statistics

	Average	Standard Deviation	Maximum
Trip distances in miles (n = 84,192)	9.28	25.05	1,533
Trip durations in minutes (n = 84,192)	20	27	990
Stop durations in minutes (n = 105,395)	274	265	1,430

Since travel patterns vary seasonally and between weekdays and weekends, the PEV-CDM subsets the NHTS data by season and by weekend versus weekday. Examination of the NHTS data also showed differences in the time of day that vehicles were utilized by vehicle type, with truck and van usage beginning earlier in the day, so the model also subsets the data by vehicle type to capture correlations between vehicle purchase and vehicle usage decisions. Table 4 breaks out vehicles in the study region sample by vehicle type, weekday/weekend, and season.

Table 4. Size of NHTS Vehicle Sample by Season and Day of the Week

Vehicle Type	Day of Week	Season			
		Winter	Spring	Summer	Fall
Car/Station Wagon	Weekday	3,438	2,508	3,300	3,463
	Weekend	1,358	1,009	1,348	1,279
SUV/Pickup/Van	Weekday	3,048	2,183	2,680	2,802
	Weekend	1,280	848	1,099	1,108
Total		9,124	6,548	8,427	8,652

The operation of the PEV-CDM, represented in Figure 1, involves four main steps: 1) creation of vehicle-based daily travel profiles; 2) calculation of PEV Compatibility Scores for each daily travel profile; 3) sampling of weekend and weekday daily travel profiles to create synthetic, week-long travel profiles; and 4) the application of the charging behavior logic to the week-long travel profiles to determine when vehicles charge and how much energy is utilized for each charging event. Because the NHTS data is limited to a single day of travel, in step 2 weekly profiles are constructed by sampling and appending five weekday and two weekend daily travel profiles within the same season and vehicle type. This process is replicated for each of the four seasons and, after the application of the charging logic, each season-week is then replicated 13 times to create a full year of charging demand. The creation of seasonal profiles allows the modeling effort to capture seasonal variation in travel patterns and to reflect seasonal differences in wind and solar availability in the dispatch model.

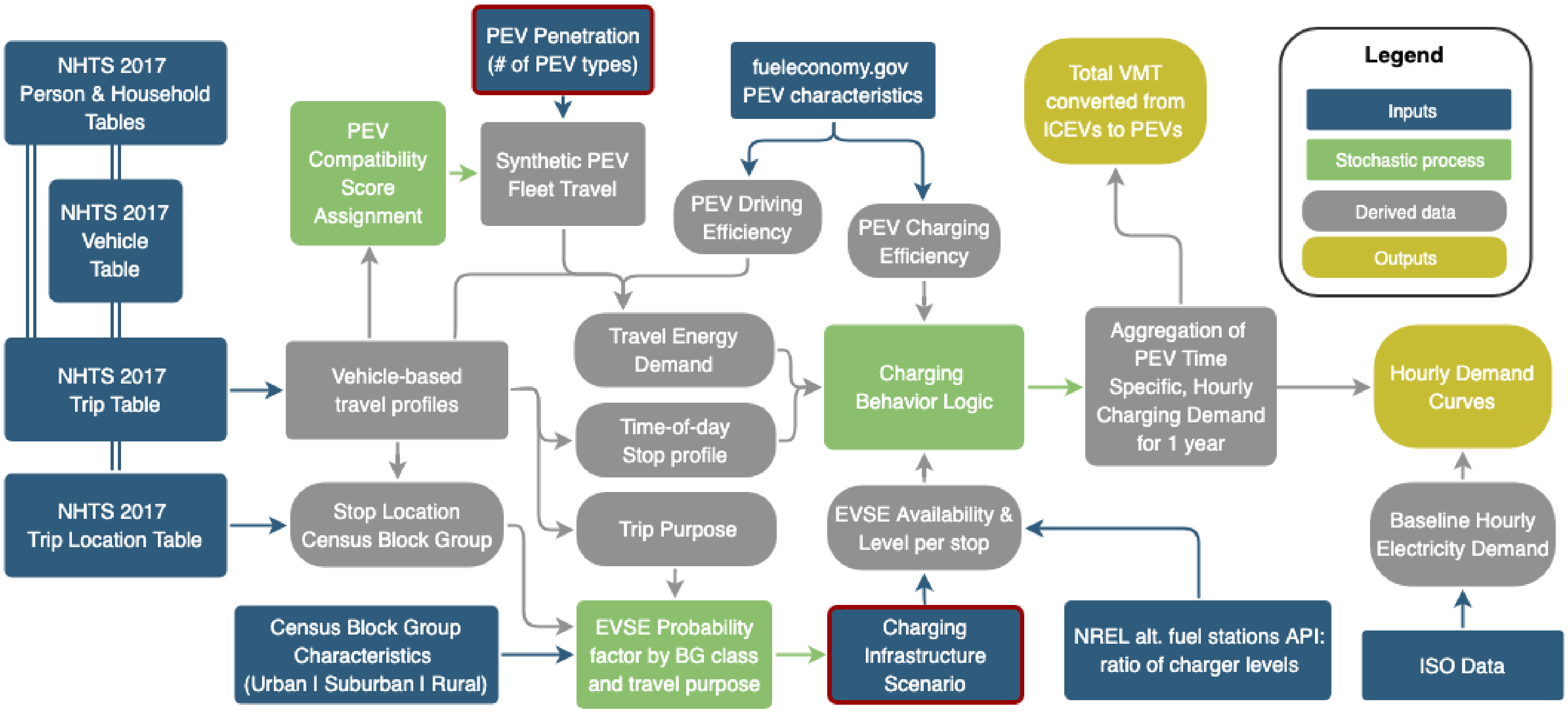


Figure 1. PEV-CDM Schematic

The creation of the vehicle-based daily travel profiles begins with the development of a vehicle trip log and corresponding stop log for each vehicle in the NHTS dataset. The trip log is constructed by eliminating the duplicate vehicle trip records that occur when multiple household members take a trip in the same vehicle at the same time and recording the start and end times, mileage, and purpose for all of the unique trips taken by each vehicle. A corresponding stop log is created for each vehicle, recording the start and end times and duration for all periods when the vehicle was not traveling as well as the purpose of the stop. Each stop is assigned a probability that charging infrastructure will be available at that stop, based on the purpose of the stop and the EVSE scenario. The EVSE availability probability is set to 1.0 by stop type for the first three scenarios: a) home stops, b) home-and-work stops, and all stops in universal EVSE scenarios, respectively. EVSE availability probabilities for the probabilistic scenario are shown in Table 5. Across all scenarios and stop types, 80% of charging is assumed to utilize Level-2 (7.2 kW) charging infrastructure. The remaining 20% of home charging events are assumed to utilize Level-1 (1.7 kW) chargers, while 20% of away-from-home charging events are assigned a DC Fast Charger (50 kW). Once the trip and stop logs are generated, three derived variables – the mileage of the longest trip of the day, the total mileage for the day, and the total number of trips taken on the day – are calculated for each profile. These values, as well as attributes of the household and primary driver of the vehicle (gender, age, and educational attainment), are appended to the daily travel profile to use in the next step, the computation of the PEV Compatibility Scores.

Table 5. EVSE Availability by Stop Type – Probabilistic EVSE Scenario

Description	Value
Probabilities of EVSE availability based on stop/destination Type	home = 0.95 work = 0.75 shopping = 0.5 social/transport = 0.3 meals = 0.4 school/medical/other = 0.3
Probability of EVSE availability based on trip location type of stop	Rural = 0.5 Suburban = 0.9 Urban = 1.0

After the vehicle-based daily travel profiles are created, each travel profile is assigned a set of PEV Compatibility Scores, indicating the relative compatibility of the profile with five different types of PEVs: a low-range BEV car, a high-range BEV car, a BEV truck/SUV, a PHEV car, and a PHEV truck/SUV. These scores are calculated based on household variables and socio-demographic characteristics of the primary driver, as well as vehicle characteristics and travel patterns. The factors that contribute to the Compatibility Scores are based on prior literature and are shown in Table 6. These scores determine the relative frequency with which particular vehicle profiles are sampled in the simulation by the PEV-CDM. For example, a vehicle profile from a single-vehicle household (multiplier of 0.8) with total VMT across all trips greater than the PEV range (multiplier of 0.5) would be sampled by the PEV-CDM only 40% as frequently (0.8*0.5) as a similar profile from a multi-vehicle household with total mileage within the PEV range. Some profiles are considered incompatible with specific PEV types (e.g., truck profiles are incompatible with PEV cars) and are never sampled for these PEVs. After the Compatibility Scores are calculated for each vehicle in the dataset, they are also multiplied by the NHTS expansion weights (developed by the NHTS program to accord for sample bias; New York and New England regional weights were used in this case). Application of the NHTS weights produces the final weights for sampling the profiles for each PEV type.

Table 6. Compatibility Score Multipliers

Variable	Multiplier	Notes
Household location	Urban: 1.0 Rural: 0.8	Rural areas are assumed to have a lower EVSE density and therefore lower PEV uptake
Household Income	Income/4 > PEV Price: 1 Income/4 < Price: 1-1000/diff	The likelihood of PEV adoption increases with household income.
Household Vehicle Count	2 or more vehicles: 1 1 vehicle: 0.8	Assumed values based on literature showing higher PEV adoption for multi-vehicle households (Axsen et al., 2016)
Driver Age	1-0.0042*(age-16)	Decreased likelihood of PEV ownership with age (Carley et al., 2013)
Driver Education	College degree: 1 Some college: 0.95 High school: 0.83	Impact of education on PEV ownership (Carley et al., 2013)
Vehicle Body Type	Auto to truck: 0 Truck to auto: 0	Assumes consumer preferences for cars versus trucks/vans are stable in this application of the model
Vehicle Fuel Type	PEV/Hybrid: 1 ICEV: 0.9	Assumes lower probability of switching from an ICEV to a PEV than from a PEV or hybrid to PEV
Longest Trip Length	Trip length < PEV range: 1 Trip length > PEV range: 0	The profile is considered incompatible with a PEV type if the longest trip is greater than the PEV's range
Total Daily Trip Miles	Total Miles < PEV range: 1 Total miles > PEV range: 0.5	Profile compatibility is reduced if the total daily mileage exceeds the PEV's range, reflecting range anxiety
Minimum Battery SOC if charging at every opportunity	SOC > 0.1: 1 SOC < 0.1: 0.7 SOC < 0: 0	Profile compatibility is reduced if SOC falls below 10% (range anxiety) and incompatible if the SOC falls to 0.

The PEV characteristics for the Compatibility Score calculations and energy demand components of the PEV-CDM are summarized in Table 7. Vehicle characteristics (electric range and electric drive efficiency) are estimated based on the 75th percentile of the performance of currently available PEVs (model years 2015 and later) as reported by FuelEconomy.gov (U.S. Deparment of Energy, 2018). Vehicle price parameters are estimated from currently available models as reported in (McDonald, 2018).

Table 7. Modeled PEV Attributes

Attribute	Low-Range BEV Car	High-Range BEV Car	Low-Range BEV Truck	PHEV Car	PHEV Truck
Electric Range (mi)	110	310	290	30	20
Drive efficiency (kWh/100 mi)	30	30	35	35	50
Cost (thousands $)	25	50	50	25	50
Fraction of modeled PEVs	0.28	0.26	0.14	0.27	0.05

Once the daily vehicle-based travel profiles have been created and weekly profiles generated, the charging logic, summarized in Figure 2, is applied to the weekly profiles. Depending on the EVSE scenario, each stop is assigned a probability of having Level 1, Level 2, or DC Fast charging infrastructure available. Stops are categorized as non-charging stops, discretionary charging stops, or mandatory charging stops. Non-charging stops include stops without charging infrastructure, where dwell times are less than 10 minutes, or where the SOC is 100%. Mandatory charging stops are stops where charging infrastructure is available and must be utilized to complete all remaining travel on that day (or the next day if it is the last stop of the day). All other stops with charging infrastructure are discretionary, and the probability of charging at these stops is shown in Figure 2.

