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Zero-Emission Heavy-Duty Vehicle Integration in Support of a 100% Renewable Electric Grid

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Zero-Emission Heavy-Duty Vehicle Integration in Support of a 100% Renewable Electric Grid

DISSERTATION

Submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Engineering

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by

Kate E. Forrest

Dissertation Committee:
Professor Scott Samuelsen, Chair
Professor Barbara Finlayson-Pitts
Professor Stephen Ritchie

2019

DEDICATION

To my family for their unconditional love and support

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NOMENCLATURE

AC	Alternating Current
BenMAP	Environmental Benefits Mapping and Analysis Program
BESS	Battery Energy Storage System
BEV	Battery Electric Vehicle
CARB	California Air Resources Board
CO_2e	Carbon Dioxide Equivalent
CPR	Current Policy Reference
DC	Direct Current
E3	Energy + Environmental Economics, Inc.
EO	Executive Order
EVSE	Electric Vehicle Supply Equipment
FCEV	Fuel Cell Electric Vehicles
GGE	Gallons of Gasoline Equivalent
GHG	Greenhouse Gas
GW	Gigawatt
HDV	Heavy Duty Vehicle
LCOE	Levelized Cost of Energy
LDV	Light Duty Vehicle
MW	Megawatt
O_3	Ozone
P2G	Power-to-gas
PEV	Plug-in Electric Vehicle
PFCEV	Plug-in Fuel Cell Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PM	Particulate Matter (PM2.5 and PM10 refer to maximum particle diameter)

NAAQS	National Ambient Air Quality Standards
RMSE	Root mean square error
SOC	State-of-charge
TAZ	Traffic Analysis Zone
V2G	Vehicle-to-grid
VMT	Vehicle Miles Traveled
VOCs	Volatile Organic Compounds
ZEV	Zero-emission vehicle

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ABSTRACT

Zero-Emission Heavy-Duty Vehicle Integration in Support of a 100% Renewable Electric Grid

By

Kate Forrest

Doctor of Philosophy in Environmental Engineering

University of California, Irvine, 2019

Professor Scott Samuelsen, Chair

For California and other parts of the world to move towards a net-zero-emission grid, potentially a 100% renewable grid, complementary technologies to support renewable solar and wind integration need to be clearly established. Specifically, the integration of variable and intermittent solar and wind renewable generation requires resources that can respond dynamically to changes in the net load in order to ensure stable grid performance. Zero-emission vehicles (ZEVs), encompassing battery electric vehicles (BEVs) and fuel cell electric vehicles (FCEVs), are uniquely positioned to (1) support variable renewable generation and provide benefits to the grid while, at the same time (2) reducing emissions from the transportation sector. Due to their disproportionately large contribution to air pollution and greenhouse gas (GHG) emissions, targeting heavy-duty vehicles (HDVs) is essential if reduction goals are to be met. This work assesses the feasibility of heavy duty ZEVs (HD-ZEVs), selecting California as the example. From a technical standpoint, more than half of Class 3-7 vehicle miles travelled (VMT) can be met with heavy-duty BEV product in development today without trip modification. Class 8 trucks have a much lower BEV feasibility due to their longer trip distances and heavy-duty FCEV product becomes more likely. The challenge becomes providing carbon-free fuel, namely renewable electricity for HD-BEVs, and renewable

hydrogen for HD-FCEVs. This study assesses the fuel supply chain impact of HD-ZEV deployment on GHG emissions and air quality for the year 2050. HD-BEVs relying on uncoordinated charging can increase peak load demand and hinder the target of achieving zero GHG emissions from the electric grid. Intelligent charging of HD- BEVs and renewable hydrogen production for HD-FCEVs are both effective methods for utilizing otherwise curtailed renewable generation for the support of a zero or near-zero emissions electric grid. This study also finds that moving towards an 80% reduction in GHG emissions from HDVs through ZEV adoption has the co-benefit of significantly reducing ozone and PM2.5 concentrations in key regions of California. In comparison, reducing grid emissions from an 80% reduction to a 100% clean electric grid has a significantly smaller, but not trivial, impact in criteria air pollutant concentrations.

Chapter 1. Introduction

1.1 Overview

The rise of anthropogenic greenhouse gas (GHG) emissions over the last century and the continued emission of criteria pollutants, predominantly tied to transportation, electricity generation, heat production, and fossil fuel production, present a critical threat to human health and the environment. The commitment of regions, such as California, to reduce their emissions in response to these impacts has led to the deployment of renewable energy technologies worldwide. It has also spurred the push for zero-emission vehicles (ZEV) to replace conventional internal combustion engine vehicles. ZEVs, chiefly battery electric vehicles and fuel cell electric vehicles, serve as a new load on the electric grid, either directly through charging or through the production of hydrogen fuel using electrolysis. Initially, ZEV deployment focused on light-duty vehicles and much of the research on both the charging infrastructure and vehicle requirements focused on the needs of the light-duty sector. However, to meet the aggressive goal of an 80% reduction in GHG emissions below 1990 levels statewide would require that not only a majority of LDVs but also a significant portion of heavy duty vehicles (HDV) to be converted to zero-emission options. The integration of light duty and heavy duty vehicles onto the electric grid system can offset GHG emissions, but it presents new challenges that must be addressed in order to achieve the ultimate goal of a robust zero GHG emission grid.

Despite the United States' withdrawal from the Paris Agreement, California has maintained and expanded its commitments to reducing its emissions to combat climate change. Governor Schwarzenegger issued Executive Order (EO) S-3-05 directing the state to reduce its

GHG emissions to 2000 levels by 2010, 1990 levels by 2020, and 80% below 1990 levels by the year 2050 [3]. The next year, California passed AB 32, establishing into law the 2020 target and ordering the California Air Resources Board (CARB) to develop a Scoping Plan to inform sectors on comprehensive strategies for achieving the reduction target [4]. California followed up this commitment with SB 32, which established an interim target of 40% below 1990 levels by 2030 [5,6]. Most recently, Governor Brown signed EO B-55-18 accelerating the previous 2050 GHG emissions reduction goal by mandating the state become carbon neutral no later than 2045 [7]. The timing of these targets are depicted in Figure 1, with historical emissions from the CARB GHG emissions inventory [8].

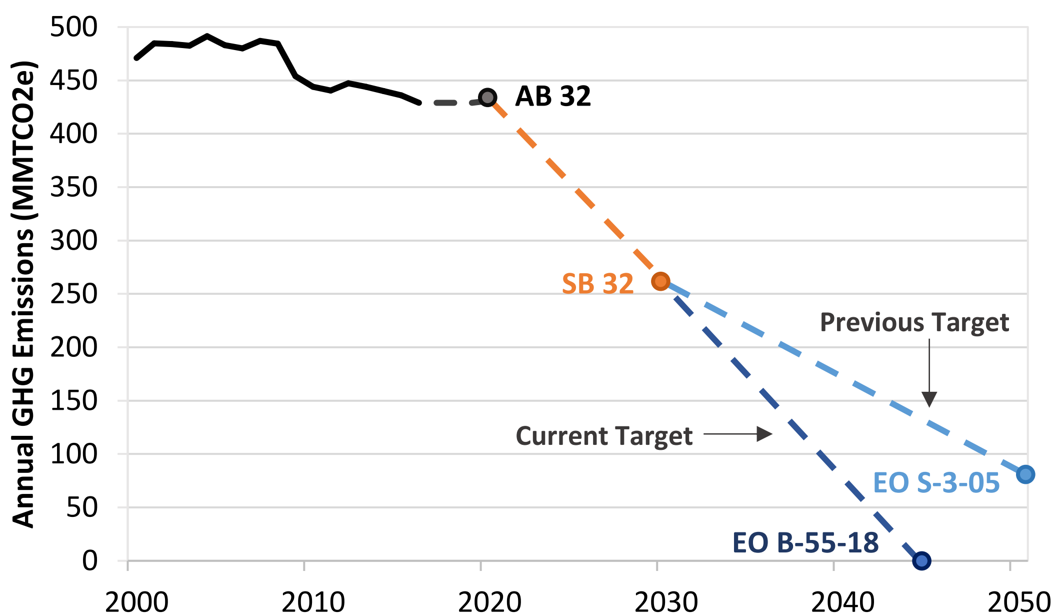


Figure 1. Projected GHG Emissions Reductions under California Policies

In order to achieve these ambitious goals, the main sources of GHG emissions must be addressed (Figure 2, data from [9]). California's most recent Scoping Plan seeks an integrated approach to meet the 2030 target, with a strong emphasis on strategies that promote co-benefits such as improved air quality, public health, and economic growth [10].

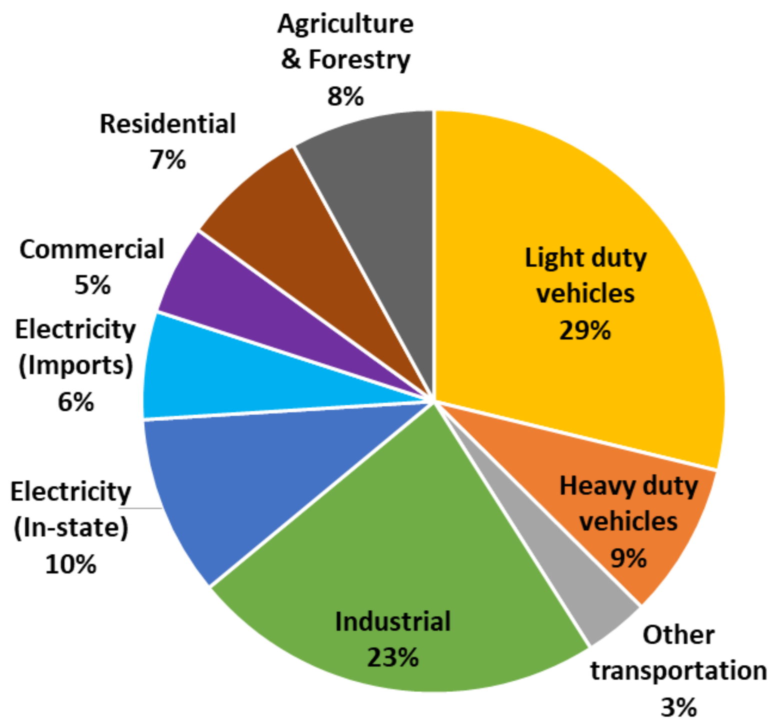


Figure 2. 2016 Total California GHG Emissions: 429.4 MMTCO$_2$e as reported by the California Air Resources Board

The promotion of strategies with air quality co-benefits highlights California's on-going challenge to meet State and National Ambient Air Quality Standards for ozone and particulate matter (PM 2.5 and/or PM 10) in numerous counties [11]. Emissions paired with the natural topography of the state result in the retention of primary pollutants and the formation of secondary pollutants at levels harmful to human health. The state's largest contributor to GHG emissions—the transportation sector—is also the largest contributor to nitrogen oxides (NOx), carbon monoxide (CO), and volatile organic carbons (VOCs), which are the precursors to ozone (Figure 3) [12]. Therefore, preferred strategies in sectors that contribute to both GHG and criteria pollutant emissions are ones that help meet both types of reduction goals.