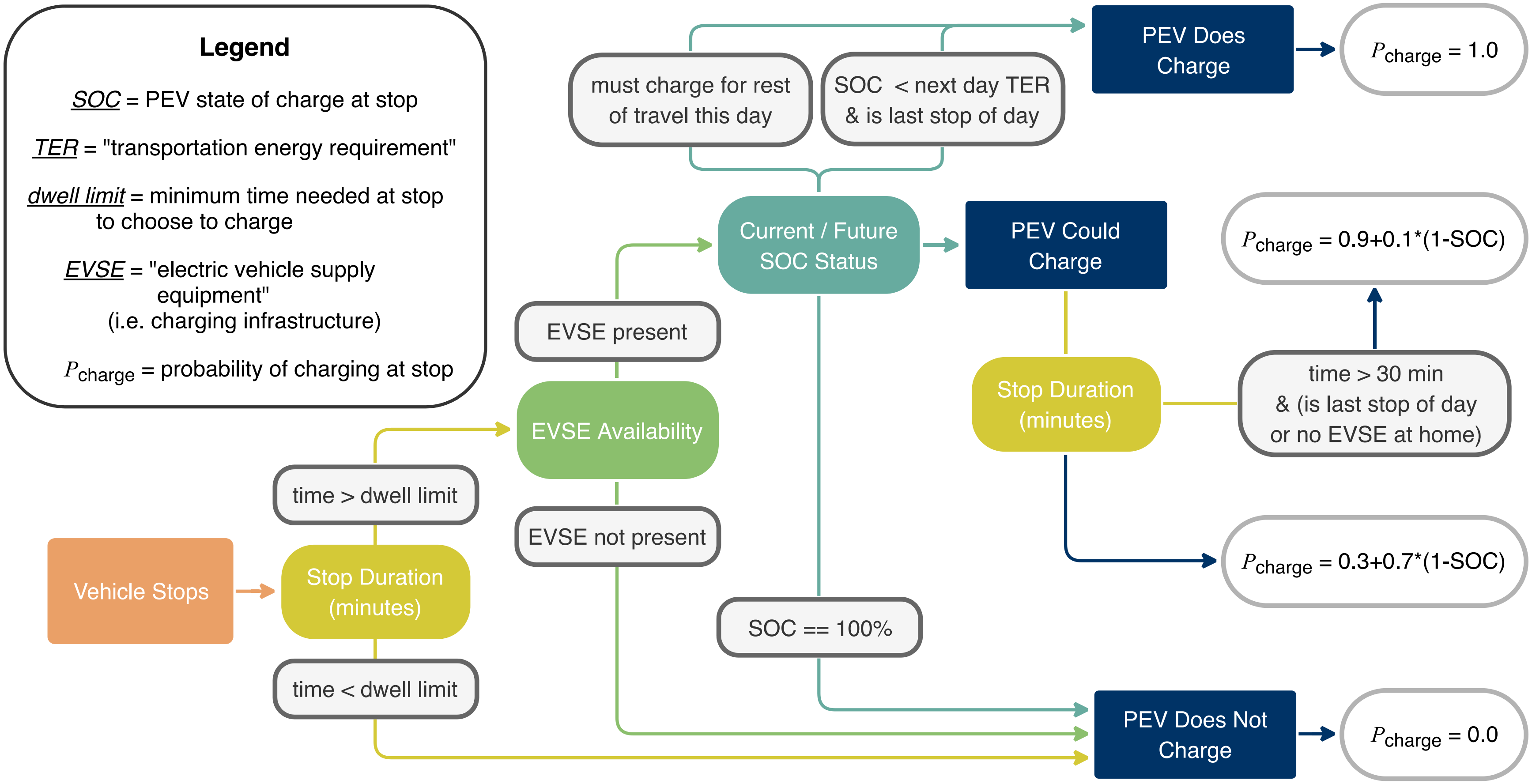


Figure 2. Charging Behavior Logic

For the initial application of the charging logic, the starting SOC is set to 100%. If the initial and final SOCs for the week do not match after this initial iteration, the charging logic is repeated using the final SOC from the previous iteration as the initial SOC in the next iteration. This process is repeated using the same vehicle profiles, decision variables, and EVSE levels used in the first iteration until the SOC at the end of any day matches the SOC on that day in the previous iteration. This method creates a continuous charging profile driven by the charging behavior logic and the empirical travel patterns from the NHTS. If the reiteration process does not converge after 16 iterations, it is aborted; this occurred approximately 2% of the time. In some instances, when the SOC at the start of a day is lower than 100%, a formerly feasible profile can become infeasible. In this case, a random vehicle profile is resampled to replace the infeasible profile. Less than 0.2% of weekly profiles required resampling. If resampling occurred within a reiteration loop, the entire weekly charging profile function was aborted and restarted with a new weekly profile. Figure 3 shows an example of a 1-week charging profile for a low-range BEV, generated under the probabilistic EVSE scenario. The top plot shows the SOC throughout the week, with an initial and final SOC just over 0.7, while the bottom shows the hourly demand associated with all charging events.

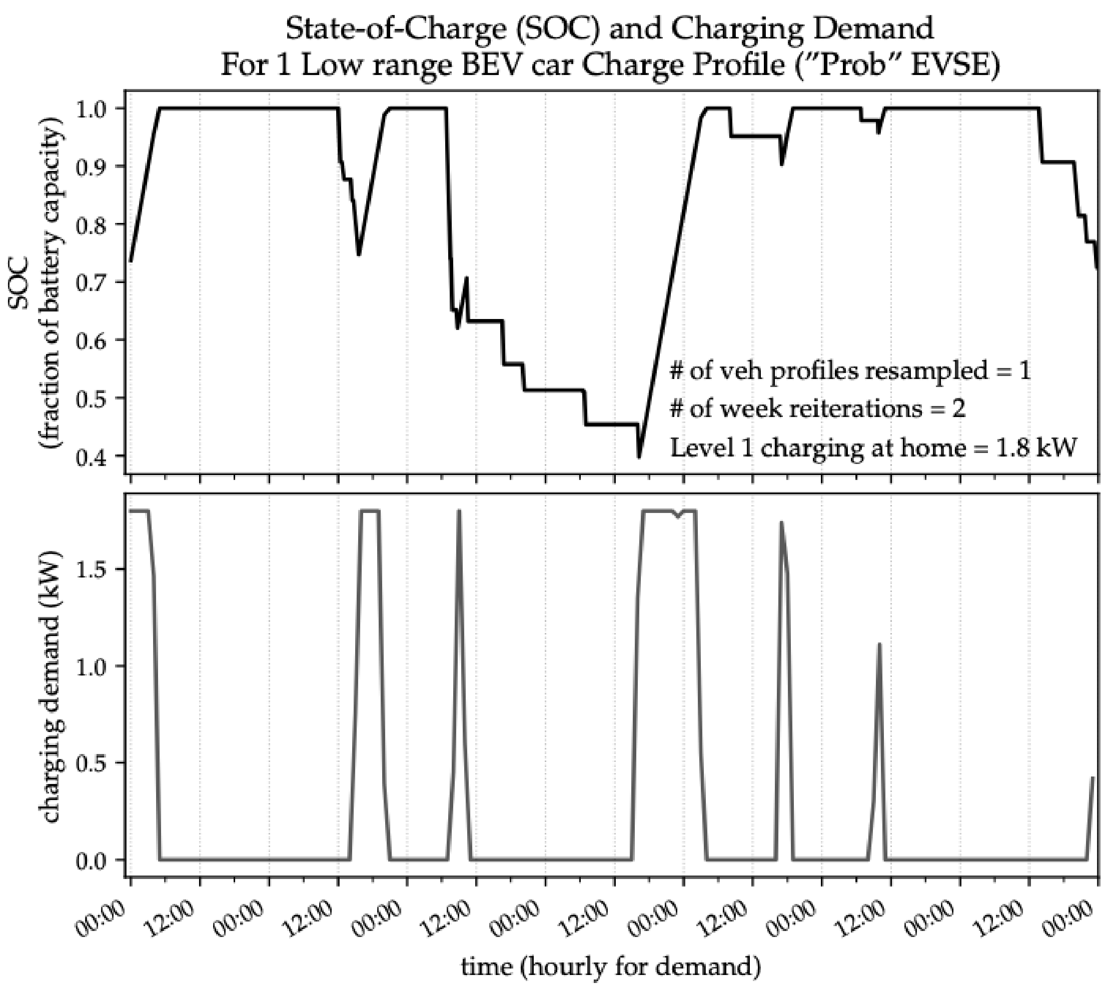


Figure 3. Example of Weekly Charging Profile for Low-range BEV

The structure of the PEV-CDM is highly flexible to modification. Changes to PEV costs and performance variables, predictors of PEV adoption, and charging behavior can easily be incorporated into the model. Likewise, alternative study regions and travel surveys can be used as the basis for the vehicle travel and stop profiles and sub-hourly time intervals can be modeled for other analytical applications.

3.2. Economic Dispatch Model and Input Data

The regional economic dispatch model optimizes the hourly power output for all modeled generating facilities to minimize the cost of meeting hourly electricity demand and expands on the model presented in Howerter (2019). The dispatch model operates on an hourly time step for one year. Model outputs include marginal generating costs, GHG and NOx emissions, and renewable energy utilization and curtailment. The application of the dispatch model incorporates extensive wind and solar generating capacity to assess the interaction between RPS and PEV charging demand.

Baseline demand data used for the dispatch model were downloaded from the independent system operators for New York (NYISO) and New England (ISO-NE) for 2016 (New York Independent System Operator, 2018; ISO New England, 2019). ISO-NE provides jurisdiction-wide, hourly load data. Load data from NYISO are reported zonally in 5-minute increments. The data from NYISO were averaged for each hour and summed across all zones to produce hourly statewide demand for New York. An 8% growth rate was applied to the hourly demand from 2016 to project demand for 2030 (EIA, 2019).

Generating capacity and performance data (heat rates, emissions rates, and fuel types) for existing generators in the region came from the EPA's 2016 Emissions and Generation Resource Integrated Database (eGRID) (US EPA, 2015). Hydro, wind, and solar generating facilities were aggregated at the state level, while all other plants are represented individually. Thermal plants missing emissions rates were assigned the average emissions rate for plants of the same fuel type and were excluded from the model if there were no plants of that type with valid data. The final dataset also excluded combustion plants with a nameplate generating capacity below 25 MW (which are not covered by the Regional Greenhouse Gas Initiative [RGGI], a GHG cap-and-trade system operating in the northeast United States), as well as plants missing primary fuel type or nameplate capacity. Electricity imports and exports were not considered in this iteration of the model.

Currently, 29 states and the District of Columbia have some form of renewable portfolio standard (RPS) requiring electricity suppliers to increase renewable energy generation. States have generally succeeded in meeting their RPS targets and approximately half of the growth in renewable generation since 2000 is related to state requirements (Barbose, 2018). In the northeast United States, 2030 RPS targets range from 25% to 70% of total generation ("State Renewable Portfolio Standards and Goals," n.d.). The authors created a 2030 RPS-compliant generating portfolio by adding sufficient additional wind and solar to meet all individual states RPS targets. Renewable generation capital costs were not considered in the optimization, under the assumption that the states would require compliance with their RPS standards. The additional nameplate wind and solar capacity required to meet the RPS targets were calculated by assuming equal generation from solar and on-shore wind and average capacity factors for the resources from 2013-2016 calculated by using the data and methodology described in James et al. (2017). Solar, wind, and hydro have $ 0/MWh marginal cost in this model and are thus always dispatched first up to their hourly maximum capacity or until further utilization of these resources in a particular hour would require an infeasible change in thermal generation between one hour and the next. Table 8 shows the installed capacity by fuel type of the modeled plants included in the 2016 eGrid data as well as the expanded capacity required to meet the 2030 RPS targets.

Table 8. RPS-Compliant Generating Capacity

Fuel Type	Average Marginal Cost ($/MWh)	Average GHG Rate (metric ton/MWh)	2016 eGrid Plants		2030 RPS Compliant Portfolio	
			Total MW	% of Total Capacity	Total MW	% of Total Capacity
Gas	$ 54.23	0.49	43,903	47	43,903	28
Solar	$ 0.00	0.00	903	1	43,900	28
Wind	$ 0.00	0.00	4,646	5	26,300	17
Oil	$ 328.53	1.15	16,379	18	16,379	10
Nuclear	$ 7.10	0.00	9,783	11	9,783	6
Hydro	$ 0.00	0.00	9,510	10	9,510	6
Coal	$ 22.95	0.97	5,834	6	5,834	4
Biomass	$ 15.46	0.32	2,093	2	2,093	1
Total			93,053	100	157,704	100

Figure 4 shows the hourly availability of wind and solar power averaged over the full year and for two individual days, March 1 and August 1. In these examples, average wind availability is quite stable over the course of the day, with a slight dip during daylight hours. Average solar availability is highly concentrated during mid-day hours, with a rapid increase between 6 AM and noon and then a rapid decrease until 6 PM. This rapid drop in available solar power drives the concern about the duck curve effect, a phenomenon in which net load (demand less the power generated by intermittent renewable) dips sharply in the middle of the day, requiring rapid, technically and economically inefficient changes in baseload generation and/or significant renewable curtailment (Coignard et al., 2018). Of course, the nature of these generating sources is such that there is considerable variation in their daily availability, as is illustrated here.

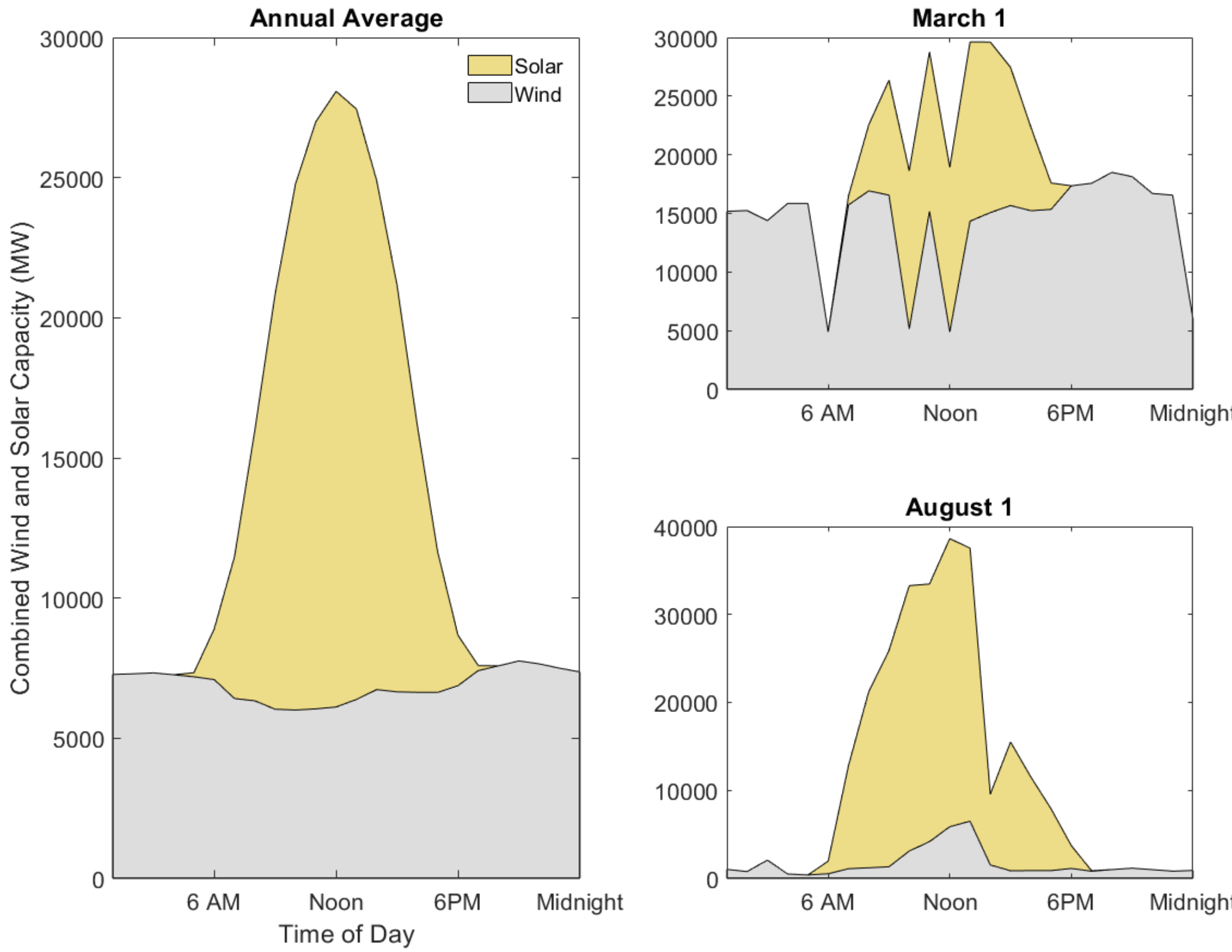


Figure 4. Availability of Wind and Solar Generating Capacity

The dispatch model is a linear optimization model that minimizes the system cost of generating electricity, given a set of power generation facilities, fuel costs, hourly demand, and emissions constraints. It operates on an hourly time-step for one year. The model is written in Julia using JuMP (Dunning et al., 2017), a domain-specific open-source modeling language for mathematical optimization, and the Gurobi solver (Gurobi Optimization, LLC, n.d.).

The formulation of the dispatch model is given in Equations 1 to 6. The decision variable is the power generation from every generator, P_g, in each hour of the year. Equation 1 is the objective function, where c_g is the fuel cost for generator g and $P_g(t)$ is the power generated by that generator in hour t, the product of which is summed annually for all generators, N_g. Fuel costs are equal to the product of the fuel price and each plant's heat rate and are set to zero for wind, solar, and hydro facilities. The power balance constraint in Equation 2 requires that total generation in each hour equals the demand in that hour, $P_d(t)$, for all hours of the year, $t \in T$. Equation 3 limits the maximum generation of each plant to the product of its maximum installed capacity, $P^{max}{}_g$, and an hourly capacity factor, $CF_g(t)$, that varies hourly for wind and solar plants and equals 1 for all other plants. Equation 4 limits the maximum change in power generation in consecutive hours, $P_g(t)$-$P_g(t$-1), for ramping constrained power plants,

$g \in \{Ramp\}$. Ramping constraints were applied to biomass, coal, and nuclear facilities using the ramp rates reported in Deloitte (2019). Equation 5 constrains the GHG emissions at levels set by RGGI, G^{max}. GHG emissions are equal to the product of each plant's GHG emissions rate, r^{GHG}, and power generation, summed for all generators and all hours. Similarly, Equation 6 constrains the NOx emissions of New York power generators for May to September ($t \in \{2880, 6552\}$), at levels set by the EPA, where r_g^{NOx} is the NOx emissions rate. Transmission constraints are omitted from this model.

$$\text{minimize} \quad \sum_{t=1}^{T} \sum_{g=1}^{N_g} c_g P_g(t) \qquad \forall t \in T \qquad \mathbf{1}$$

$$\text{s.t.} \quad \sum_{g=1}^{N_g} P_g(t) = P_d(t) \qquad \forall t \in T \qquad \mathbf{2}$$

$$P_g^{min} \leq P_g(t) \leq P_g^{max} * CF_g(t) \qquad \forall t \in T \qquad \mathbf{3}$$

$$\left|P_g(t) - P_g(t-1)\right| \leq D_g^{max} \qquad \forall g \in \{Ramp\} \qquad \mathbf{4}$$

$$\sum_{t=1}^{T} \sum_{g=1}^{N_g} P_g(t) * r_g^{GHG} \leq GHG^{max} \qquad \mathbf{5}$$

$$\sum_{t=2880}^{t=6552} \sum_{g \in NY} P_g(t) * r_g^{NOx} \leq {NO_x}^{max} \qquad \mathbf{6}$$

Model outputs include the hourly generation and emissions for each power plant in the model. In addition, the marginal cost of generation is the dual variable of the power balance constraint shown in Equation 2, while the GHG cost is the dual variable of the emissions constraint in Equation 5 of the optimization formulation.

4. Results and Discussion

4.1. PEV-CDM: Vehicle Charging Demand

For each modeled scenario, the PEV-CDM outputs aggregate hourly charging demand, charging demand by stop type, and total PEV electric VMT. Here we consider several aspects of these results that have implications for grid operations: charging demand as a share of baseline demand, seasonal and daily patterns in the timing of charging demand, the degree of alignment between charging demand and wind and solar availability, and the extent to which charging demand impacts interhour variability in total demand. In addition, we look at the relationship between stop type and charging demand under the universal EVSE scenario.

Seasonal and annual energy demand resulting from PEV charging is summarized in Table 9. Total energy consumption for PEV charging is dependent on the EVSE scenario, since more widespread charging infrastructure means that higher-mileage daily travel profiles are compatible with PEV range and charging characteristics. For 15% PEV penetration, charging increases annual electricity demand by between 1.9% and 2.2% of baseline demand (home-only and universal EVSE scenarios, respectively). At the seasonal level, total charging demand for all EVSE scenarios is highest in the summer and fall and lowest in the spring and winter, reflecting underlying variability in travel patterns. Although absolute demand is highest in the summer, total and hourly average PEV charging demand, as a share of baseline electricity demand, is highest in the fall for all EVSE scenarios. This shows that both travel and electricity consumption increase in the summer, but that there is a decrease in baseline electricity consumption in the fall while travel is still high. Looking at peak PEV charging demand, the peak hour of demand for the PEV occurs in the home scenario in the fall. In all seasons, the peak hour of PEV demand under the home charging scenario was higher than that of both the work and probabilistic scenarios, even though the total annual and average hourly demand are lower. This implies that even with unmanaged charging, the addition of public infrastructure helps to reduce peak demand to a certain extent as charging is more evenly spread out throughout the day.