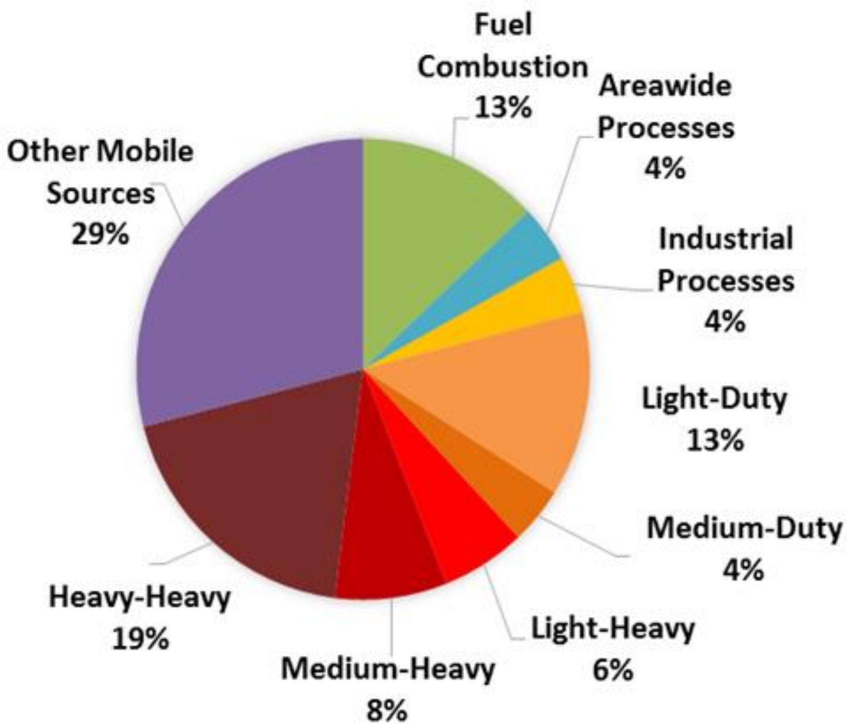


Figure 3. 2015 California Daily NOx Emissions: 2300 tonnes as reported by the California Air Resources Board

A complement to California's statewide GHG emissions goals is the passage of legislation targeting individual sectors. For addressing emissions from the production of electricity, California has adopted a series of renewable portfolio standards (RPS) between 2002 and 2018 requiring that the percentage of electricity sales coming from renewable resources grows to meet a certain level by the committed date (SB 1078, SB 107, SB X1-2, SB 350, and SB 100) [13–17]. The state's current targets can be summarized as follows: 33% of electricity procurement coming from renewables by 2020 (SB X1-2), 44% by 2024, 52% by 2027, and 60% by 2030 (SB 100) [15,17]. SB 100 additionally calls for the California electric grid to be carbon neutral by 2045. The distinction between carbon neutral and renewable is important, as large hydropower plants greater than 30 MW in the state are generally considered carbon neutral but not renewable [18]. This classification in California stems from concerns that large hydropower plants have a large environmental footprint (including habitat destruction) not captured by emissions metrics [19].

California has also set a range of emissions regulations and future vehicle targets for addressing emissions from the transportation sector. Governor Brown has passed executive orders directing the state to support ZEV deployment efforts including setting the target of 1.5 million ZEVs by 2025 (EO B-16-12) and expanding ZEV adoption to 5 million by 2030 (EO B-48-18) [20,21]. EO B-48-18 also expanded targets for hydrogen fueling stations to 200 stations (previously 100) and 250,000 EV charging stations, including 10,000 DC fast charging stations, by 2025 [21]. In late 2018, the California Air Resources Board voted for the “Innovative Clean Transit” measure to move California’s public transit agencies to 100% zero-emission buses by 2040 [22].

To meet these targets, the state has implemented programs that include credits, grants, loans, and rebates. For example, the Alternative and Renewable Fuel and Vehicle Technology Program (ARFVTP) and the Air Quality Improvement Program were created under AB 118 in 2007 to fund programs for the development of new and advanced clean fuels and vehicles and the improvement of air quality through vehicle-related projects, respectively [23]. The Advanced Clean Car Program was developed to guide automakers in reducing both GHG and criteria pollutants through multiple new regulations for light-duty vehicles including fuel economy targets and the promotion of zero and near-zero-emission vehicles [24]. The ZEV program, a part of the Advanced Clean Car Program, mandates automakers provide zero-emission vehicle options to consumers through a credit-based system and although it was originally created to reduce air pollutant emissions, it now sets credit levels that account for both air quality and GHG emissions targets [25]. Considered in the roll-out of these credits are ZEV deployment scenarios that meet the state's 2050 emissions reduction goal. One of these scenarios is presented in Figure 4. Reducing GHG emissions to 80% below 1990 levels by 2050 would require almost 90% of the LDV fleet to be ZEVs by 2050 and more than half of the remaining vehicles to be hybrid options [24].

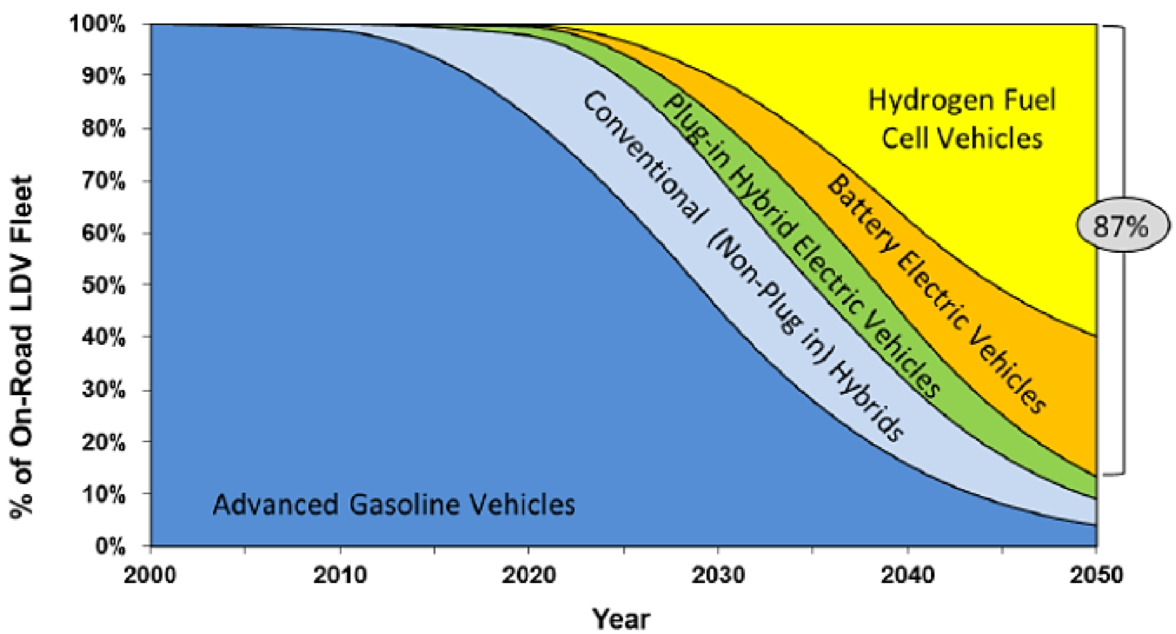


Figure 4. A Scenario for 80% Reduction in Passenger Vehicle GHG Emissions [24]

To support EO B-16-12, the governor's office released a roadmap to meeting the ZEV target called "the ZEV Action Plan" [26]. In 2016, a new action plan was released and in 2018 updates to the 2016 ZEV Action Plan were announced following the signing of EO B-48-18 [27]. The ZEV Action Plan not only covers regulations and programs for LDVs, but also HDVs. Heavy-duty specific efforts highlighted in the 2016 plan include incentive programs, such as the California Hybrid and Zero-Emission Truck and Bus Voucher Incentive Program, which helps offset the higher cost of lower emission HDVs, as well as pilot projects, such as testing the feasibility of zero-emission drayage trucks at California ports [28]. Overarching these programs is the Sustainable Freight Action Plan, commissioned under EO B-32-15, which has set the following targets: a) 25% increase in system efficiency, b) 100,000 zero-emission capable vehicles and equipment by 2030, and c) increased freight competitiveness to promote economic growth within the state [29,30]. Future targets and plan updates are expected in the coming years as state agencies evaluate the success or failure of different strategies and as California moves closer to its sustainability goals.

The advancement of the established targets is dependent on the state's ability to implement strategies under an integrated approach. The simultaneous evolution of the electric grid and the transportation sector presents a unique challenge to ensure that emission reduction efforts in each sector support rather than disrupt efforts in the other. In particular, integrating a high level of variable renewable generation can lead to issues of energy imbalance, increased ramping requirements, and power quality concerns. Transitioning the transportation sector to ZEVs without considering grid dynamics can exacerbate these issues, increasing grid-related emissions [31]. Alternatively, if ZEVs are utilized as a flexible resource that can be coordinated with the electric grid, they can support a highly renewable electric grid [32–35].

It has been previously established that in order to achieve and maintain the emissions reduction potential of a high renewable portfolio with up to 100% renewable penetration, variable renewable generation needs to be partnered with low to zero-emission resources that can respond quickly and reliably in order maintain grid performance [36–43]. ZEVs (e.g., plug-in electric vehicles and fuel cell electric vehicles) have emerged as promising dispatchable grid resources that may provide flexible support to renewable generation, while additionally reducing emissions from the transportation sector. This in turn can offset needed capacity of other grid resources, reducing system costs and ensuring emissions reductions.

Previous studies examining the dynamics of vehicle-grid integration have focused on plug-in light-duty vehicles (LDVs) [34,36,44–46]. While LDVs are currently a much greater contribution of the ZEVs deployed worldwide, HDVs make up a disproportionate amount of the energy consumed for transportation and, California's GHG and air pollutant emissions targets cannot be met without converting a significant portion of the HDV fleet to ZEVs. To do this effectively, the potential impact of ZEV HDV deployment need to be quantified. The different charging and fueling scenarios of zero-emission HDVs versus LDVs can provide insight into their roles in meeting grid emissions reduction targets and, conversely, the role of the grid to meet transportation emissions reduction targets. Evaluating 100% clean electricity[1] portfolio options with vehicle integration will provide insight into the flexibility of these strategies to adapt to shifting and growing electricity demand associated with efforts of other sectors to reduce their own emissions. It may also provide an opportunity to identify system inefficiencies, new redundancies, and/or additional support requirements to ensure a robust grid.

1.2 Goal

The goal of this dissertation is to identify and assess the role of zero-emission heavy-duty vehicle deployment scenarios to achieve a robust, 100% clean electric grid system.

[1] 100% clean electricity incorporates both renewable resources and large hydropower plants (>30 MW), which are considered carbon-neutral but not renewable in California. In some regions, large hydropower is considered renewable and therefore studies examining 100% renewables may include large hydropower in the energy mix. The focus of this study is California's 2045 100% clean electricity goal and therefore large hydropower will be included in the final portfolio mixes developed.

This work examines the strengthening interdependency of transportation and the electric grid to identify key co-benefits of addressing emissions reductions in multiple sectors. The results of this work will inform on the sector requirements for California to reach the ambitious target of an 80 percent reduction in GHG emissions compared to 1990 levels by 2050, and a goal of 100% clean generation.

1.3 Objectives

To meet this dissertation goal, the following objectives were established:

Objective 1. Develop an understanding of vehicle flexibility to integrate renewable energy and the additional balancing requirements to achieve up to 100% renewable penetration into the California grid.

Objective 2. Simulate electricity and hydrogen demand to achieve transformation of the heavy-duty vehicle sector to zero-emission vehicles.

Objective 3. Develop strategies that achieve a) 80% reduction in GHG emissions from the electric grid and b) a 100% clean electric grid with vehicle-grid integration.

Objective 4. Evaluate the impact of zero-emission vehicle integration on grid balancing requirements, GHG emissions, air quality, and levelized cost of energy.

Chapter 2. Background and Literature Review

2.1 Barriers to a 100% Renewable Electric Grid

While there may be a few regions in the world where there are sufficient, reliable hydropower and/or geothermal resources to meet most electricity demands (eg. Iceland), a vast majority of regions seeking to reduce their emissions and increase renewable use will most likely rely heavily on wind and solar energy to meet their energy needs [47,48]. The integration of variable renewable generation (i.e. solar and wind technologies) can lead to less efficient operation of other generation resources and a greater reliance on resources that can respond dynamically to changes in the net load [49,50]. The severity of specific problems, such as high ramping rates of balancing generation resources, is dependent on the net load profile [35]; however, problems such as intermittency, over-generation, and increased ramping of balancing generation are common among systems with a significant percentage of variable renewable generation [50].

As renewable capacity increases, the disparity between renewable generation and electricity demand becomes more pronounced, requiring greater efforts to shift renewable generation using energy storage technologies and/or manipulate load demand profiles in order to utilize available renewable electricity [50–53]. If these efforts are not sufficient to resolve the time discrepancy between renewable generation and electric load demand, periods of renewable over-generation will result in curtailment (or export of electricity to the degree feasible) and periods with insufficient renewable generation will still require other, dispatchable grid resources; renewable utilization will not be maximized [51]. A 100% renewable grid will only be achieved if sufficient renewable generation can be utilized either directly (when produced) or indirectly (through renewable fuels or battery energy storage) to satisfy electric load demand 100% of the time. Determining the barriers and solutions to 100% renewable generation for the California electric grid in 2050 will require determining the future electric load demand, future renewable capacity requirements, and the resulting net load dynamics that must be balanced.

2.1.1 Future Electric Load Demand

Electricity load demand in California is projected to increase, tied to population growth as well as the electrification of sectors such as heating and transportation that have traditionally relied on fossil fuel inputs. Per capita electricity demand has remained relatively flat since the 1970s tied to energy efficiency measures, with reported 2017 consumption around 7,300 kWh/person, see Figure 5 [54–56]. Therefore, historically, total statewide growth in electricity demand has been proportional to population growth.