Table 9. PEV Charging Demand by Scenario

		5% PEV penetration				15% PEV penetration			
		home	work	prob	univ	home	work	prob	univ
Total Demand (GWh and % of baseline)	Annual	2,001 0.65%	2,119 0.69%	2,119 0.69%	2,258 0.73%	6,001 1.94%	6,352 2.05%	6,357 2.06%	6,775 2.19%
	Winter	464 0.60%	493 0.63%	493 0.63%	524 0.67%	1,390 1.79%	1,480 1.90%	1,479 1.90%	1,573 2.02%
	Spring	441 0.63%	465 0.67%	463 0.66%	490 0.70%	1,323 1.89%	1,394 2.00%	1,392 1.99%	1,469 2.10%
	Summer	553 0.62%	580 0.65%	584 0.65%	622 0.70%	1,656 1.85%	1,738 1.95%	1,751 1.96%	1,867 2.09%
	Fall	544 0.75%	580 0.80%	579 0.80%	622 0.86%	1,631 2.26%	1,740 2.41%	1,736 2.40%	1,866 2.58%
Average Hourly Demand (MWh and % of baseline)	Winter	212 0.57%	226 0.60%	226 0.60%	240 0.63%	636 1.70%	678 1.81%	677 1.80%	720 1.91%
	Spring	200 0.61%	211 0.64%	210 0.64%	222 0.67%	599 1.84%	632 1.92%	630 1.91%	665 2.00%
	Summer	250 0.61%	263 0.63%	264 0.64%	282 0.67%	750 1.83%	787 1.90%	793 1.91%	845 2.01%
	Fall	249 0.74%	266 0.78%	265 0.78%	285 0.83%	747 2.22%	797 2.34%	795 2.33%	855 2.48%
Maximum Hourly Demand (MWh and % of baseline)	Winter	736 1.93%	624 1.64%	699 1.83%	738 1.94%	2,201 5.78%	1,873 4.91%	2,094 5.48%	2,220 5.80%
	Spring	561 1.73%	495 1.54%	531 1.63%	559 1.72%	1,679 5.17%	1,481 4.63%	1,593 4.88%	1,670 5.13%
	Summer	625 1.78%	588 1.68%	609 1.74%	781 2.23%	1,882 5.33%	1,750 5.00%	1,819 5.19%	2,339 6.68%
	Fall	848 2.63%	693 2.16%	779 2.44%	818 2.55%	2,533 7.91%	2,083 6.49%	2,346 7.31%	2,455 7.61%

The impact of PEV charging on the overall demand curve for the average day is shown in Figure 5. Unmanaged PEV charging increases demand for all hours of the day, with the greatest increase during the late afternoon and evening. Without time-of-day charging incentives or other managed charging regimes, charging demand contributes relatively little to overall demand in the overnight and early morning hours, when the baseline demand is lowest.

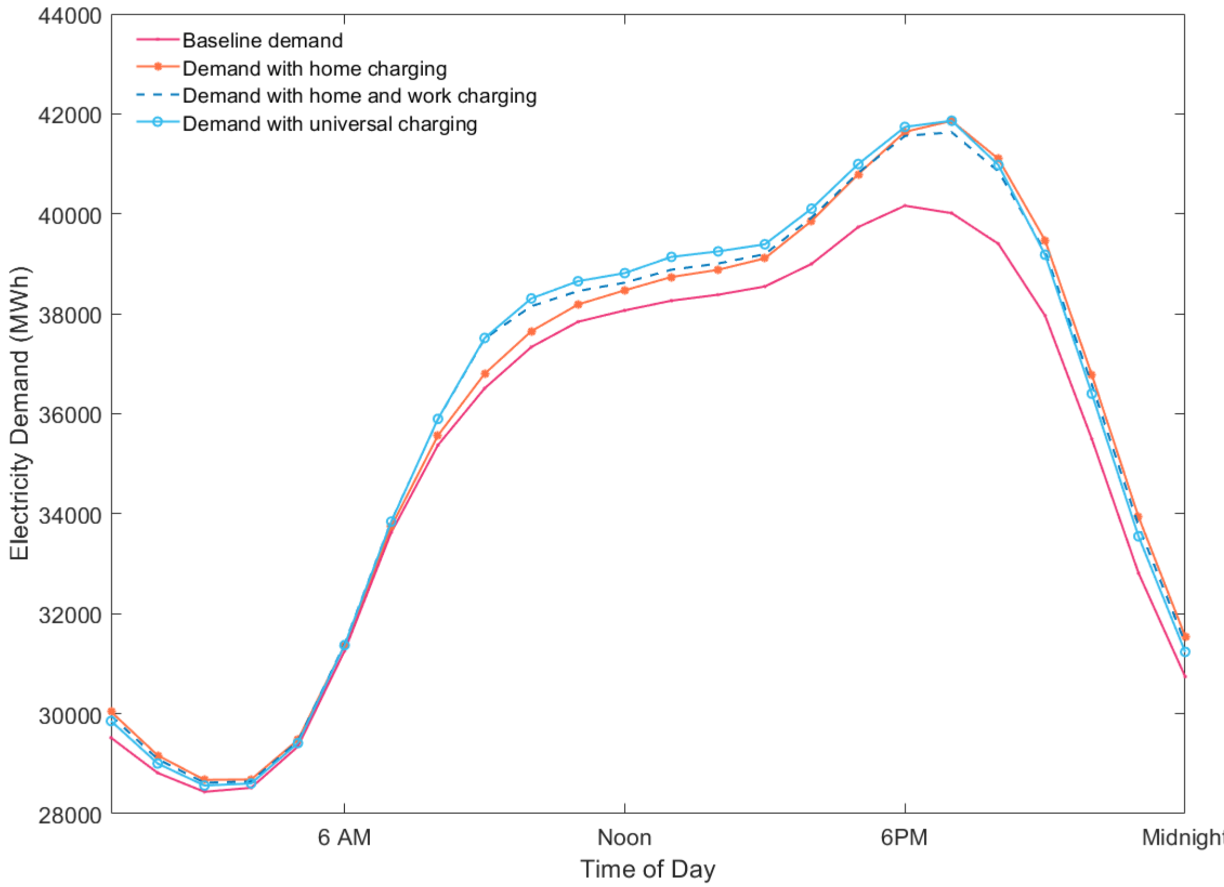


Figure 5. Average Hourly Demand – Baseline and 15% PEV Scenarios

Figure 6 shows the aggregate PEV demand for Friday and Saturday of each season to illustrate both the seasonal and daily variability in the timing of PEV charging demand. Weekday charging demand is bimodally distributed, peaking in the morning hours as PEV drivers arrive at work and in the evening as they return home. Weekend charging demand, in contrast, peaks in midday as trip making is less constrained by work and school travel. Similarly, reflecting the constraints of work and school travel, total weekday charging demand is relatively consistent across the seasons, but weekend travel shows considerable variation by season, with highest demand in summer, followed by fall.

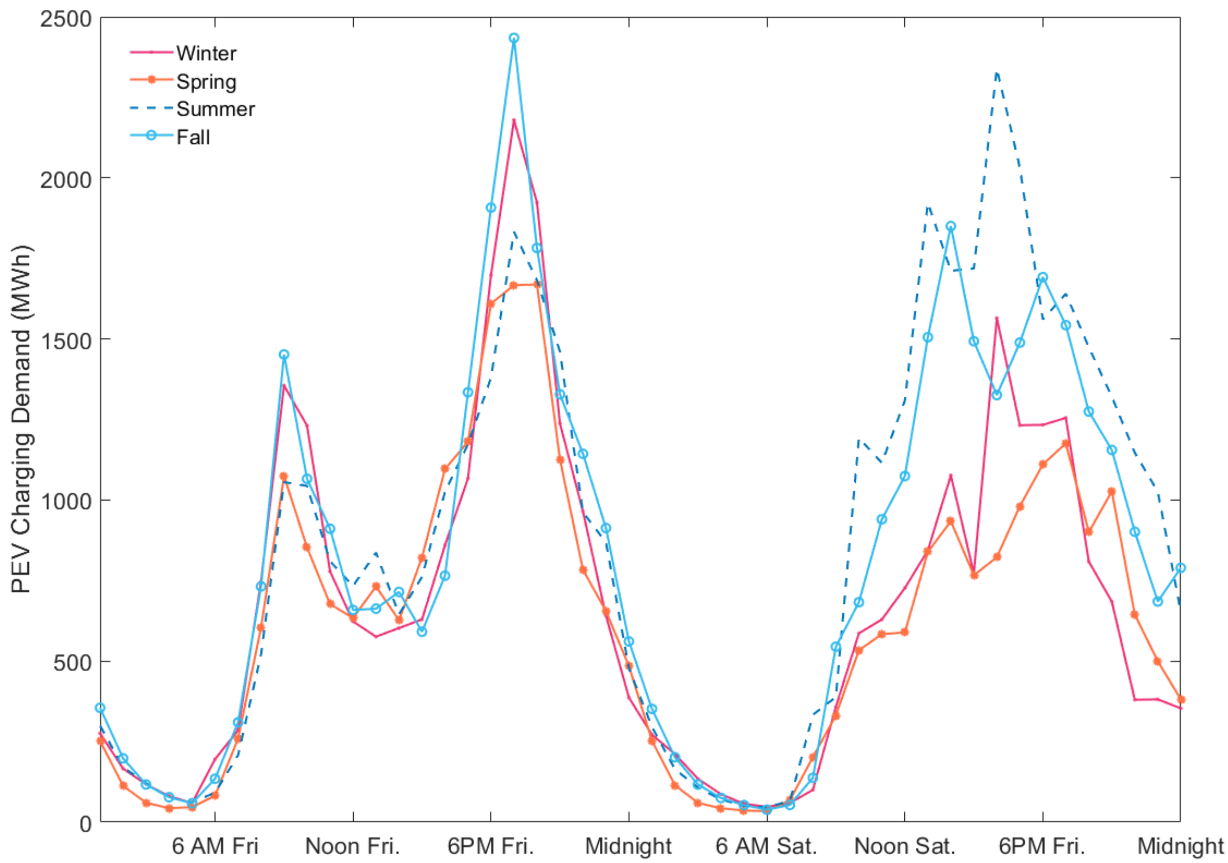


Figure 6. Differences in the Distribution of Weekday vs Weekend Demand (15% PEV penetration, universal EVSE availability)

To illustrate the degree of temporal alignment between charging demand and renewable generation, Figure 7 compares the share of daily PEV demand to the share of combined wind and solar availability for each hour of the average day. PEV demand for the probabilistic EVSE scenario has been omitted from this figure to improve visual clarity; if included, it would fall between the home-only and universal EVSE scenarios for all hours of the day. Since combined wind and solar availability on average is highest at midday (as illustrated in Figure 4 and shown in grey here), charging demand during this period can be beneficial for ensuring these energy sources are fully utilized. Consistent with expectations, expanding the availability of away-from-home charging opportunities in both the work and universal EVSE scenarios increases daytime charging, coinciding with solar energy availability. Daytime charging demand is highest with universal EVSE availability and lowest in the home-only scenario. Given the charging assumptions utilized in PEV-CDM, PEV demand in all scenarios increases through the late afternoon and evening as combined wind and solar availability fall, exacerbating the duck curve effect.

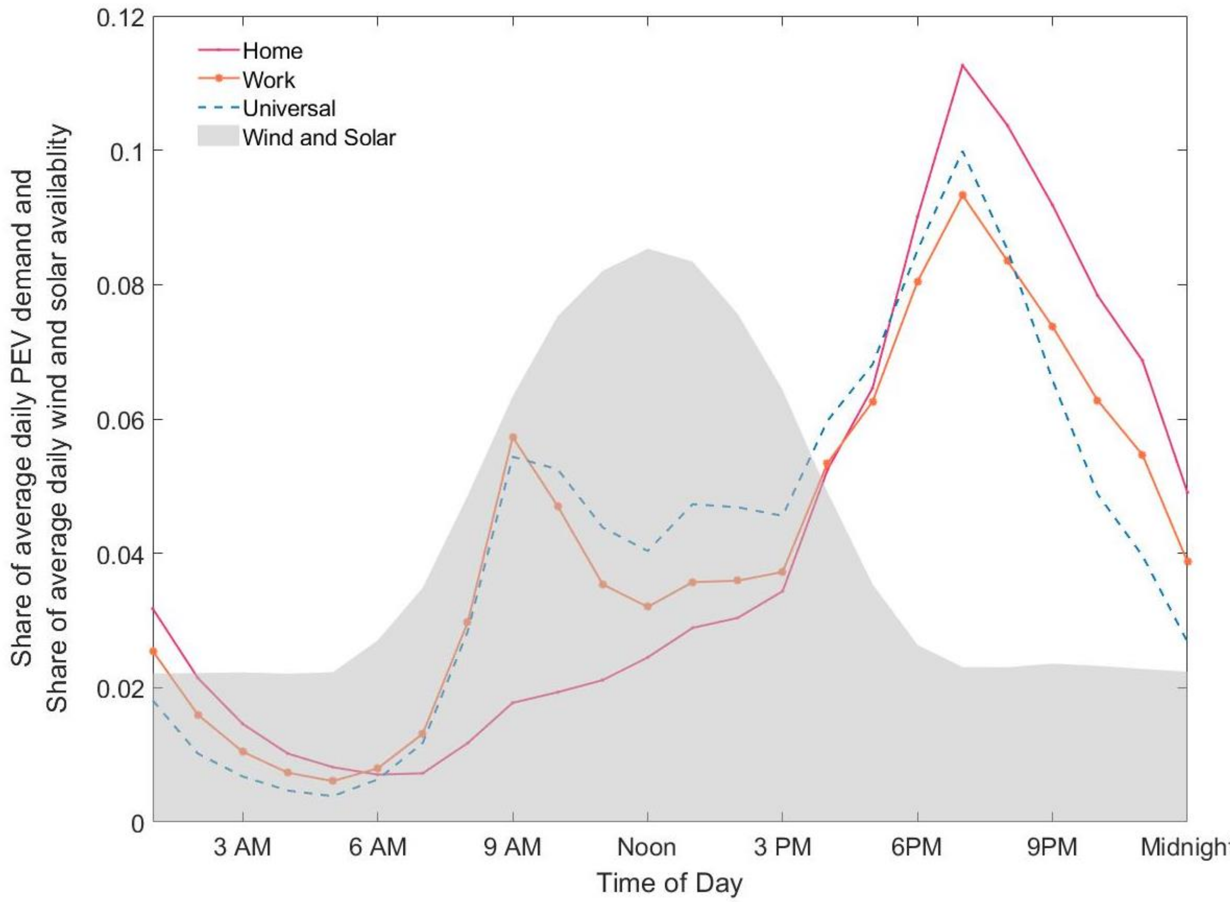


Figure 7. Impact of EVSE Availability on the Temporal Correspondence between PEV Demand and Combined Wind/Solar Availability

Another important aspect of charging demand on grid operations is the extent to which charging increases or decreases the hourly variability in electricity demand. Larger and more rapid changes in demand require more active load following (tracking) by generating facilities and can increase operating costs and complexity. Table 10 summarizes the hourly changes in electricity demand for the baseline demand scenario and the 15% PEV penetration for each of the four EVSE availability scenarios. These results show that interhour variability in electricity demand increases with EVSE availability. The universal EVSE availability scenario has the highest average change and the largest standard deviation in hourly electricity demand. While PEV charging demand increases interhourly changes in demand, the magnitude of this increase is modest relative to the existing baseline variability at the 15% penetration level. As noted in Smart and Salisbury (2015), simple time-of-day pricing, which incentivizes PEV users to begin charging at a specific hour, is likely to result in more dramatic swings in hourly demand than charging behavior governed by trip stop timing as modeled in the PEV-CDM.

Table 10. Interhour Changes in Electricity Demand

Change in Hourly Demand (MWh)	Baseline	EVSE Scenario - 15% PEV Penetration			
		Home Only	Work	Probabilistic	Universal
Median	841.8	946.0	964.5	961.7	980.0
Mean	1,100.5	1,204.4	1,219.4	1,216.9	1,237.4
Maximum	4,272.4	4,481.2	4,433.2	4,486.4	4,545.8
Stand Deviation	925.3	975.9	981.6	985.5	1,001.6
10th Percentile	129.9	148.3	158.9	149.9	144.8
90th Percentile	2,586.3	2,746.8	2,783.5	2,779.4	2,821.8

Finally, the PEV-CDM also summarizes charging demand by stop purpose. The universal EVSE scenario provides insight into the potential charging demand that could be met at different stop types and can inform EVSE siting priorities. Consistent with existing empirical research, home charging accounts for the largest share of PEV charging demand in the universal EVSE scenario (55.6%), while work charging accounts for the second-largest share of charging demand (17.3%). This reflects a combination of the frequency of trips to home and work (see Table 2) as well as the relatively long duration of stops at these locations. Figure 8 compares the frequency of away-from-home stops with the share of PEV charging demand that occurs at each stop type. Following work stops, social/recreational and then shopping stops represent the largest shares of non-home charging demand. Notably, the social/recreational stops accounted for a higher share of non-home charging demand than their share of stops, which may indicate that the trips are likely to occur later in the day's trips sequence (e.g., after work or school), resulting in a comparatively low SOC at these stops. These results support incentives for workplace charging infrastructure development since nearly 40% of all non-home charging occurred at work stops and the work EVSE scenario shifted a significant fraction of PEV charging demand into daylight hours.

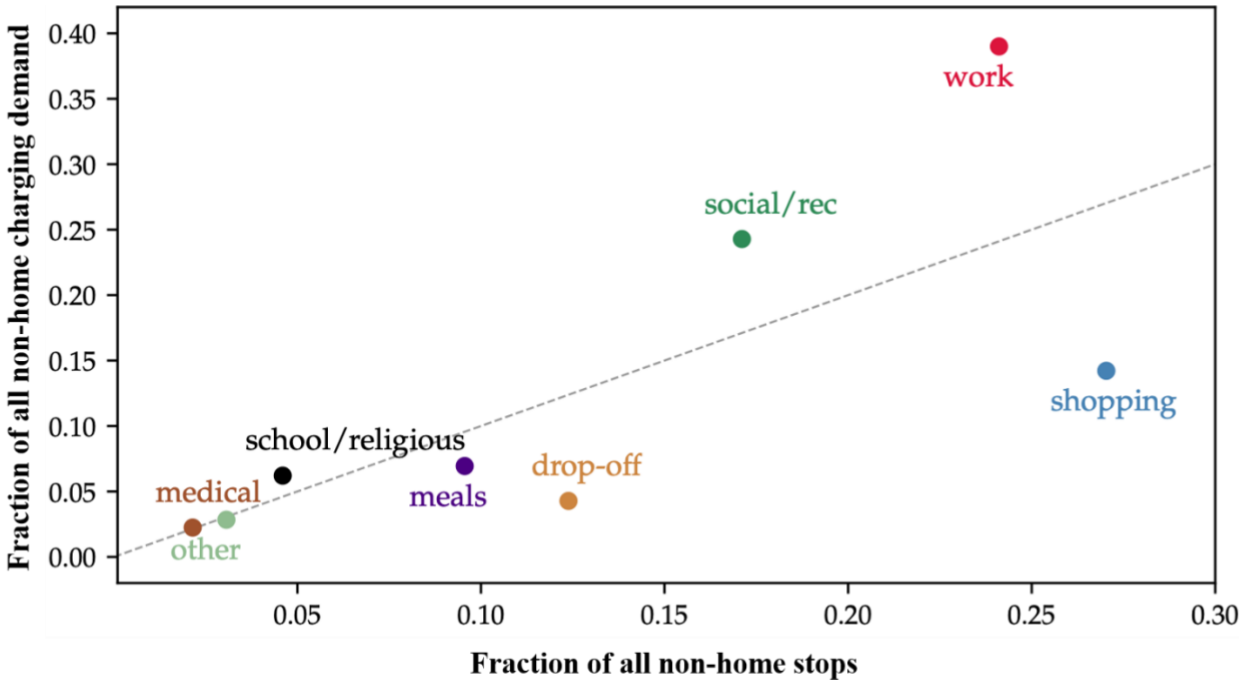


Figure 8. Away-from-home Charging Demand by Stop Type and Stop Frequency with Universal EVSE Availability

Consistent with prior research, the PEV-CDM results suggest that total PEV charging demand at 15% PEV penetration is unlikely to tax aggregate existing generating capacity. Instead, grid impacts are more likely to result from the timing of PEV charging relative to peak demand and relative to wind and solar availability. The quantification of hourly charging demand, consistent with real-world travel behavior, allows for the integration of travel behavior with economic dispatch modeling and other grid modeling tools.

4.2. Power Generation and Associated Emissions Results

The regional economic dispatch model was run for nine PEV scenarios, with hourly electricity demand for PEV charging varying between runs. Since the RPS-compliant generating portfolio for 2030 used in the application of the model includes a 10-fold increase in installed wind and solar capacity, the GHG emissions constraint (Equation **5**) was not binding in any of the model runs. Comparing dispatch model run results across scenarios shows the impact of PEV charging and EVSE availability on afternoon ramping of thermal generators (the duck curve effect), the net change in GHG emissions across the transportation and electric power sectors, changes in total generation by fuel type, as well as the impact of charging demand on the utilization of wind and solar resources. Since the impacts of the 5% and 15% PEV penetration levels differ in magnitude but are otherwise broadly similar, the text and figures in the section focus on the 15% PEV model runs.

As discussed previously, substantial solar generating capacity, like that assumed for the RPS-compliant generating portfolio, can drive down the utilization of thermal generators during midday hours, requiring these generators to rapidly increase their power output in the later afternoon and evening hours as solar availability wains. Figure 9 shows the average hourly load faced by thermal generators during the summer months, exhibiting the characteristic "duck curve" shape in the baseline model run and for all EVSE scenarios. The addition of PEV charging demand does modestly increase the minimum demand facing the thermal generating facilities, especially with universal EVSE availability, but also increases the evening peak, exacerbating the overall rate at which thermal generation increases through the late afternoon and evening. While this level of ramping is feasible within the constraints included in the dispatch model, the model omits constraints on minimum operating time and start-up costs. Consequently, actual grid operation would likely require additional steps to mitigate the magnitude of thermal ramping, such as the increased curtailment of solar generation, the development of significant electricity storage capacity, or the implementation of managed PEV charging regimes.