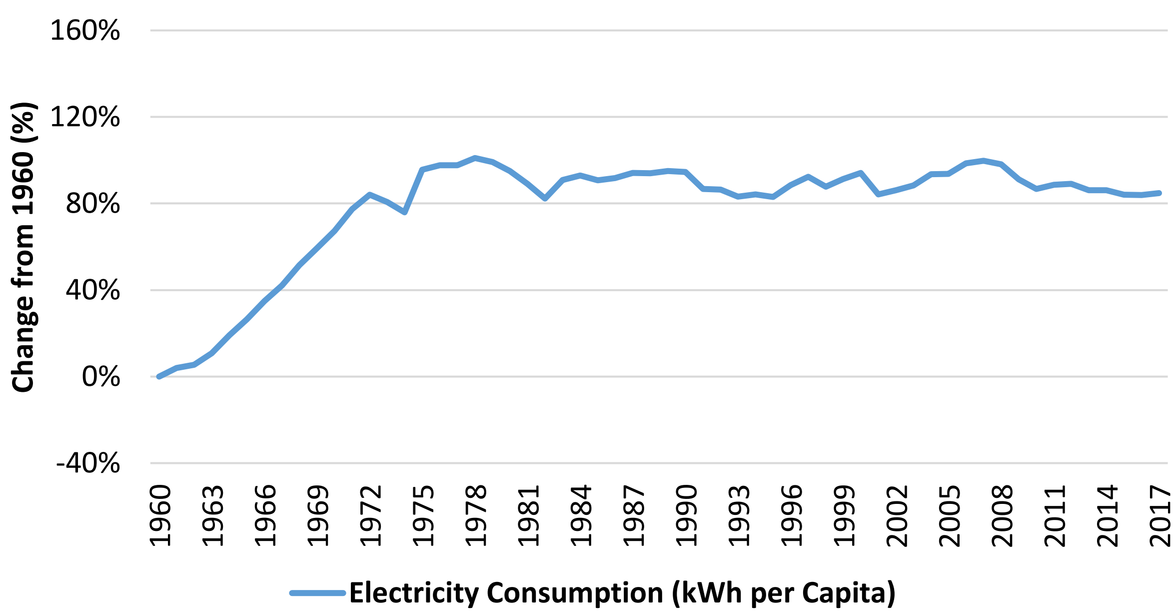


Figure 5. Historical Trends in California per Capita Electricity Consumption (1960 to 2017).

State estimations of future demand assume that total demand will continue to grow with population, but may be offset with greater adoption of energy efficiency measures [57,58]. Additionally, estimations indicate that demand will also grow in response to the added load requirements of electric vehicles as well as the electrification of industry, commercial, and/or residential processes [58].

Not only does increased electrification add to total electric load demand [59], it can also alter the timing of demand, affecting the operation and performance of generation resources [60]. Estimations for future shifts in the daily load profile are dependent on technology adoption assumptions, as well as assumptions on future needs for cooling and heating (eg. whether climate change impacts are considered), but most studies examining future load assume efficiency improvements and electrification of processes that currently rely on fossil fuel inputs [59–64]. Wei et al. (2013) found that in order to meet California's 2050 goals, significant adoption of energy efficiency measures and electrification of transportation and building heat demand are needed, which will result in electricity demand in winter shifting to a morning peak (associated with added heating demand) and demand for the rest of the year shifting to a later evening peak [59]. Ebrahimi, MacKinnon, and Brouwer (2018) also found that electrification resulted in increased loads during the morning and evening times [64], and Tarroja et al. (2018) further concluded that these additions do not align well with renewable generation availability [60].

California state agencies' PATHWAY project, ordered by the California Energy Commission, the California Public Utilities Commission, and the California Air Resources Board, and conducted by Energy + Environmental Economics, Inc. (E3) developed a techno-economic analysis tool to evaluate pathways to meet California's 2050 GHG emissions reduction goals [57]. In the development of the PATHWAYS model, future load demands were modeled for defined subsectors, which are intended to be aggregated to form future statewide electricity load profiles. The load profiles incorporate future demand changes and technology turnover, such as for heating, cooling, and lighting [65]. The established state-level profile for 2050 in PATHWAYS will be used in this study.

2.1.2 Renewable Energy Resources

A portfolio of renewable energy technologies is available to provide renewable electricity generation. Mature technologies that are commercially available today include geothermal, solar photovoltaic panels, concentrated solar power, wind (on-shore and off-shore), biopower (biogas and biomass), and small hydropower.[2] Each technology has its own constraints, and are not without trade-offs. For example, wind and solar are by far the most abundant resources, but utilizing them requires significant land area [37,66] and, due to their variable nature, deploying wind and solar power technologies requires additional support strategies to manage power supply intermittency [67–69]. At high variable renewable penetrations, the effort to manage intermittency may require a significant investment in additional capacity and may still not yield a 100% renewable grid [43]. Biopower resources, on the other hand, can be utilized in conventional power plants (either as baseload or load-following) [70]. Biofuel/biomass resources are less abundant than solar and wind and are tied to specific feedstocks that affect the quality, cost, and emissions potential of the resulting fuels

[2] The renewable classification of hydropower varies by region; California does not consider hydroelectric plants with a power capacity greater than 30 MW to be renewable [81].

[71]. Additionally, while considered “carbon neutral,” biopower can still emit criteria pollutants that contribute to air pollution, tied to negative impacts on human health [72,73]. Biopower for electricity production, while feasible, utilizes a limited resource that may serve other uses that have a greater emissions-reduction potential. For example, there has been a focus on bio-resources for transportation applications where electricity and hydrogen as fuels are challenging or infeasible to utilize [74–77]. Geothermal generation is most often operated as baseload power, i.e. it supplies a relatively flat output with little ramping of power up or down in order to match changes in load demand [78]. The baseload performance of geothermal plants is at least partially driven by the economics of these plants, which have historically required a high capacity factor to ensure sufficient revenue to offset fixed and variable costs [79]. Increasing dispatch flexibility of geothermal plants is possible, with some systems already able to ramp up and down significantly [78]. Another option is to add storage or additional turbines to the system to provide flexibility while the geothermal portion of the plant runs as baseload [79]. Both of these strategies may increase operational costs [78,79]. Lastly, small hydropower plants are moderately dispatchable. Potential outflow from these plants is dependent on upstream flow, and their ability to time water releases is dependent on reservoir capacity, turbine constraints, and water demands for other uses, such as environmental flows (eg. water temperature control) [80]. Small hydropower capacity in California is relatively limited compared to solar and wind. Future capacity growth of hydropower is constrained by location availability and regulatory hurdles [81].

Current renewable generation within California is a combination of all the above technologies, with solar being the dominant utilized resource, followed by wind (on-shore only) and geothermal, see Figure 6 for an example day's generation profiles in 2018 summed across the state, data from [82].

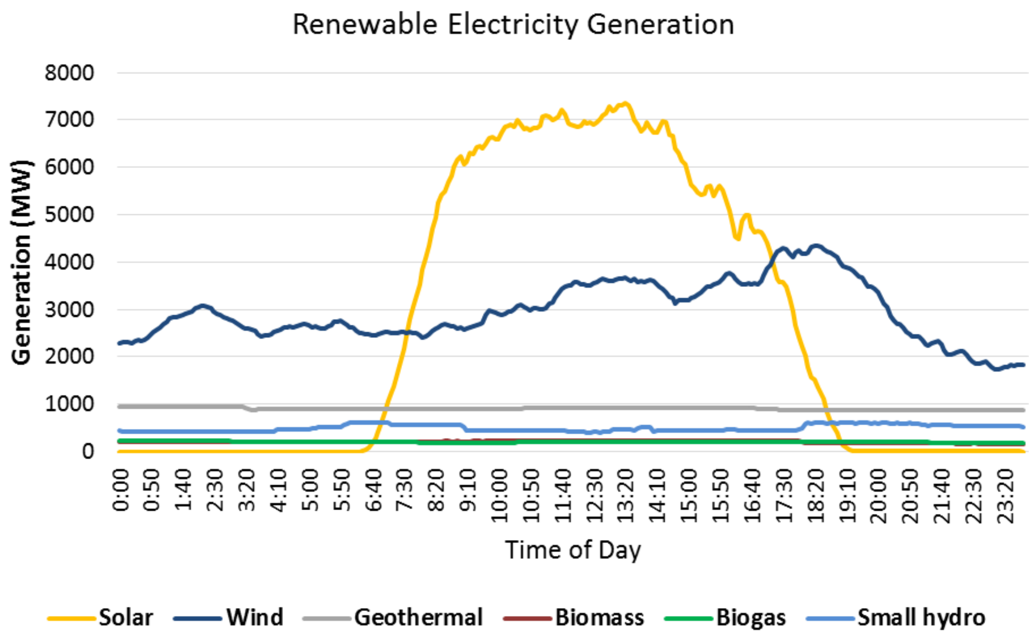


Figure 6. Renewable generation in California for a sample day in 2018

Most renewable technologies are projected to increase to the year 2050 [57]. The capacity projections in PATHWAYS' pre-set scenarios are based on estimations for generation needs to meet future load demand and satisfy GHG reduction goals. The growth of individual technologies includes considerations for technical feasibility and economic constraints and result in future renewable capacity dominated by solar and wind [65]. This analysis uses the baseline capacity projections modeled by E3.

2.1.3 Balancing Net Load Dynamics to Meet 100% Renewables

The future net load profile can be determined by incorporating projections for electricity load demand and renewable capacity growth. Net load is the electric load demand minus renewable generation. In the perfect balance of renewable generation and demand, the net load would be zero. Where a misalignment of renewable generation and load exists, the net load becomes a series of positive and negative values, corresponding to periods of insufficient and excess generation, respectively, see Figure 7. The challenge then becomes to add or shift generation (or load) in order to reduce the net load to at least zero.

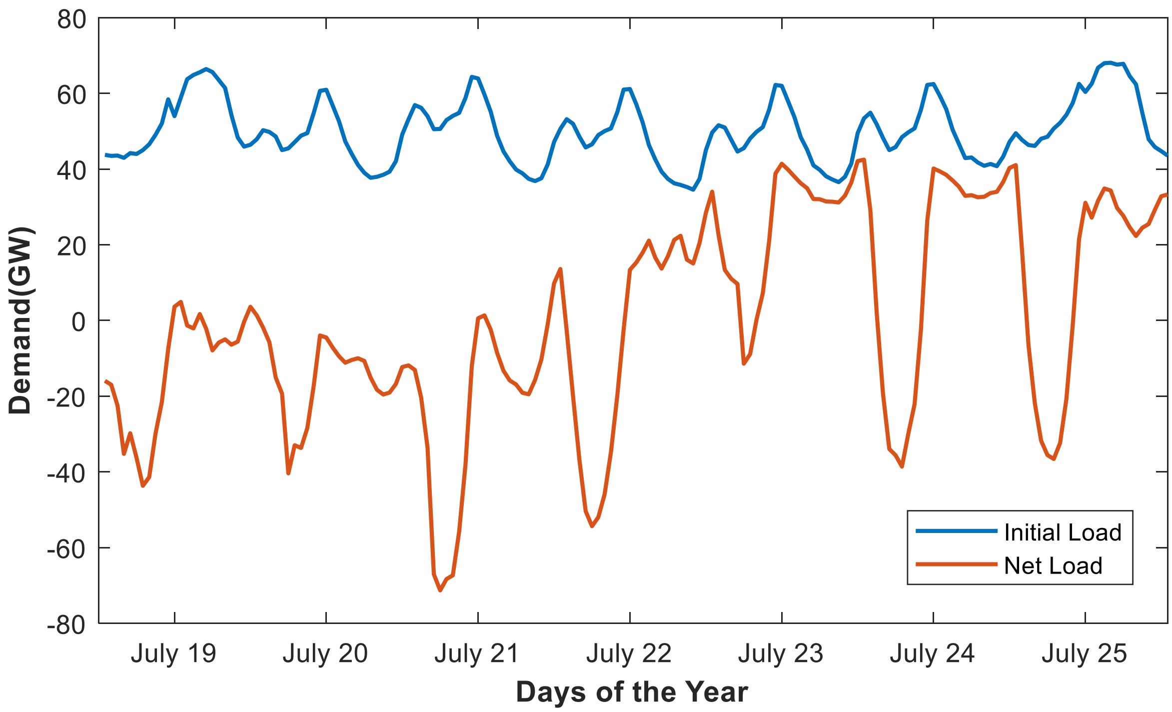


Figure 7. Load and Net Load for a week in the year 2050, using PATHWAYS baseline assumptions

The specific challenges that need to be addressed can be categorized by the timescale at which they affect the grid. Power output from variable renewable generation can vary across all timescales, with real-time small fluctuations impacting power quality [83]. Larger fluctuations require additional support strategies that can balance the net load changes, either by providing generation or reducing load demand when renewable generation drops [84]. In general, literature agrees that high variable renewable grids result in a need for more flexible generation that can compensate for increased fluctuations in the net load [36,38,41,51,61,85]. Solar has a distinct generation profile which consists of a significant increase in power output as the sun rises and a significant drop to zero when the sun sets. In California, the decline in solar generation coincides with peak electricity demand, resulting in a large increase in demand in a short period of time that other generation resources must ramp up to meet. Wind fluctuations are less consistent at the day scale and changes tend to occur more slowly [86]. On average, wind generation peaks in the evening and is at a minimum during the middle of the day [87,88]. Wind generation may, therefore, provide some generation when solar is low or not available and result in a smoother net load than solar alone [88].

The growth in solar and wind capacity on the grid increases the ramping requirements of the grid, in terms of both overall ramping magnitude and rate [51,89], see Figure 8. In Figure 8b, it is assumed that renewables are curtailed when net load demand drops below zero and therefore the negative values do not contribute to ramping requirements. For example, if the net load between hour 1 and hour 2 changes from -10 GW to 10 GW, the ramping demand for the grid would be 10 GW (10 GW minus 0 GW). When examining the net load, the most prominent increases in ramping occur in the morning between 7 and 9 am (ramp down) and in the early evening between 6 and 8 pm (ramp up). These periods also coincide with an increase and decrease in solar generation, respectively. Peak electricity demand occurs during the early evening period when the greatest amount of ramping up is required. According to the California Independent System Operator, maximum ramping rates vary by season as well, with lower maxima in the summer, despite peak load occurring during that time [90]. This trend is consistent for the 2050 scenario depicted in Figure 8, and is due to improved alignment of renewable generation and electricity demand during those months.

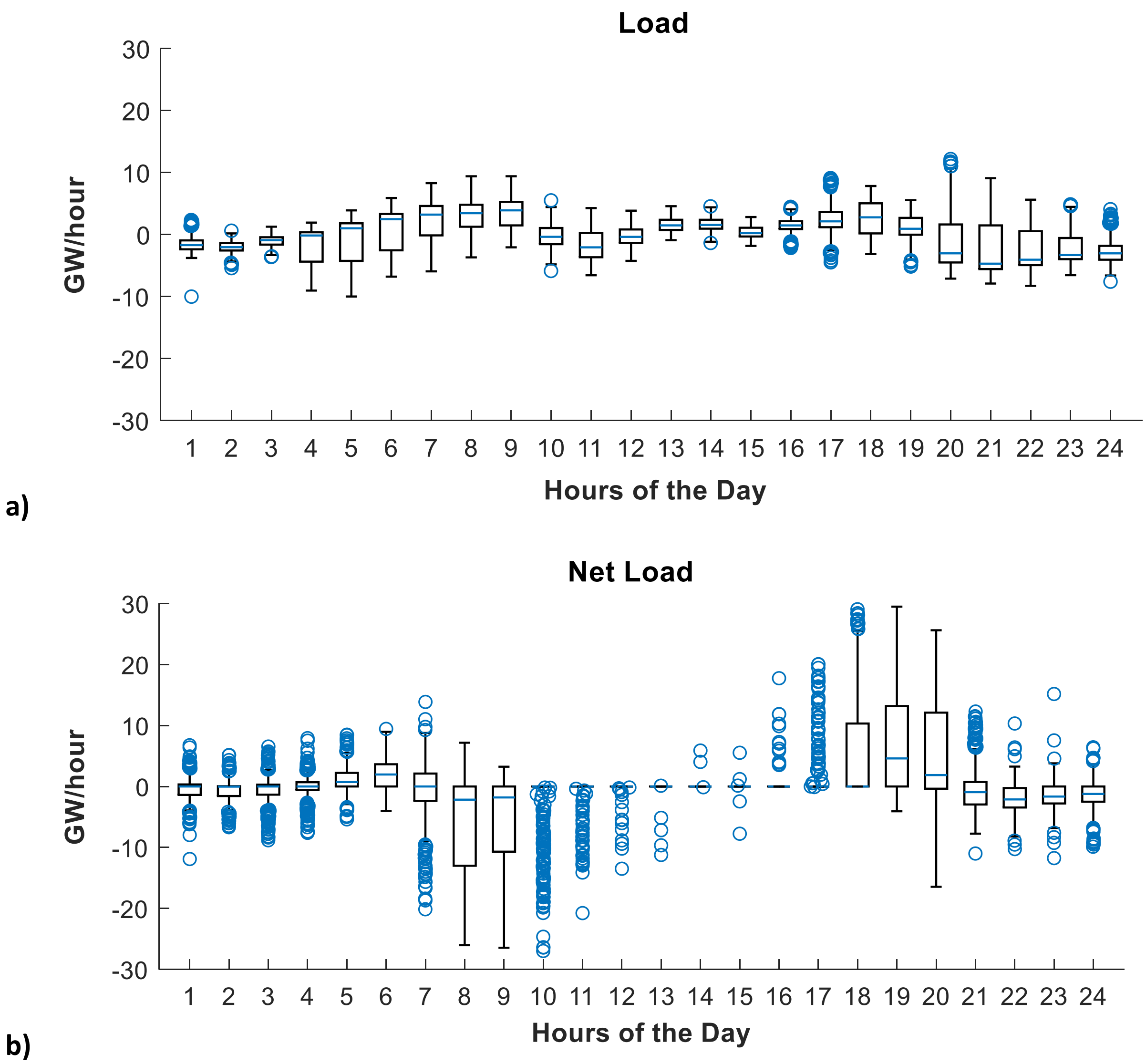


Figure 8. 2050 Ramping demand for a) electric load demand and b) net load demand assuming PATHWAYS renewable capacity values in baseline 2050 compliant scenarios

Further exploration of seasonal variability shows that solar and wind generation can have strong seasonal trends, which can affect renewable penetration and flexibility requirements for the grid. Solar generation peaks in summer (June-September for California), corresponding to longer days and higher solar irradiance values [91]. Seasonal wind trends vary regionally, driven by local conditions [92]. In California, current wind generation is at a minimum December-January, peaks in June and then declines the rest of the year [92,93]. The combined seasonality of wind and solar availability results in distinct periods of the year with high or low generation of renewable electricity, see Figure 9. Despite a theoretical annual renewable penetration of 90% in the case illustrated, the hourly load met by solar and wind varies from 20 to 100%, due to the misalignment of load and solar and wind generation. The average monthly load met by solar and wind varies from 53 to 79%, due to seasonal variability in solar and wind generation. The implications of this pattern are demonstrated by Tarroja, Shaffer, and Samuelsen (2018), who found that the limiting period for a 100% renewable grid for the year 2050 is winter, when renewable generation is insufficient to meet demand and concluded that large-scale seasonal storage capacity is required if excess summer generation is to be used to meet the deficit [43].

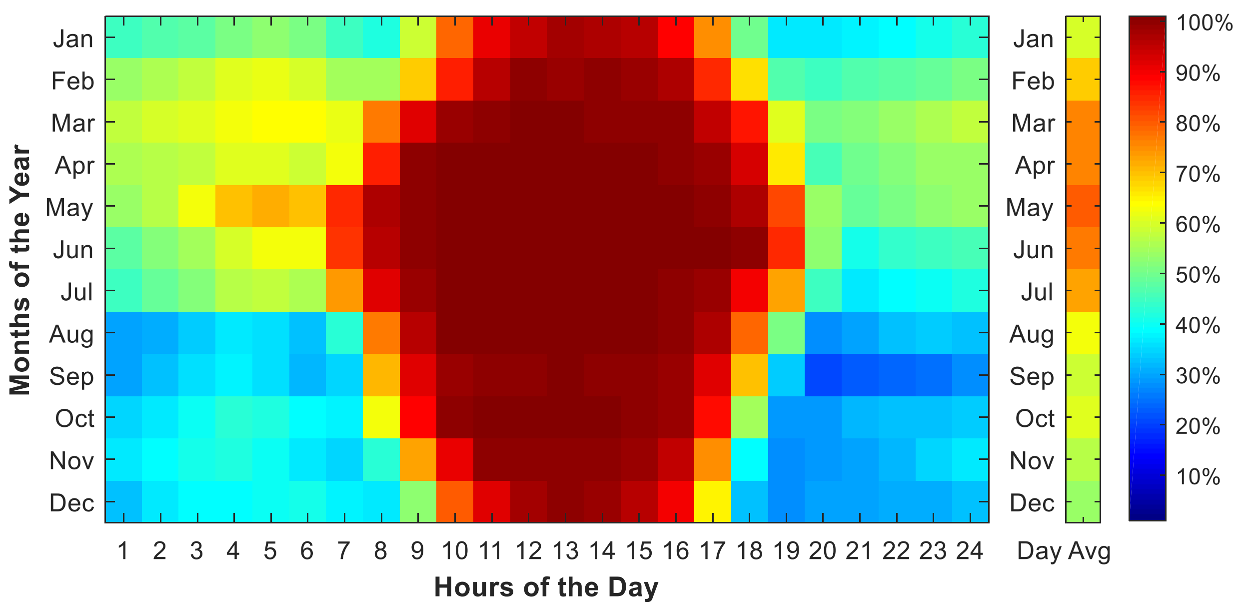


Figure 9. Percent hourly load met by solar and wind and the monthly average for a 2050 grid using PATHWAYS baseline assumptions for load, solar, and wind

The challenges outlined here indicate a need for a comprehensive suite of strategies that can address problems at multiple timescales. Proposed solutions for overcoming variable renewable generation challenges include: over-building renewable capacity [36,43], increasing flexible generation and/or removing baseload generation [51,94], expanding energy storage capacity [50,52,95,96], expanding demand response of flexible load demand [97,98], including vehicle-grid integration [32,35,44,84], and increasing grid interconnectivity with regional expansion [85,99,100]. Different strategies are well-suited for different challenges and adopting them may result in trade-offs.

Overbuilding solar and wind capacities has some advantages. Tarroja et al. (2018) found that increasing solar and wind capacities above generation needs reduces the material mass requirements to reach 100% renewable penetration [43]. Budischak et al. (2013) found that it was more cost-effective to overbuild renewable capacity than add additional storage [36]. However, trade-offs exist: allowing curtailment during periods of over-generation leads to lost revenue at the plant level and underutilization of available generation resources [101]. While some curtailment may be more cost-effective, and overbuilding capacity may reduce the net load demand, there are diminishing returns for expanding renewable capacity above demand and this strategy would most likely still require additional management strategies to achieve a 100% renewable grid for California [43,102].

A major focus of literature examining renewable integration is that increased flexibility is needed from the generation mix in order to reach high renewable penetrations [38,41,50,51,69,85,89,94,103]. Denholm and Hand (2011) and Li, Paster, and Stubbins (2015) found that removing baseload generation resources and replacing them with flexible generation increases renewable penetration [50,51]. Lew et al. (2010) concluded that in order to balance new net load variability, dispatchable generation should increase their flexibility as characterized by response time, ramp rate (change in power output per unit of time), minimum uptime and/or downtime constraints, and maximum turndown (i.e. minimum part load condition) [94]. While thermal plants have been a central focus of grid flexibility, flexibility requirements of high renewable grids may be met through a variety of grid resources [53].

Energy storage is one example of a supply-side resource that can increase grid flexibility. Energy storage technologies range in composition, scale, and functionality. Prominent technologies include pumped hydropower, different chemical configurations of battery energy storage and flow batteries, compressed air, flywheels, thermal energy storage, hydrogen storage, and supercapacitors [96,104]. V2G-enabled vehicles may also be considered a form of energy storage [105]. Energy storage technologies that can respond at the millisecond range—conventional and flow batteries, flywheels, and supercapacitors—can provide real-time power quality management [106]. Most energy storage technologies are able to handle intermittency at the minute to day scale, and select technologies such as hydrogen storage have the potential to provide longer-term storage [96,107]. A more detailed discussion of generation-side zero-emission technology options for grid balancing services is presented in Section 2.3.

Flexibility is not limited to generation-side strategies. Demand-side management, particularly demand response, can also provide flexibility. Under demand response programs, participants agree to shift or reduce their load during periods when a change in load will support grid stability [108]. Utilizing demand response can reduce the cost of energy, improve renewable integration, and may help to decrease overall generation capacity requirements [97]. Historically, the California ISO (CAISO) has had much lower demand response contributions compared to other U.S. ISOs [109]. Currently, the state is leading a coordinated effort between stakeholders and researchers to evaluate the potential scale of demand response, requiring the investigation of potential flexible loads [110]. Future flexible loads may come from a variety of sources. Industrial, commercial, and residential loads that have set daily patterns may become flexible with smart appliances and improved, real-time communication with the grid [111]. New and future loads may also be flexible, most relevantly, plug-in vehicles and electrolyzers used to produce renewable hydrogen [31,111]. In order to take full advantage of the state's demand response potential, CAISO will need these load sources to respond dynamically to changes on the grid.