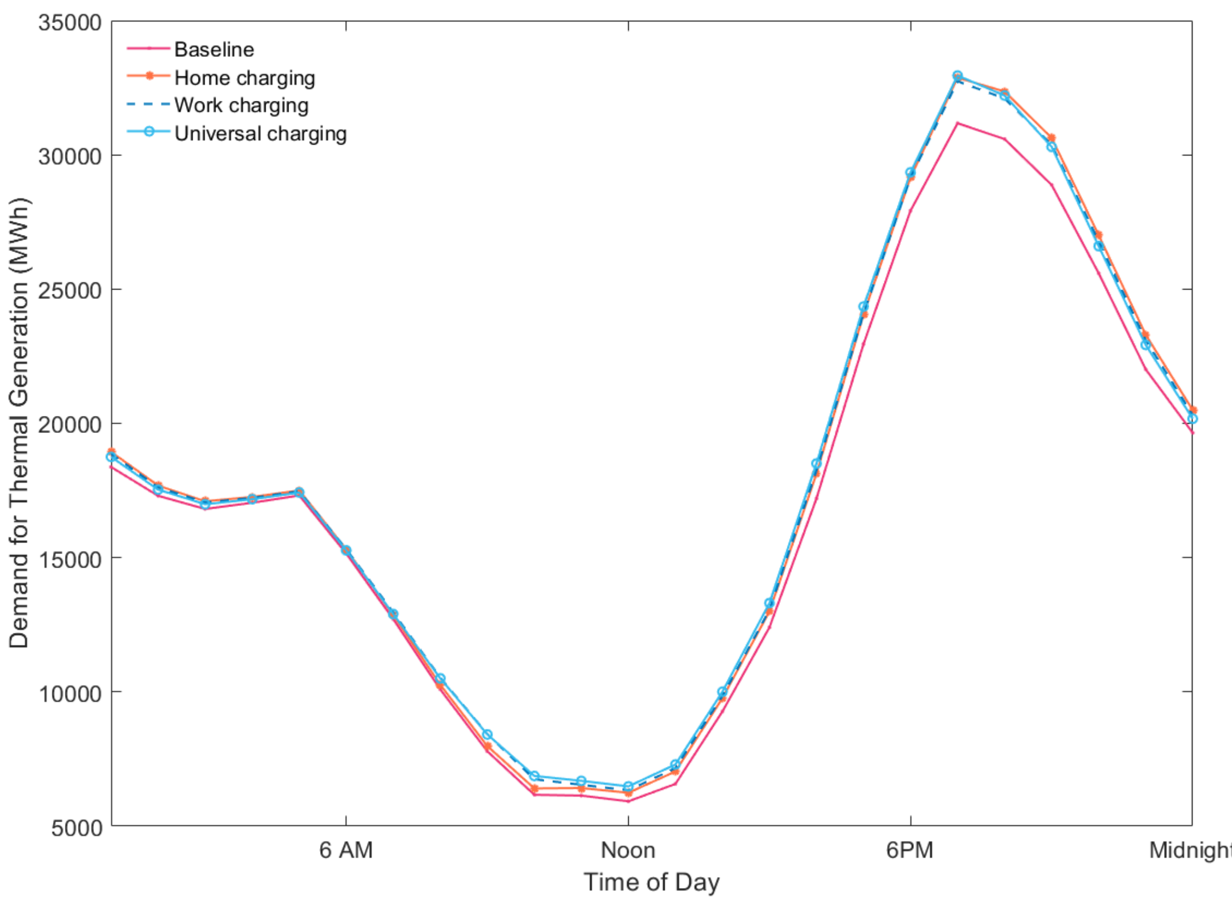


Figure 9. Average Demand for Thermal Generation June 1 - August 31

A summary of the net change in GHG emissions for each model run is shown in Table 11. The baseline model run, with no additional PEVs, has the lowest total generation and GHG emissions from generation because it has the lowest electricity demand. The GHG emissions from ICEVs for the baseline scenario were calculated by multiplying the annual total mileage for non-PEV passenger vehicles reported in the NHTS sample by an assumed emissions rate of 404 gram/mile, the equivalent of 22 miles per gallon. For each PEV scenario, the ICEV mileage is reduced by the electric VMT calculated by the PEV-CDM. In general, as PEV penetration and EVSE availability increase, generation and direct GHG emissions from power generation also increase. However, net GHG emissions decrease as PEV penetration and EVSE availability increase since the GHG emissions from in-vehicle gasoline consumption fall more quickly than the GHG emissions from power generation increase. Despite higher demand in the workplace and probabilistic EVSE scenarios, direct GHG emissions from power generation are lower in these scenarios than the home-only EVSE scenario, as more PEV demand in the home-only scenario is concentrated during the afternoon/evening demand peak, forcing more expensive and higher emitting generators to be dispatched. Overall, the shift towards PEVs and expansion of EVSE availability is effective at reducing net GHG emissions and has minimal impact on average generating costs.

Table 11. Generating Costs and System-wide GHG Emissions

Additional PEV Penetration	EVSE Scenario	GHG Emissions (Metric Tons)				Percent Reduction	Total Gen. Cost (MM)	Total Generation (GWh)
		Electricity Generation	ICEV VMT	Total	Reduction			
0%	N/A	25,734,435	85,191,910	110,926,345	N/A	N/A	1,537.97	308,480
5%	Home	26,551,657	82,707,464	109,259,121	1,667,224	1.5%	1,580.05	310,476
	Work	26,534,378	82,576,689	109,111,067	1,815,278	1.6%	1,579.03	310,592
	Probabilistic	26,541,911	82,576,851	109,118,762	1,807,583	1.6%	1,579.65	310,593
	Universal	26,552,377	82,418,623	108,971,000	1,955,346	1.8%	1,580.42	310,732
15%	Home	28,193,632	77,743,286	105,936,918	4,989,427	4.5%	1,666.01	314,464
	Work	28,160,012	77,350,988	105,511,000	5,415,345	4.9%	1,663.06	314,814
	Probabilistic	28,173,770	77,346,823	105,520,593	5,405,752	4.9%	1,664.98	314,819
	Universal	28,204,236	76,871,248	105,075,484	5,850,861	5.3%	1,667.56	315,236

The 15% PEV penetration scenarios increased generation by all generating types relative to the baseline scenario, but the generator types utilized most varies by EVSE scenario. Figure 10 shows the additional hourly generation by fuel type for the average day relative to the baseline model run, while Figure 11 shows the average change in generation for the work and universal EVSE scenarios relative to the home-only scenario. As discussed in relation to Figure 7, additional demand for PEV charging is highest in the evening hours in all EVSE scenarios, but the availability of away-from-home charging in the workplace, probabilistic, and universal scenarios results in a higher proportion of charging demand being met during daytime hours. The majority of the additional demand for electricity from 5:00 PM through the nighttime hours is met by expanded natural gas generation. Increased coal generation is the second largest contributor to meeting PEV demand during this period. Consequently, the shift towards away-from-home charging during the daytime hours is effective at reducing both gas and coal generation in favor of higher utilization of renewable and nuclear-generating facilities.

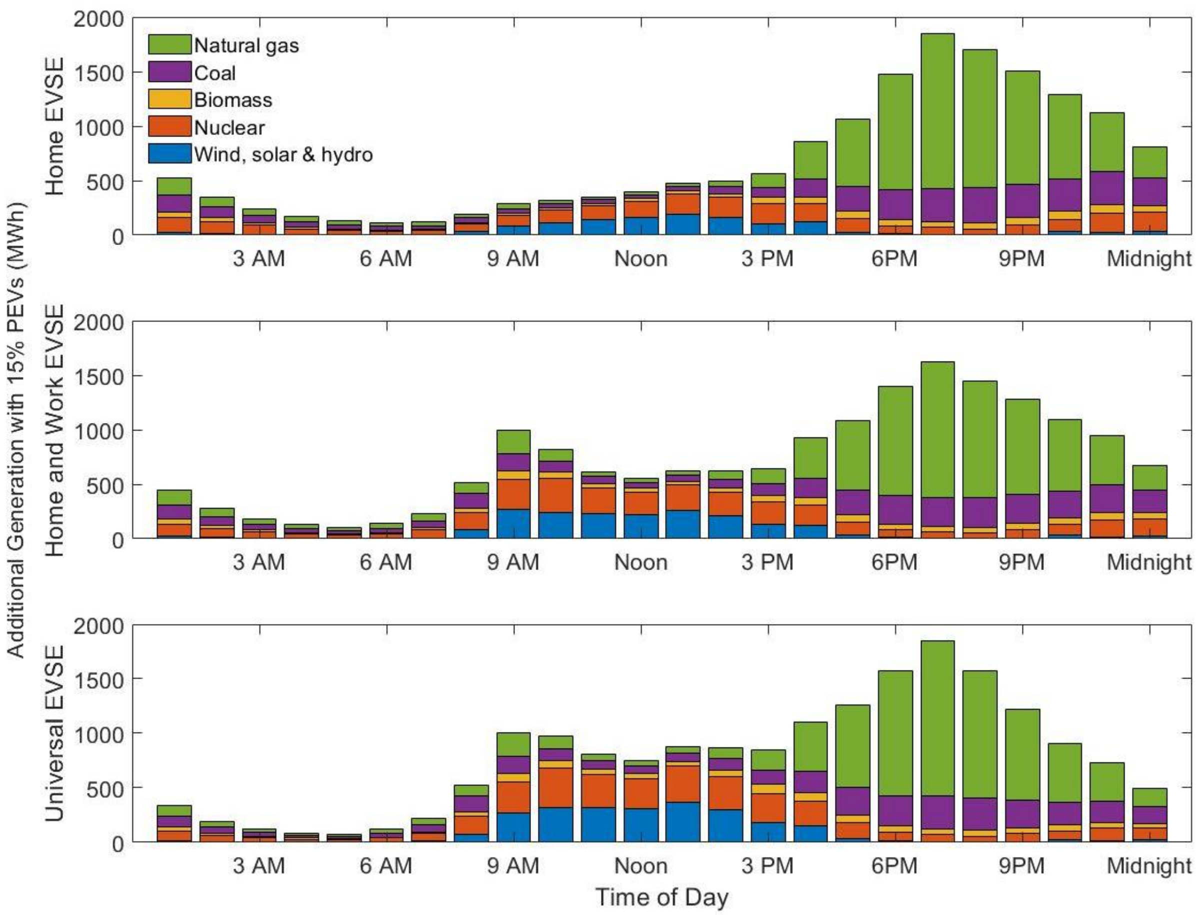


Figure 10. Differences in generation between baseline and 15% PEV penetration scenarios