In addition to installing new power plants or other grid resources, researchers have found that renewable integration can be improved through regional coordination of renewable resources. As previously stated, renewable resources may have regionally varying hourly output tied to local conditions. Aggregating generation from renewable resources over a large geographical region can reduce the number of hours with no renewable generation and can create a smoother overall profile [87,112]. Huber, Dimkova, and Hamacher (2014) determined that larger regions with moderate penetration of variable renewable generation had lower flexibility requirements compared to small regions [85]. Schaber et al. (2012) and Delucchi and Jacobson (2011) determined that increasing regional interconnections decreased the need for energy storage [100,112]. King et al. (2011) found that flexibility reserves required to ensure grid stability can be reduced by implementing an energy imbalance market that allows for electricity sales between other regions [89]. This approach takes advantage of the smoothing effect of aggregating renewable generation across a larger area and the sharing of generation resources for ancillary requirements.

This analysis will focus on vehicles and related infrastructure as flexible loads, as well as supportive generation-side strategies for achieving up to a 100% renewable grid. There will be a discussion on how demand-side management (eg. demand response to reduce peak load demand) may affect results, including the identification of periods of the year where demand response may help lower infrastructure costs and improve grid performance.

2.2 Transportation Considerations for the Deployment of Zero-Emission Vehicles

ZEVs are in a unique position to provide flexible support to variable renewable generation, as they can utilize resources that allow for the transportation sector to reach low emission targets to also provide benefits to the grid. Not only can the production of hydrogen for fuel cell vehicles through power-to-gas (P2G) pathways provide load following and load shifting services, coordinated charging of plug-in vehicles can provide similar support and vehicle to grid (V2G) charging can further increase renewable utilization and provide additional support like spinning reserve and frequency regulation by discharging back to the grid [32,113]. Previous research focused on the deployment of light duty plug-in ZEVs found that when charging is coordinated, renewable integration can increase and both grid and vehicle emissions can be reduced [32,46]. They also found that the deployment of a large fleet of plug-in electric vehicles with V2G charging can offset the need for stationary energy storage in order to achieve high renewable utilization (above 75%) [32]. Because California has called upon the transportation sector to transition to ZEVs, it can be expected that a significant number will be available to provide services, if the appropriate infrastructure and charging strategies are adopted [114].

The transportation sector is diverse, consisting of all modes of transport: vehicles (on-road and off-road), airplanes, shipping, and rail [9]. This work focuses on the on-road vehicle portion of the transportation sector. Not only do these vehicles make up a majority of transportation demand, the zero-emission alternatives for these vehicles are closer to being adopted with options either in late development or commercially available today. This indicates that widespread adoption of ZEVs could be achieved by 2050, the time period investigated in this analysis. On-road vehicles types range in both size and use [1,115]. Vehicles can be divided into a) light-duty vehicles, which are of a low gross vehicle weight and are primarily used for personal travel and b) heavy-duty vehicles, which are distinguished from the light-duty sector both by their weight (greater than 8500 pounds) and their use (mainly for commercial applications) [116,117]. The heavy-duty vehicle sector is a diverse collection of vehicles designed for a broad list of applications from goods delivery and transport to waste pick-up and disposal [116,118].

Conventional on-road vehicles rely on internal combustion engines (ICE) running on fossil fuels (eg. gasoline, diesel). The suitability of different ZEVs to replace a given conventional ICE vehicle is dependent on their ability to meet the travel demands of the vehicle they would be replacing. Key factors in assessing suitability are: vehicle fuel economy, travel patterns-both the frequency and length of trips—, access to electric vehicle supply equipment (EVSE), and charging/vehicle-to-grid (V2G) intelligence. These factors can vary between individual vehicles as well as across different vehicle types.

When examining the transition to ZEVs at the regional or state level, it is important to determine the fraction of the ICE vehicle population that can be replaced with battery electric vehicles, fuel cell electric vehicles, or either, as well as determine whether the travel demands of certain vehicles may prohibit them from being replaced by either ZEV type. In the case that either ZEV type could be adopted, an evaluation of priorities may be used to determine a range of optimal mixes between BEV and FCEV deployment. In the case that a portion of vehicles cannot readily be replaced by either ZEV type, alternative strategies may be assessed given the known constraints that prohibit the ZEV adoption.

2.2.1 Zero-Emission Vehicle Options

By definition, ZEVs do not emit any GHG emissions or criteria pollutants from the tail-pipe. Currently, two ZEV technology options that are commercially available: battery electric vehicles (BEVs) and fuel cell electric vehicles (FCEVs). Some OEMs are researching plug-in fuel cell electric vehicles (PFCEVs), an option that combines the efficiency and connectivity of a BEV with the longer range and reduced weight of a FCEV [119]. Mercedes-Benz has announced a PFCEV model, but the current focus by most automakers is on BEVs and FCEVs [120].

BEVs and FCEVs both rely on electric motors, but have different fuel inputs and operational considerations. BEVS use batteries to provide an electric current to the vehicle motor, while FCEVs use fuel cells, which create a current by splitting hydrogen molecules. A variety of BEV and FCEV models are available on the market today, each with its own technical specifications (Table 1, Table 2). Most of the ZEVs options available are light-duty vehicles. These vehicles range from passenger vehicles to SUVs and trucks. In general, the fuel economy (sometimes referenced to as fuel efficiency) for BEVs range between 0.25 (passenger vehicles) up to 0.51 kWh/mi (for larger SUVs). Average fuel economy for FCEVs range from 60 to 67 mi/kg. The vehicle range for different ZEVs varies significantly, depending on the size of the battery or fuel tank, see Table 1. Estimated range of the vehicle may also vary from the observed range, depending on the fuel economy achieved during a specific drive cycle [121,122]. While a majority of Light-duty ZEV options are currently smaller, passenger vehicles, automakers are setting up to release larger SUV and truck models to accommodate the full range of LDV vehicle types [120,123,124].

Table 1. Examples of Light-Duty Zero-Emission Vehicle Models and Technical Specifications

Vehicle Make & Model	ZEV Type	Vehicle Type	Battery Size (kWh), H2 Capacity (kg)	Est. Fuel Efficiency (kWh/mi or mi/kg)	Est. Range (mi)
Audi e-tron [125]	BEV	SUV	95	0.44-0.51	200-230
BMW i3 [126]	BEV	Auto	42	0.29	153
Chevy Bolt [127]	BEV	Auto	60	0.27	238
Ford Focus Electric [128]	BEV	Auto	33.5	0.31	115
Hyundai Ioniq [129]	BEV	Auto	28	0.25	124
Tesla Model 3 [130]	BEV	Auto	75	0.26	310
Tesla Model X [123]	BEV	SUV	100	0.34-0.38	289-295
Honda Clarity Fuel Cell [131]	FCEV	Auto	1.7, 5.5	67	360
Hyundai Nexo [124]	FCEV	SUV	1.6, 6.3	60	380
Toyota Mirai [132]	FCEV	Auto	1.6, 4.7	67	312
Mercedes GLC F-CELL* [120]	PFCEV	SUV	13.5, 4.4	0.22 and 180	270-478**

*Announced, ** Depending on tank pressure

Zero-emission HDVs are an emerging market with a few larger vehicles options, and several automakers developing the drivetrains and vehicle body designs for future models, with reported zero-emission HDV fuel economy varying by make and vehicle class, see Table 2. Future improvements and new vehicle models for all ZEV classes are expected in the coming years as ZEV technologies mature and legislation pushes for greater deployment of ZEVs [116].

Table 2. Examples of Heavy-Duty Zero-Emission Vehicle Models and Technical Specifications

Vehicle Make and Model	ZEV Type	Vehicle Type	Class	Battery Size (kWh), H2 Capacity (kg)	Estimated Fuel Eff. (kWh/mi or mi/kg)	Range (mi)
BYD [133]	BEV	Bus	7,8	324,500	>1.86,>1.97[+]	156, 255
BYD [134]	BEV	Day cab	8	435	>2.47[+]	124 (full-load), 167 (half-load)
BYD [135]	BEV	Cab Chassis/ Step Van	6	221	>1.68[+]	124 (Full load)-125
Cummins [136]*	BEV	Truck	7	140	>1.33[+]	100-300
Daimler/ Mercedes [137]*	BEV	Truck	7	240	>1.84[+]	Up to 124
Einride [138]*	BEV	Autonomous truck	8	200	1.6	124
Lightning Systems [139]	BEV	Van	2B-3	43, 86	0.55	60,120
Navistar eStar [140]**	BEV	Van	3	80	0.74	99.4
Smith Newton [141]**	BEV	Truck	6	80, 120	1.34	60, <= 150
Smith Newton [140]**	BEV	Van	6	80	1.41	99.4
Tesla [142]*	BEV	Truck	8	800 (est.)	<2	300, 500
Zenith Motors [143]	BEV	Van	2B-3	51.8-74.5	>0.65[+]	80-135
Proterra [144]	BEV	Bus	7-8	220,440	1.46-2.32	93-234
Phoenix Motorcars [145]	BEV	Flatbed	4	105	>1.0[+]	100
Nikola/Bosch [146]*	FCEV	Truck	8	240 kWh, 9 kg	Not available	500-750
Toyota/Kenworth [147]	FCEV	Truck	8	12 kWh, 40 kg	6 mi/kg	200, 300 (Gen 2)
Van Hool/UTC Power [148]**	FCEV	Bus	8	53 kWh, 50 kg	4.79 mi/kg	240 (est.)
US Hybrid [149]	PFCEV	Step Van	3	28 kWh, 9.78kg	1.18-1.47 kwh/mi, 12.8 mi/kg	125

[+]Range assumes depth of discharge 95% of battery capacity, *Announced, ** On-road test

Current and near future models report fuel efficiencies ranging from approximately 0.5 to 2.5 kWh/mi, depending on vehicle class and vehicle configuration. While vehicle designs range by vehicle size and application, the design and manufacturing of the drive-train may be applied across body types. For example, Toyota, in a press release, detailed its efforts to apply knowledge gained through their development of the Toyota Mirai for the design and operation of their larger heavy-duty FCEV truck [147].

Fuel economy is projected to improve for all vehicle types tied to advancements in vehicle design and changes in fuel type, with E3 projecting the average fuel economy for light-duty vehicles to reach around 40 mi/gallons of gasoline equivalent (GGE) by 2050 and efficient ICE LDVs achieving 80 mi/GGE [150]. Fuel efficiency for heavy-duty vehicles is also projected to increase, with advancements in design and the transition to alternative fuels [116]. Because battery and fuel cell electric vehicles for heavy-duty applications are emerging technologies, OEMS and researchers anticipate significant advancements in fuel economy and range [116]. For example, between 2017 and 2019 Toyota increased the range of its class 8 fuel cell drayage truck from 200 mi to 300 mi [147].

Future ZEV population levels are dependent on which vehicle classes are offered as ZEVs and what the technical specifications of vehicles offered are, specifically fuel economy and range, because ZEVs will only replace ICE vehicles if vehicle demands can be met. Assuming vehicle availability, ZEV adoption rates are dependent on fleet turnover rates and economic drivers [151]. Several studies have projected likely ZEV population growth to 2050 [75,152]. This work will use the scenarios developed for the E3 Pathways Model to explore a range of possible ZEV penetration levels [150]. Additionally, a high hydrogen case is included to complement the high electrification case that assumes an almost total adoption of ZEVs by 2050. These scenarios are presented in Section 5.3.

2.2.2 Present and Future Vehicle Energy Demands

As previously discussed in Section 1.1, vehicles contribute to a significant portion of California's energy consumption. Energy consumption is not uniform across the different vehicle classes nor fuel type, see Table 3 for daily fuel consumption in the year 2012 [1].

Table 3. EMFAC Daily Fuel Consumption for Vehicle Categories

Vehicle Category	Year 2012			
	Gasoline (GGE)	**Diesel (DGE)**	**Natural Gas (GGE)**	**Electricity (GGE)**
Light-Duty Vehicles	3.9E+07	1.0E+05	0	2.3E+04
Buses	2.7E+05	2.1E+05	1.7E+05	2.0E+02
Light-Heavy Duty Vehicles	2.2E+05	9.5E+05	0	0
Medium-Heavy Duty Vehicles	4.9E+05	1.5E+06	0	0
Heavy-Heavy Duty Vehicles	6.7E+04	5.4E+06	5.1E+04	0

A majority of light-duty vehicles use gasoline, with a small portion of vehicles running on electric drive trains. Alternatively, heavy-duty vehicles tend to be diesel or natural gas vehicles, with little to no adoption of zero-emission options. Despite light-duty vehicles making up about 90% of VMT and 50% of vehicles on the road, heavy-duty vehicles have a disproportionate impact on fuel consumption and related vehicle emissions [1]. While heavy-heavy duty vehicles make up only 16% percent of the heavy-duty vehicle fleet, they travel over a third of total heavy-duty VMT and are responsible for half of HDV fuel consumption (Figure 10), data from [1].

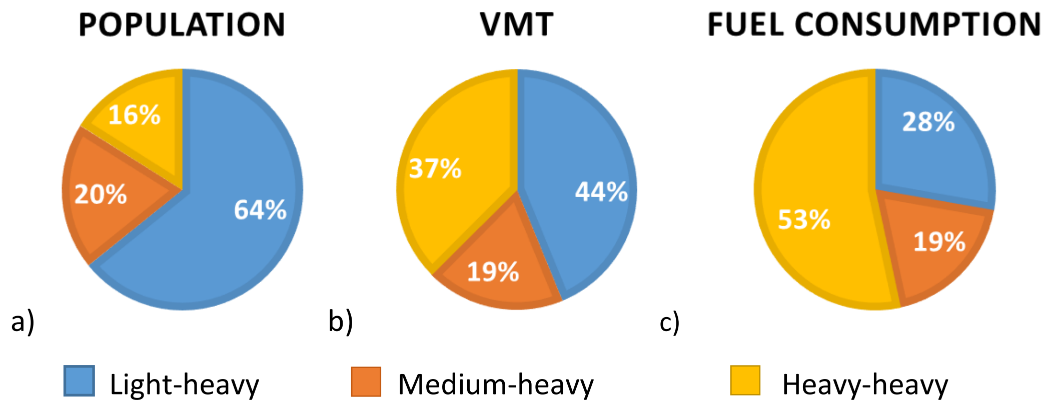


Figure 10. Breakdown of California heavy-duty vehicles by a) population, b) vehicle miles traveled, and c) fuel consumption gallons of gasoline equivalent (GGE) as reported by EMFAC

Vehicle energy demand is expected to continue to grow, with the scale of vehicle fuel consumption growth dependent on future changes to annual distance traveled and fuel economy/efficiency. Generally, VMT increases with population and economic growth [153]. Assuming historical trends in VMT growth, total VMT is projected to increase past the year 2050, see Figure 11, data from [2].

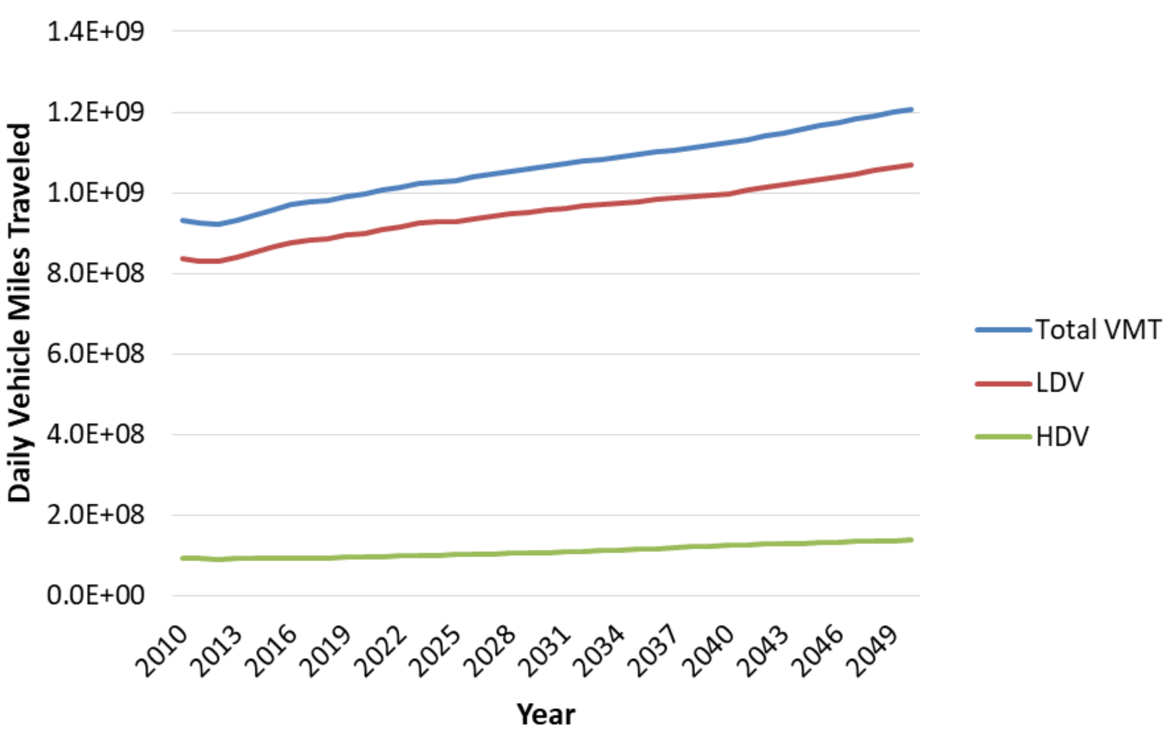


Figure 11. California Daily Vehicle Miles Traveled ARB Baseline Projections to 2050

While LDV VMT is generally assumed to increase with population, fuel cost and the availability of other transit choices can affect VMT, with higher fuel costs reducing VMT and increased access to vehicles increasing VMT [154]. Additionally, the growth of ridesharing services and the prospect of autonomous vehicles add additional uncertainty surrounding future VMT [155]. HDV VMT associated with different commodities may be influenced by varying economic drivers [117]. Fuel economy, measured in miles per gallon of fuel (eg. gasoline, diesel, or natural gas), can vary depending on vehicle age, type, and weight. Fuel economy declines with increased gross vehicle weight as well as increased cargo weight; it can decline 20-40% from empty to a full payload [156]. It is, therefore, important to consider average vehicle loads when calculating fleet-wide fuel economy.

2.2.3 Vehicle Travel Patterns

Vehicles are used for a wide range of transportation tasks from personal travel to commercial transport of goods and services. The timing and length of miles traveled are dependent on a vehicle's type as well as the individual needs of the vehicle's owner. Distinct travel pattern emerge when looking at the VMT distribution for a population of vehicles sorted by vehicle category. Understanding these travel patterns is key when considering transitioning these vehicle categories to ZEV options.

2.2.3.1 Light-duty Vehicle Travel Patterns

The travel behavior of LDVs has been well captured in previous national and statewide surveys, such as the 2009 National Household Travel Survey, which aggregated state household surveys including the California Household Travel Survey, since updated in 2013 [157,158]. The

LDV population has distinct weekday and weekend travel patterns, see Figure 12, data from [157].

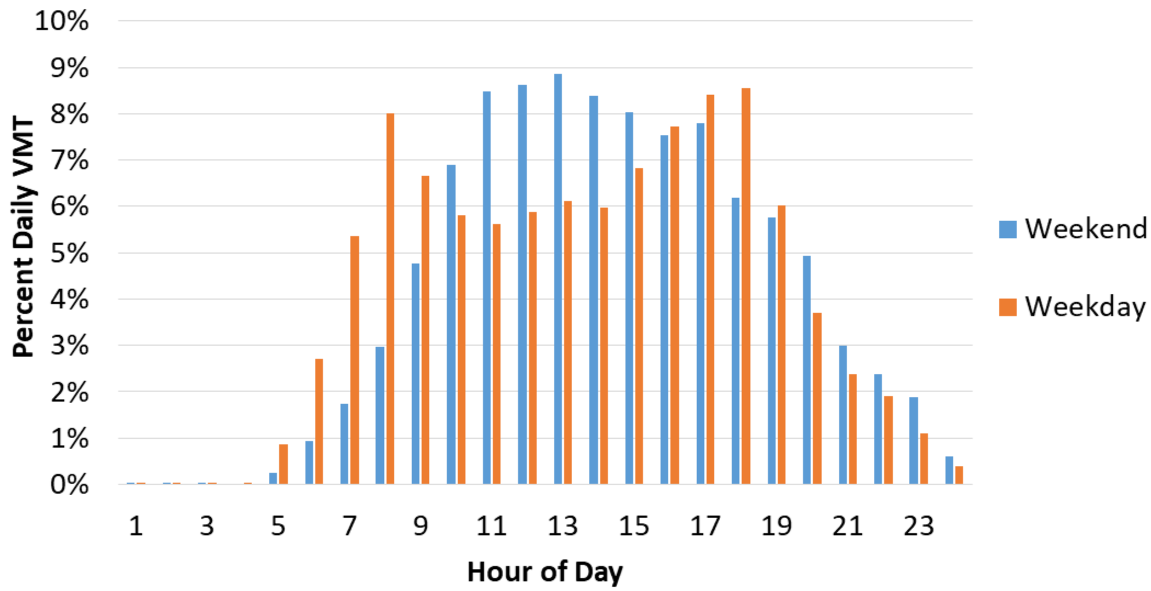


Figure 12. Light-Duty Vehicle Hourly VMT Distribution

These general patterns are consistent across U.S. regions, although the average distance traveled and the exact distribution of trips may vary [157]. During the week, a majority of vehicles leave home in the morning to go to work and then in the early evening, these vehicles tend to leave work and go home. This results in a bimodal distribution of VMT. On the weekends, morning VMT is low, with a single peak in VMT occurring in the late afternoon. Trip destinations are more likely to be personal, such as shopping or recreation, on Saturday and Sunday [114]. Overall, LDVs tend to dwell most often at home, followed by work [159]. If EVSE were placed in these two locations, it would cover more than half of all dwell periods and satisfy most charging needs [114]. California vehicle surveys and associated modeling work have stated that on average, LDVs travel about 32-36 miles a day, with an average trip distance of around 7-8 miles [2,114,159]. The distribution of daily VMT is skewed to the right with a majority of daily travel under 50 miles [158].

2.2.3.2 Heavy-duty Vehicle Travel Patterns

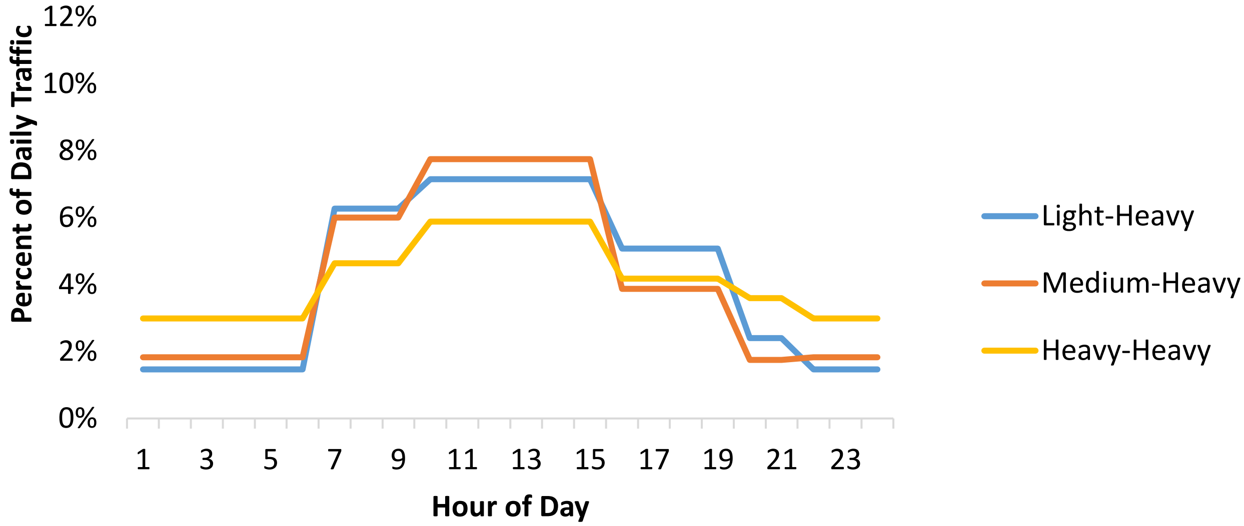
Heavy-duty vehicle travel patterns are more diverse than light-duty vehicles, and studies examining HDV behavior are less consistent both in terms of methodology and values reported, such as values for the timing and scale of HDV VMT, see Table 4, Figure 14. There is currently a coordinated effort to better quantify heavy-duty vehicle travel patterns due to the important role they play in both air quality and climate change [116,118,160,161]. Vehicle surveys conducted over the last 20 years have compiled data on individual vocations and vehicle types, as well as capturing statewide vehicle statistics [118,160,161]. Several regional and statewide models have been developed using collected data to assist in planning and emission reduction efforts, eg. [2,162–164]. These models range in both model inputs and insights that can be gained from their use.