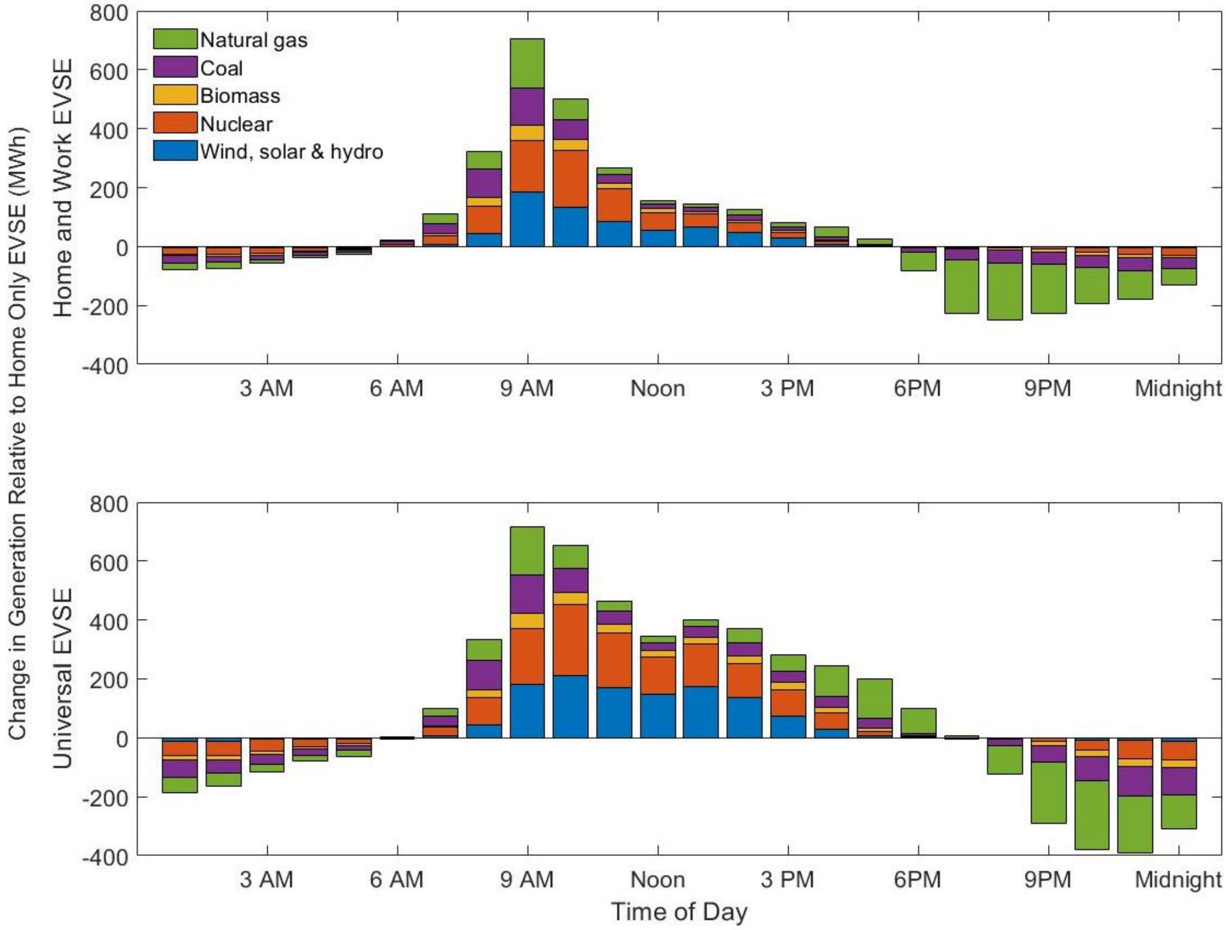


Figure 11. Differences in Generation Relative to Home-only EVSE Scenario (15% PEVs)

The change in the utilization of renewable resources is quantified in Table 12. PEV charging demand resulted in the decreased curtailment of renewable generation in all EVSE scenarios. The greatest reduction in renewable curtailment is achieved with universal EVSE availability, as would be expected. These model results demonstrate that higher PEV penetration levels or managed charging could further reduce the curtailment of these renewable resources. The generating capacity in the model substantially exceeds the level needed to meet PEV demand and thus, in the absences of plant retirements, could meet the energy needs of significantly higher PEV penetrations.

Table 12. Renewable Curtailment by EVSE Scenario

Curtailment	PEV Scenario				
	0%	15% Home	15% Work	15% Prob	15% Univ
Hours with Curtailment	3,236	3,174	3,152	3,154	3,134
Average Hourly Curtailment (MWh)	2,813	2,716	2,662	2,664	2,621
Maximum Hourly Curtailment (MWh)	29,194	28,968	28,735	28,740	28,563
Total Annual Curtailment (GWh)	9,104	8,622	8,391	8,403	8,214

Conclusions

High market penetration of PEVs and renewable power generation are major technological strategies for GHG emissions reductions across the transportation and electric power sectors. PEV charging and renewable energy availability (especially for wind and solar) have important and unavoidable temporal constraints and the alignment between charging times and renewable power availability has critical emissions and important cost implications. The modeling efforts described here provide a valuable approach for understanding the interactions between these two strategies, while exploring a range of assumptions about EVSE availability, charging preferences, and power-generating options using real-world travel data to create realistic charging demand opportunities, including by location type.

Driving times as well as EVSE availability are unavoidable determinants of the timing of vehicle charging. Given the charging logic implemented in the PEV-CDM, when charging infrastructure was available at more stop locations, a larger portion of charging demand was shifted off-peak and into the morning hours relative to home-only charging scenarios. This was true even without incentives or managed pricing schemes. Unique to this model was the sensitivity of the results to widespread EVSE availability also leading to higher overall charging demand, since higher-mileage vehicle profiles were compatible with PEV performance in these 15% scenarios. The results also provide evidence of the particular importance of workplace charging. Even in the scenario with universally available charging infrastructure, 39% of all non-home charging demand occurred at workplaces, and work stops had the highest percentage of non-home charging events. All EVSE scenarios result in increased peak demand and increased generation by non-renewable generating sources. This indicates that pricing or other incentive mechanisms that influence charging decisions could result in lower cost, lower emissions outcomes.

Several additional refinements and applications of both the PEV-CDM and regional economic dispatch model will be the focus of future work. For the PEV-CDM, these include sensitivity analysis surrounding the probability of charging at discretionary charging locations, as well as the impact of time-of-use pricing and other incentive structures. Both require improved data on driver decision-making, including parameters around charging choices of non-early adopters. The current probabilities reflect relatively conservative charging behavior that may result in drivers maintaining a higher SOC by charging more frequently than may be realistic as PEV ranges increase. In addition, as the PEV market rapidly changes, the PEV range attributes that influenced which vehicle travel profiles were included in the PEV-CDM may become dated; future scenarios could consider different range and efficiency characteristics.

It is crucial that PEV charging demand profiles be based on real-world travel data. As PEV range performance increases substantially beyond the distances traveled by most vehicles in a single day, the traditional one-day travel survey becomes a major limitation in combined transportation and energy sector models. Travel survey data collected over a multiday or multiweek timeframe, potentially using passive methods with mobile devices, would capture the behavior of individuals across multiple days. Moreover, those who routinely travel long distances as well as less frequent long-distance intercity travelers may require the utilization of DC Fast Charging Corridors; modeling these behaviors would require more extensive travel data than is currently collected. Improvements to the regional dispatch model should include the consideration of alternative capacity expansion options and optimization of energy storage capacity, including the potential use of PEVs for storage.

References

Ahmadi, L., Elkamel, A., Abdul-Wahab, S., Pan, M., Croiset, E., Douglas, P., Entchev, E., 2015. Multi-period optimization model for electricity generation planning considering plug-in hybrid electric vehicle penetration. Energies 8, 3978–4002.

Andervazh, M.-R., Javadi, S., 2017. Emission-economic dispatch of thermal power generation units in the presence of hybrid electric vehicles and correlated wind power plants. IET Gener. Transm. Distrib. 11, 2232–2243. https://doi.org/10.1049/iet-gtd.2016.1508

Audoly, R., Vogt-Schilb, A., Guivarch, C., Pfeiffer, A., 2018. Pathways toward zero-carbon electricity required for climate stabilization. Appl. Energy 225, 884–901. https://doi.org/10.1016/j.apenergy.2018.05.026

Axsen, J., Goldberg, S., Bailey, J., 2016. How might potential future plug-in electric vehicle buyers differ from current "Pioneer" owners? Transp. Res. Part Transp. Environ. 47, 357–370. https://doi.org/10.1016/j.trd.2016.05.015

Axsen, J., Wolinetz, M., 2018. Reaching 30% plug-in vehicle sales by 2030: Modeling incentive and sales mandate strategies in Canada. Transp. Res. Part Transp. Environ. 65, 596–617. https://doi.org/10.1016/j.trd.2018.09.012

Brady, J., O'Mahony, M., 2016. Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data. Sustain. Cities Soc. 26, 203–216. https://doi.org/10.1016/j.scs.2016.06.014

Calnan, P., Deane, J.P., Ó Gallachóir, B.P., 2013. Modelling the impact of EVs on electricity generation, costs and CO2 emissions: Assessing the impact of different charging regimes and future generation profiles for Ireland in 2025. Energy Policy 61, 230–237. https://doi.org/10.1016/j.enpol.2013.05.065

Carley, S., Krause, R.M., Lane, B.W., Graham, J.D., 2013. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. Transp. Res. Part Transp. Environ. 18, 39–45. https://doi.org/10.1016/j.trd.2012.09.007

Coignard, J., Saxena, S., Greenblatt, J., Wang, D., 2018. Clean vehicles as an enabler for a clean electricity grid. Environ. Res. Lett. 13, 054031. https://doi.org/10.1088/1748-9326/aabe97

Daina, N., Sivakumar, A., Polak, J.W., 2017. Electric vehicle charging choices: Modelling and implications for smart charging services. Transp. Res. Part C Emerg. Technol. 81, 36–56. https://doi.org/10.1016/j.trc.2017.05.006

Deloitte, 2019. Assessing the flexibility of coal-fired power plants for the integration of renewable energy in Germany [WWW Document]. URL https://www2.deloitte.com/content/dam/Deloitte/fr/Documents/financial-advisory/economicadvisory/deloitte_assessing-flexibility-coal-fired-power-plants.pdf (accessed 2.22.21).

Dowds, J., Hines, P.D., Blumsack, S., 2013. Estimating the impact of fuel-switching between liquid fuels and electricity under electricity-sector carbon-pricing schemes. Socioecon. Plann. Sci. 47, 76–88.

Dunning, I., Huchette, J., Lubin, M., 2017. JuMP: A modeling language for mathematical optimization. SIAM Rev. 59, 295–320.

EIA, 2019. Annual Energy Outlook 2019 [WWW Document]. URL https://www.eia.gov/outlooks/aeo/ (accessed 7.31.19).

Federal Highway Administration, 2017. 2017 National Household Travel Survey. U.S. Department of Transportation, Washington, DC.

Foley, A., Tyther, B., Calnan, P., Ó Gallachóir, B., 2013. Impacts of Electric Vehicle charging under electricity market operations. Sustain. Dev. Energy Water Environ. Syst. 101, 93–102. https://doi.org/10.1016/j.apenergy.2012.06.052

Franke, T., Krems, J.F., 2013. Understanding charging behaviour of electric vehicle users. Transp. Res. Part F Traffic Psychol. Behav. 21, 75–89. https://doi.org/10.1016/j.trf.2013.09.002

Galen L. Barbose, 2018. U.S. Renewables Portfolio Standards: 2018 Annual Status Report.

Gu, W., Yu, H., Liu, W., Zhu, J., Xu, X., 2013. Demand Response and Economic Dispatch of Power Systems Considering Large-Scale Plug-in Hybrid Electric Vehicles/Electric Vehicles (PHEVs/EVs): A Review. Energies 6, 4394–4417. https://doi.org/10.3390/en6094394

Gurobi Optimization, LLC, n.d. Gurobi Optimizer [WWW Document]. Gurobi. URL https://www.gurobi.com/products/gurobi-optimizer/ (accessed 12.10.21).

Hardman, S., Chandan, A., Tal, G., Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. Renew. Sustain. Energy Rev. 80, 1100–1111. https://doi.org/10.1016/j.rser.2017.05.255

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Figenbaum, E., Jakobsson, N., Jochem, P., Kinnear, N., Plötz, P., Pontes, J., Refa, N., Sprei, F., Turrentine, T., Witkamp, B., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transp. Res. Part Transp. Environ. 62, 508–523. https://doi.org/10.1016/j.trd.2018.04.002

Hardman, S., Shiu, E., Steinberger-Wilckens, R., 2016. Comparing high-end and low-end early adopters of battery electric vehicles. Transp. Res. Part Policy Pract. 88, 40–57. https://doi.org/10.1016/j.tra.2016.03.010

Helveston, J.P., Liu, Y., Feit, E.M., Fuchs, E., Klampfl, E., Michalek, J.J., 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. Transp. Res. Part Policy Pract. 73, 96–112. https://doi.org/10.1016/j.tra.2015.01.002

Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resour. Energy Econ. 33, 686–705. https://doi.org/10.1016/j.reseneeco.2011.02.002

Hilshey, A.D., Hines, P.D., Rezaei, P., Dowds, J.R., 2013. Estimating the impact of electric vehicle smart charging on distribution transformer aging. IEEE Trans. Smart Grid 4, 905–913.