When exploring individual vehicle behavior, data show travel patterns can vary by vocation [118]. For example, school buses have distinct travel demand peaks: morning, when children are picked up for school and mid-afternoon: when children are dropped off after school. Additionally, there may be regionally variations in the timing and distance of vehicle travel for the same vocation, depending on regional planning and regulated hours of operation. For example, the port of Long Beach and the Port of Oakland handle similar import/export goods, but have different hours of operation, leading to distinct VMT profiles; Long Beach has overnight vehicle operations, while Oakland’s profile is closer to the traditional work day, ending operations around 6 pm [160].

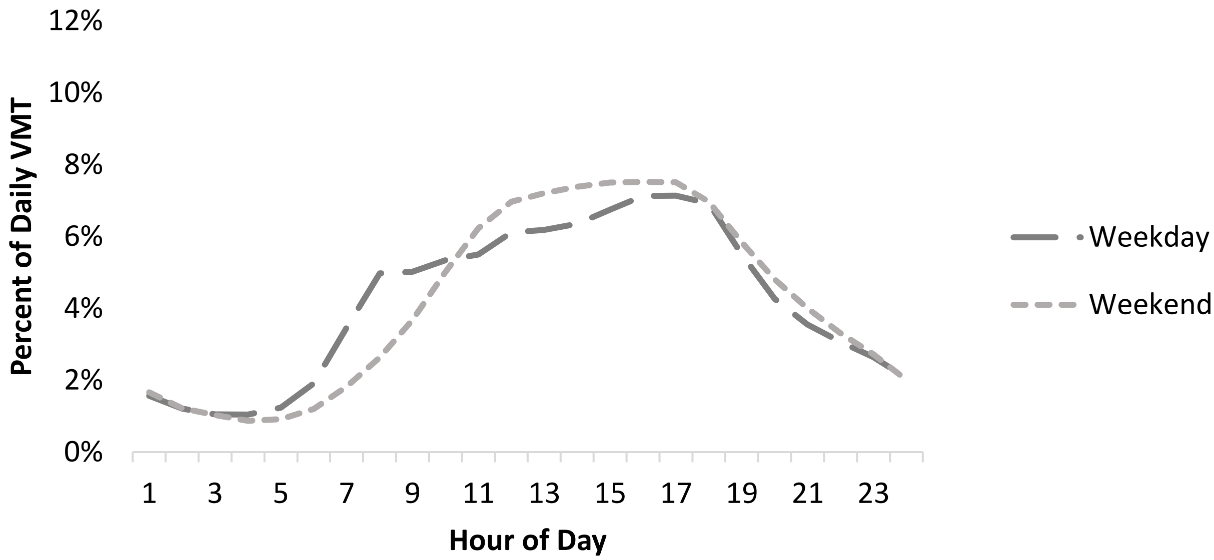
Table 4. Relevant Models and Surveys for California Heavy-Duty Transportation Studies

Model(*)/ Dataset	Organization	Description/Features	Year
CA-VIUS [161]	Caltrans	California survey for updated, expanded information on HDV characteristics	2016-2017
CSTDM (Short and Long Distance Commercial)* [117]	Caltrans	By commodity and weight (light-heavy, medium-heavy, and heavy-heavy)	2010
California Statewide Freight Forecasting Model (CSFFM)* [165]	Caltrans	Freight network model to be used as a planning tool; compatible with CSTDM	2007
California Hybrid, Efficient and Advanced Truck Research Center (CalHEAT) [116]	CALSTART/California Energy Commission	Research to develop a roadmap for California to achieve a clean heavy duty transportation sector	2010-2012
Freight Analysis Framework FAF^3* [166]	Federal Highway Administration (FHWA)	Commodity based truck volume, tonnage, and VMT for long distance travel along highways	2007
EMFAC* and VISION* [1,2]	California Air Resources Board (CARB)	By vehicle and fuel type, annual, spatially resolved to regions	2012
Fleet DNA [118]	NREL	Vehicle type (limited categories); trip data including drive cycle statistics	2008-2014
Heavy Duty Diesel Truck Survey [160]	CARB/UC Riverside	Activity data for medium-heavy and heavy-heavy duty vehicles	2015
Heavy Duty Truck Model* [162]	So. California Association of Governments (SCAG)	Regional travel by weight (light-, medium-, and heavy-heavy) within Southern California	2008
Heavy-Duty Truck Activity Data [167]	FHWA and CARB/Battelle	Activity data by gross vehicle weight (5 categories); four regions within CA	1999
Sparse Matrix Operator Kernel Emissions (SMOKE)* [168]	U.S. EPA	Activity and emission profiles spatially allocated across the state; profiles applied in this study are from EMFAC vehicle categories	2012
Texas Commercial Vehicle Survey [169]	Texas Department of Transportation	Vehicle trip data by vehicle class and commodity	2009-2010
Travel Demand Model (Truck Model)* [163]	San Diego Association of Governments	Regional travel for all modes; internal and external truck flows based on SCAG and FAF models	2008
Truck Activity Monitoring System (TAMS) [170]	Caltrans/UC Irvine	Data collection system for spatial and temporal distribution of vehicles in California	2017-present
MOtor Vehicle Emission Simulator (MOVES)* [171]	U.S. EPA	Activity and fuel inputs for calculating region-specific vehicle emission factors and developing emission inventories	2011
Vehicle Inventory and Use Survey (VIUS) [172]	U.S. Census Bureau	U.S. survey of heavy-duty vehicle characteristics; California sub-set	2002
Vehicle Volume Distributions By Classification [173]	FHWA/Washington State Transportation Center and Chaparral Systems Corporation	Vehicle volume and VMT distributions by road type, vehicle class, and day of week	1997

When examining heavy-duty vehicle travel patterns aggregated to a regional level, considering populations of vehicles across numerous vocations, a more homogeneous profile emerges, see Figure 13 and Figure 14. These results show that HDV VMT tends to peak in the middle of the day, with some variability depending on road type, driving direction, day of the week, and vehicle class [162,167,173]. The heavy duty model used for planning purposes by the Southern California Association of Governments (SCAG) assumes a greater weight of nighttime trips by heavy-heavy duty vehicles (GVW > 33,000 lbs.), compared to light-heavy (8,500 – 14,000 lbs.) and medium-heavy (14,001-33,000 lbs.) [162]. Hypotheses on why the share of day versus overnight travel varies by survey/model/vehicle class include that nighttime travel may be dependent on a) the size and regional scope of the vehicle population sampled, b) regional differences in traffic constraints, and c) truck vocations captured. Exploring this further, a heavy duty diesel truck survey conducted by the University of California, Riverside, found that a number of vehicle vocations operated during the day, peaking midday with low to no operation overnight, including refuse, construction, beverage distribution, and local moving; however, some vocations had a more evenly distributed profile, with vehicles, such as in-state line-haul trucks and agriculture, operating throughout the day and night [160]. Similarly, a study across 19 states in the U.S. by the Washington State Transportation Center and Chaparral Systems Corporation for the Federal Highway Administration observed that long-distance drivers were more likely to travel at night and stated that traffic congestion, prevalent in major California cities, influenced night-time driving patterns [173].

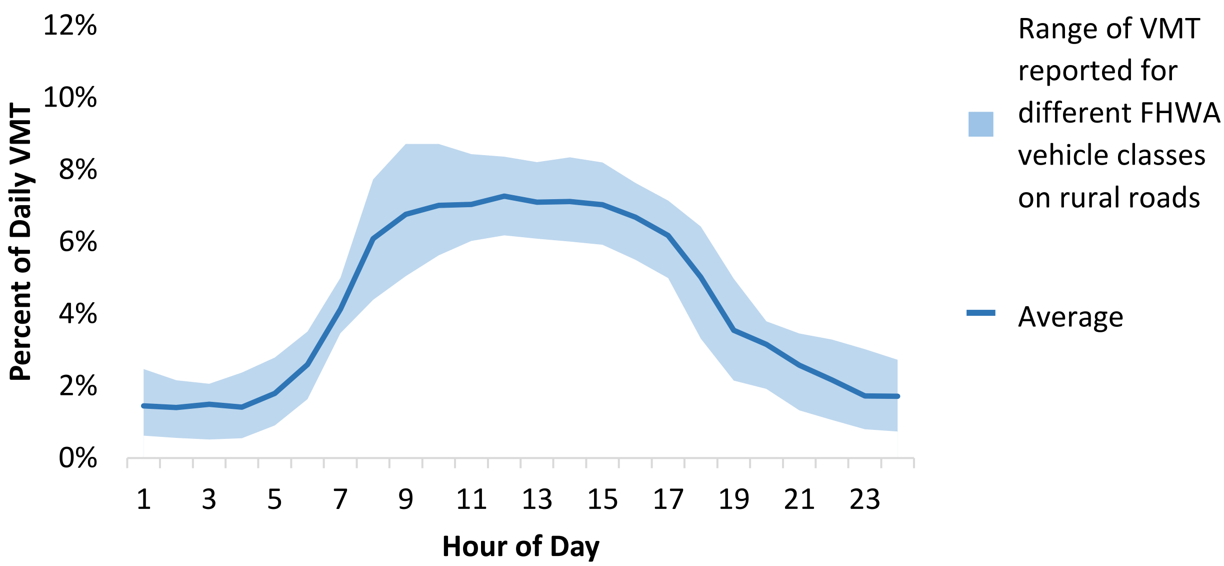


a) *2008 Southern California Association of Governments Heavy-Duty Vehicle Model. Time of day factors are divided into hourly estimates to approximate heavy-duty populations on the road.*

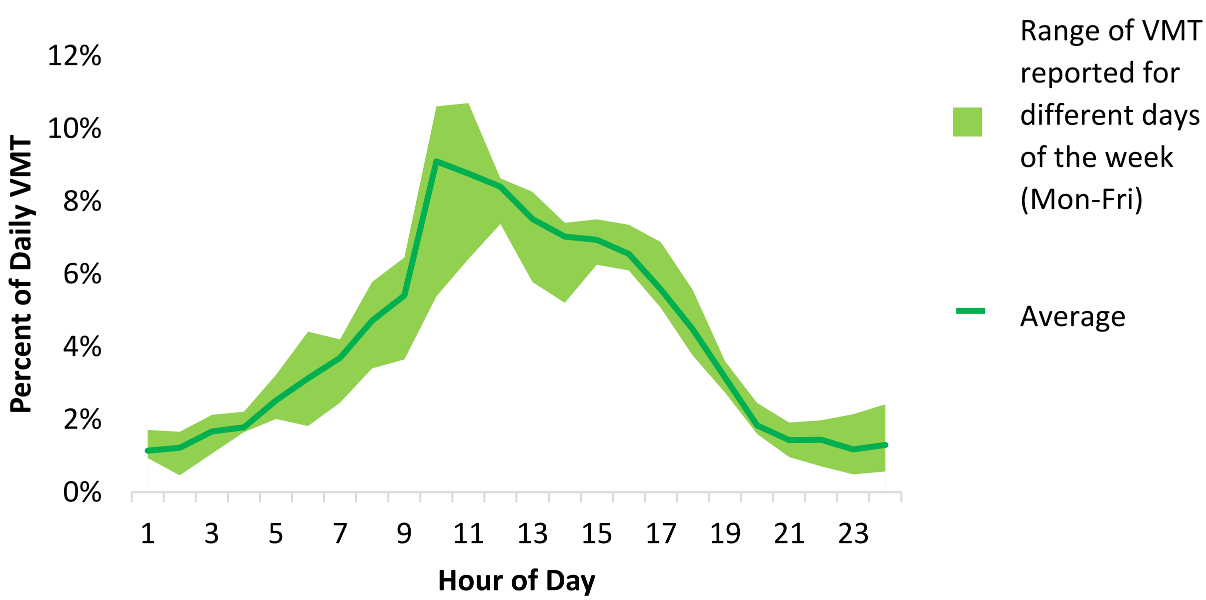


b) CARB Heavy Duty Vehicle Statewide Activity Profile Applied in SMOKE

Figure 13. Traffic and VMT Distributions Reported in Previous HDV Models



a) 1997 Washington State Transportation Center and Chaparral Systems Corporation Study for the Federal Highway Administration



b) 1999 Battelle Study for California Air Resources Board

Figure 14. VMT Distributions Reported in Previous HDV Surveys

Caltrans in its short distance commercial vehicle model has "fleet allocators" operating throughout the day and predominantly at night, while all other vehicle types (organized into "industrial, wholesale, retail, service, transport, and handling") operate during the day with peak travel during the middle of the day [117]. Caltrans defines fleet allocators as, "businesses where vehicles operate on regular, and thus relatively fixed, routes rather than making stops in response to individual requirements (e.g., parcel delivery/pick-up)" [164]. Stefan, McMillan, and Hunt (2005) elaborate on this description, providing examples such as garbage pick-up trucks and police [174]. Assuming these patterns, changing the percent of fleet allocators operating within California can strongly influence the overall hourly distribution of VMT.