Howerter, S.E., 2019. Modeling Electric Vehicle Energy Demand and Regional Electricity Generation Dispatch for New England and New York. The University of Vermont and State Agricultural College.

Hu, L., Dong, J., Lin, Z., 2019. Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach. Transp. Res. Part C Emerg. Technol. 102, 474–489. https://doi.org/10.1016/j.trc.2019.03.027

IPCC, 2014. Summary for Policymakers. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

ISO New England, 2019. Energy, load and demand reports: Demand [WWW Document]. URL https://www.iso-ne.com/isoexpress/web/reports/load-and-demand (accessed 5.8.19).

James, E.P., Benjamin, S.G., Marquis, M., 2017. A unified high-resolution wind and solar dataset from a rapidly updating numerical weather prediction model. Renew. Energy 102, 390–405. https://doi.org/10.1016/j.renene.2016.10.059

Javid, R.J., Nejat, A., 2017. A comprehensive model of regional electric vehicle adoption and penetration. Transp. Policy 54, 30–42. https://doi.org/10.1016/j.tranpol.2016.11.003

Kim, S., Yang, D., Rasouli, S., 2016. Periodicity analysis of charging behavior of electric car drivers: Latent class hazard models, in: 13th International Conference on Design and Decision Support Systems in Architecture and Urban Planning, DDSS 2016. Technische Universiteit Eindhoven, Faculteit Bouwkunde.

Lane, B.W., Dumortier, J., Carley, S., Siddiki, S., Clark-Sutton, K., Graham, J.D., 2018. All plug-in electric vehicles are not the same: Predictors of preference for a plug-in hybrid versus a battery-electric vehicle. Transp. Res. Part Transp. Environ. 65, 1–13. https://doi.org/10.1016/j.trd.2018.07.019

Latinopoulos, C., Sivakumar, A., Polak, John, 2017. Modeling Electric Vehicle Charging Behavior: What Is the Relationship Between Charging Location, Driving Distance, and Range Anxiety? Presented at the Transportation Research Board 96th Annual Meeting.

Leard, B., Linn, J., Munnings, C., 2019. Explaining the Evolution of Passenger Vehicle Miles Traveled in the United States. Energy J. 40. https://doi.org/10.5547/01956574.40.1.blea

Lee, J.H., Chakraborty, D., Hardman, S.J., Tal, G., 2020. Exploring electric vehicle charging patterns: Mixed usage of charging infrastructure. Transp. Res. Part Transp. Environ. 79, 102249. https://doi.org/10.1016/j.trd.2020.102249

Lee, J.H., Hardman, S.J., Tal, G., 2019. Who is buying electric vehicles in California? Characterising early adopter heterogeneity and forecasting market diffusion. Energy Res. Soc. Sci. 55, 218–226. https://doi.org/10.1016/j.erss.2019.05.011

Lund, H., Kempton, W., 2008. Integration of renewable energy into the transport and electricity sectors through V2G. Energy Policy 36, 3578–3587. https://doi.org/10.1016/j.enpol.2008.06.007

Martin, E., Shaheen, Susan, Zohdy, I., 2016. Understanding Travel Behavior. FHWA.

McCollum, D., Krey, V., Kolp, P., Nagai, Y., Riahi, K., 2014. Transport electrification: A key element for energy system transformation and climate stabilization. Clim. Change 123, 651–664. https://doi.org/10.1007/s10584-013-0969-z

McDonald, L., 2018. EV Statistics of the Week: Range, Price and Battery Size of Currently Available (in the US) BEVs. URL https://evadoption.com/ev-statistics-of-the-week-range-price-and-battery-size-of-currently-available-in-the-us-bevs/ (accessed 4.2.19).

McGuckin, N., Fucci, A., 2018. Summary of Travel Trends 2017 National Household Travel Survey (No. FHWA-PL-18-019). Federal Highway Administration. https://doi.org/10.2172/885762

Mersky, A.C., Sprei, F., Samaras, C., Qian, Z. (Sean), 2016. Effectiveness of incentives on electric vehicle adoption in Norway. Transp. Res. Part Transp. Environ. 46, 56–68. https://doi.org/10.1016/j.trd.2016.03.011

Miller, I., Arbabzadeh, M., Gençer, E., 2020. Hourly Power Grid Variations, Electric Vehicle Charging Patterns, and Operating Emissions. Environ. Sci. Technol. 54, 16071–16085. https://doi.org/10.1021/acs.est.0c02312

Moro, A., Lonza, L., 2018. Electricity carbon intensity in European Member States: Impacts on GHG emissions of electric vehicles. Contrib. Electr. Veh. Environ. Chall. Transp. WCTRS Conf. Summer 64, 5–14. https://doi.org/10.1016/j.trd.2017.07.012

Morrison, G.M., Yeh, S., Eggert, A.R., Yang, C., Nelson, J.H., Greenblatt, J.B., Isaac, R., Jacobson, M.Z., Johnston, J., Kammen, D.M., Mileva, A., Moore, J., Roland-Holst, D., Wei, M., Weyant, J.P., Williams, J.H., Williams, R., Zapata, C.B., 2015. Comparison of low-carbon pathways for California. Clim. Change 131, 545–557. https://doi.org/10.1007/s10584-015-1403-5

Narassimhan, E., Johnson, C., 2018. The role of demand-side incentives and charging infrastructure on plug-in electric vehicle adoption: analysis of US States. Environ. Res. Lett. 13, 074032. https://doi.org/10.1088/1748-9326/aad0f8

Nazari, F., Mohammadian, A. (Kouros), Stephens, T., 2019. Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure. Transp. Res. Part Transp. Environ. 72, 65–82. https://doi.org/10.1016/j.trd.2019.04.010

New York Independent System Operator, 2018. Energy market and operation data: Custom reports [WWW Document]. URL https://www.nyiso.com/custom-reports?report+rt_actual_load (accessed 5.8.19).

Niesten, E., Alkemade, F., 2016. How is value created and captured in smart grids? A review of the literature and an analysis of pilot projects. Renew. Sustain. Energy Rev. 53, 629–638. https://doi.org/10.1016/j.rser.2015.08.069

Pareschi, G., Küng, L., Georges, G., Boulouchos, K., 2020. Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data. Appl. Energy 275, 115318. https://doi.org/10.1016/j.apenergy.2020.115318

Parks, K., Denholm, P., Markel, T., 2007. Costs and Emissions Associated with Plug-In Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory. National Renewable Energy Laboratory, Golden.

Peng, M., Liu, L., Jiang, C., 2012. A review on the economic dispatch and risk management of the large-scale plug-in electric vehicles (PHEVs)-penetrated power systems. Renew. Sustain. Energy Rev. 16, 1508–1515. https://doi.org/10.1016/j.rser.2011.12.009

Pleßmann, G., Blechinger, P., 2017. How to meet EU GHG emission reduction targets? A model based decarbonization pathway for Europe’s electricity supply system until 2050. Energy Strategy Rev. 15, 19–32. https://doi.org/10.1016/j.esr.2016.11.003

Plötz, P., Schneider, U., Globisch, J., Dütschke, E., 2014. Who will buy electric vehicles? Identifying early adopters in Germany. Transp. Res. Part Policy Pract. 67, 96–109. https://doi.org/10.1016/j.tra.2014.06.006

Samaras, C., Meisterling, K., 2008. Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: Implications for policy. Environ. Sci. Technol. 42, 3170–3176. https://doi.org/Article

Sierzchula, W., Bakker, S., Maat, K., van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Policy 68, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043

Smart, J., Schey, S., 2012. Battery Electric Vehicle Driving and Charging Behavior Observed Early in The EV Project. SAE Int. J. Altern. Powertrains 1. https://doi.org/10.4271/2012-01-0199

Smart, J.G., Salisbury, S.D., 2015. Plugged In: How Americans Charge Their Electric Vehicles (No. INL/EXT-15-35584). Idaho National Lab. (INL), Idaho Falls, ID (United States). https://doi.org/10.2172/1369632

Sovacool, B.K., Axsen, J., Kempton, W., 2017. The Future Promise of Vehicle-to-Grid (V2G) Integration: A Sociotechnical Review and Research Agenda. Annu. Rev. Environ. Resour. 42, 377–406. https://doi.org/10.1146/annurev-environ-030117-020220

State Renewable Portfolio Standards and Goals [WWW Document], n.d. URL http://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx (accessed 6.27.19).

Sun, X.-H., Yamamoto, T., Morikawa, T., 2015. Charge timing choice behavior of battery electric vehicle users. Transp. Res. Part Transp. Environ. 37, 97–107. https://doi.org/10.1016/j.trd.2015.04.007

Taljegard, M., Göransson, L., Odenberger, M., Johnsson, F., 2019. Impacts of electric vehicles on the electricity generation portfolio – A Scandinavian-German case study. Appl. Energy 235, 1637–1650. https://doi.org/10.1016/j.apenergy.2018.10.133

U.S. Department of Energy, 2018. Fuel Economy Web Services [WWW Document]. URL https://www.fueleconomy.gov/feg/ws/ (accessed 3.28.19).

US EPA, 2021. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2019 (No. EPA 430-R-21-005).

US EPA, 2015. Emissions & Generation Resource Integrated Database (eGRID) [WWW Document]. US EPA. URL https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid (accessed 7.31.19).

Vithayasrichareon, P., Mills, G., MacGill, I.F., 2015. Impact of electric vehicles and solar PV on future generation portfolio investment. IEEE Trans. Sustain. Energy 6, 899–908.

Wang, B., Dehghanian, P., Zhao, D., 2020. Chance-constrained energy management system for power grids with high proliferation of renewables and electric vehicles. IEEE Trans. Smart Grid 11, 2324–2336. https://doi.org/10.1109/TSG.2019.2951797

ZEV Task Force, 2018. Multi-state ZEV action plan 2018-2021.

Data Summary

Products of Research

This study used publicly available data from the 2017 National Household Travel Survey, the New York Independent System Operator load data, the Independent System Operator New England load data, and the Emissions & Generation Resource Integrated Database.

The National Household Travel Survey data can be downloaded from the Oak Ridge National Laboratory here: https://nhts.ornl.gov/. The following citation is recommended for users of the data: U.S. Department of Transportation, Federal Highway Administration, 2017 National Household Travel Survey. URL: http://nhts.ornl.gov.

The New York Independent System Operator data can be downloaded here: https://www.nyiso.com/custom-reports?report+rt_actual_load. The following citation is recommended for users of the data: New York Independent System Operator, 2018. Energy market and operation data: Custom reports. URL https://www.nyiso.com/custom-reports?report+rt_actual_load.

The Independent System Operator New England load data can be downloaded here: https://www.iso-ne.com/isoexpress/web/reports/load-and-demand. The following citation is recommended for users of the data: ISO New England, 2019. Energy, load and demand reports: Demand. URL https://www.iso-ne.com/isoexpress/web/reports/load-and-demand.

The Emissions & Generation Resource Integrated Database data can be downloaded from the Environmental Protection Agency here: https://www.epa.gov/egrid. The following citation is recommended for users of the data: US EPA, 2015. Emissions & Generation Resource Integrated Database (eGRID). US EPA. URL https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid.

Data Format and Content, Data Access and Sharing, and Reuse and Redistribution

The data can be downloaded in a variety of formats from the sources noted above.