In addition to the HDV hourly VMT distribution being distinctly different from LDVs, the average trip length and vehicle-miles per day for HDVs can also vary between HDV sub-categories, see Table 5. Presented in Table 5 are the average values by subcategory for daily VMT per vehicle stated in EMFAC for the base year of 2012. Values collected by CalHEAT are presented for comparison. Light-heavy duty vehicles (Class 2b/3) tend to travel around the same distance or slightly farther per day as LDVs (Class 1-2a), but they tend to take more frequent, shorter trips [1,116]. Heavy-heavy duty (class 8) vehicles have an average daily VMT per vehicle 2-5 times greater than light- and medium-heavy duty vehicles [1]. Medium-heavy and heavy-heavy duty vehicles have a significant range in daily VMT/vehicle, with EMFAC reporting agriculture vehicles traveling very short distances (16-17 miles/day) and out of state vehicle categories traveling the farthest (>100 miles/day).

Table 5. Heavy-Duty Vehicle Average Daily Vehicle Distance and Trip Data by Sub-Category

Vehicle Category	**VMT/vehicle (Avg.)** EMFAC 2017 [1]	**VMT/vehicle/day** CalHEAT [116]	
Light-Heavy	34 – 39 (36)	57*	94* (overall)
Medium-Heavy	17 – 170 (50)	–	
Heavy-Heavy	16-256 (122)	150-233*	

*Annual values averaged over 365 days to yield daily average. 21,000 annual miles per vehicle reported for Class 2B/3 vans and pick-up trucks, 55,000 miles for short haul, and 85,000 miles for over-the-road tractors. Assuming fewer operating days within the year will yield higher VMT estimates [116].

Two major statewide surveys have been conducted to explore truck travel behavior in California in the last 20 years [161,172]. The 2002 Vehicle Inventory and Use Survey (VIUS) was the last in a series of surveys examining private and commercial truck travel behavior across the U.S., with survey results available by state [172]. In 2016-2017, a new survey was conducted in California to replace the previous 2002 VIUS survey results for planning purposes [175]. This new survey endeavored to improve the documentation of commercial trucks travel statistics for vehicles traveling within and through the state [176].

The two surveys have distinct differences in how trip behavior was captured and what the results indicate. In the 2002 VIUS, California trip length frequency was reported for the total truck population (all classes), see Table 6, data from [172]. These results show travel skewed heavily towards short distance trips, with long distance trips greater than 200 miles making up less than 6% of the on-road, reported sample. In the 2017 CA-VIUS survey, trip length frequencies were more greatly resolved: trip length frequencies were reported by vehicle class, grouped here into vehicle categories to be consistent with the model developed later in this work (light-heavy: 8,501-14,000 lbs., medium-heavy: 14,001-33,000 lbs., and heavy-heavy duty: > 33,000 lbs.). Additionally, trip frequency distributions could be separated further based on vehicle registration, allowing analysis of trends between in-state and out-of-state vehicles [161].

*Table 6. VIUS 2002-California Reported Truck Range of Operation (Trip Length Frequency)**

Range of Operation	Percent of Sample	Percent of On-road, Reported Sample
50 mi or less	53.6%	71.2%
51 – 200 mi	17.5%	23.3%
201 mi +	4.1%	5.5%
Off-road, not reported, not applicable	24.7%	--

*Excludes some light-duty truck and van types [172]

In the 2017 survey, trips by in-state registered light-heavy and medium-heavy duty vehicles are heavily weighted towards distances less than 50 miles, but the survey found a greater share of trips longer than 50 miles compared to the 2002-VIUS survey. Additionally, light-heavy duty vehicles were found to have more trips greater than 500 miles from home base compared to medium-heavy duty vehicles. Heavy-heavy duty vehicles were found to have a more even distribution of trips across the different trip distance categories, with a larger portion of vehicles traveling over 50 miles per trip from their home base compared to all other categories. Out-of-state trucks tend to have longer distance trips compared to vehicles registered in the state, with a high percentage of trips greater than 500 miles (>20% for light-heavy duty, and >70% for medium-heavy and heavy-heavy duty). Examining the weighted results of the survey, 95% of the light- and medium-heavy duty VMT comes from vehicles registered in California. For heavy-heavy duty, it is 70%. Sorting trip distributions by home base state and registration resulted in the same distribution percentages, with 96% of vehicles calling the state in which the vehicle was registered “home base” [161].

The distinction of "home base" is important, because, while LDVs tend to dwell at locations such as work, home, and school, HDVs tend to dwell mostly at their "home base." Home base can range from warehouses to airports, depending on the vehicle vocation. For example, data from a commercial vehicle survey in Corpus Christi, Texas show that vehicles in the region spend, on average, less than an hour per dwell period at non-home base locations compared to 6-16 hours at home base locations [169]. Understanding where and when HDVs dwell is crucial for planning charging infrastructure. Not only will the locations determine the placement of EVSE, the length of dwell periods will dictate the charging rates needed to meet energy requirements without affecting travel demands.

2.2.4 Vehicle Deployment Strategies

The widespread adoption of ZEVs would shift vehicle emissions from tailpipes to power plants, either through increased electricity demand for charging or for hydrogen production (assuming renewable hydrogen is used). The effect of ZEVs on greenhouse gas and criteria pollutant emissions is therefore dependent on the electricity mix as well as charging strategies utilized [31,177,178]. ZEV adoption has the potential to reduce both greenhouse gas and criteria pollutant emissions by utilizing renewable power resources and switching to more efficient power trains [179,180]. To what degree ZEVs utilize renewable power is dependent on how ZEVs and the associated infrastructure are deployed [35,113,181].

2.2.4.1 Battery Electric Vehicle Charging Strategies and Infrastructure Considerations

BEV impacts on the grid are dependent on how and when vehicles charge. This is, in part, determined by vehicle travel patterns, as well as infrastructure build-out [32,140].

Different charging strategies for grid-connected vehicles can be distinguished by their level of grid connectivity and intelligence. The primary types of charging strategies considered for BEV deployment include:

- *Immediate charging*—Vehicle begins charging when plugged in and stops when the battery's state-of-charge (SOC) reaches 100% or vehicle is unplugged, whichever comes first. The vehicle does not communicate with the grid.
- *Time-of-Use charging*—Vehicle charging is planned around a basic cost function with two or more different costs at set times of the day. Usually weekdays follow one TOU profile and weekends and holidays follow another. The hourly costs do not change based on day-to-day changes in load and generation, but may be different for a defined "summer" and "winter" period, see Figure 15 [182–184]. The charging time can be planned, either by 1) the owner waiting to plug in at the cheaper time, or 2) setting a smart plug or charger that is timed to turn on at a scheduled time [130]. In the future, there could be direct communication with the grid, having the grid send a signal to the car to charge, however, this control strategy is more likely to be applied in the case of smart charging. The limitation of having a tiered pricing schedule is that it only accounts for the general curve of the net load profile and not the day to day variation in generation or demand conditions.

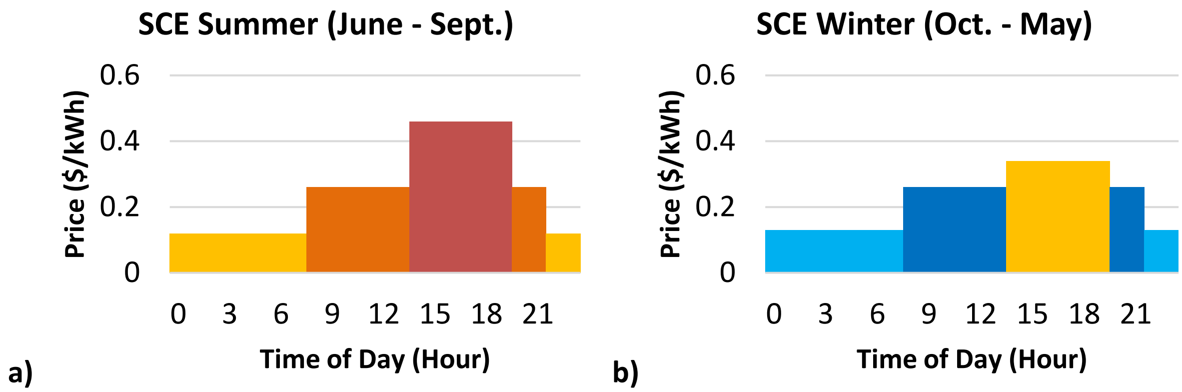


Figure 15. An Example Electric Vehicle Time-of-Use Schedule: Southern California Edison EV rates for weekday a) summer and b) winter. Price does not include fixed daily fee for connection.

- *Smart charging*—Vehicle charging is scheduled using a cost optimization with a highly resolved cost function based on the electric grid's net load profile [45]. The algorithm considers the vehicle's trips and dwell periods to determine the least cost periods to charge in order to meet the day's travel demands. Scheduling vehicle charging can provide grid benefits including renewable integration and load smoothing, which reduces ramping demands on power plants [185]. The different optimization methods based on the type charging control are:
    - *Centralized Control* —a centrally-situated aggregator receives stationary load forecasts and vehicle travel demands, including dwell times and locations. The aggregator computes and disseminates the charging schedule for each vehicle in the connected system [186]. This approach is dependent on having accurate forecasts of both grid and vehicle conditions in order to compute the optimal timing of vehicle charging [187]. Methods for determining the appropriate charging schedules may vary depending on grid structure and identified

priorities, as well as assumptions made about the flexibility of vehicle charging [188,189].

- *Decentralized (or Distributed) Control* — the planning of charging events is controlled by the vehicle and not a central aggregator. Each vehicle receives a cost signal and decides its charging schedule based on its travel constraints. Vehicle decisions are then conveyed back to the grid and a new cost signal is produced that incorporates the added load. The rate at which the cost signal is updated affects the net profile; less frequent updates are less computationally intensive but result in greater net load fluctuations that power plants must ramp up and down to meet [34,187,190]. Chiang et al. (2018) found that decentralized charging yielded increased reliance on peaker plant generation compared to centralized charging, with update times up to 120 minutes having similar GHG emissions impacts as centralized control but with increased air quality impacts [187].

- *Vehicle-to-grid charging*—Vehicle charging follows the same strategy as smart charging but the controller now accounts for bi-directional flow of current, allowing the vehicle to discharge back to the grid. Again, vehicle charging can be controlled through a centralized or decentralized mechanism. Under a V2G charging strategy, vehicles can plan charging events to correspond with renewable generation and discharge during peak load times to balance the grid [45]. In fact, V2G-enabled vehicles have the potential to participate in a range of grid services, from frequency regulation to spinning reserve, if their operations are aggregated into a responsive unit [191]. Similar to smart charging, vehicle-to-grid charging has been deployed in pilot projects and the control and communication strategies are still being tested [192]. Juul et al. (2015) tested multiple scheduling methods for a fleet of BEVs to provide frequency regulation to the grid in real-time and developed a new scheme that improved the service performance at higher capacity commitments. They also suggest that future work into scheduling optimization methods can further improve load-following accuracy [193].

Realizing the optimal scheduling of vehicle charging is dependent on the availability of sufficient electric vehicle charging infrastructure. Infrastructure considerations include the location and charging power, or level, of electric vehicle supply equipment [194]. A description of different charging levels is presented in Table 7. The lower value estimates presented include additional component losses including AC/DC conversion losses and transformer losses [195]. Vehicle discharging results in greater losses compared to charging, driven by greater conversion and transformer losses.

Table 7. Charging Levels and Technical Specifications

Charging Level	**Charging Power Range**	**Configurations** [194,196]	**AC/ DC**	**Charging Eff. (%)** [195,197]	**Discharging Eff. (%)** [195]
Level 1	1.44 to 1.9 kW	120 V, 12-20 A	AC	80-85	64-81
Level 2	3 to 19.2 kW	208/240 V, 16-80 A	AC	89-95	70-91
Level 3	25 kW +	208-480 V,≤40 kW 208-480 V,≤90 kW 208-600 V,≤240 kW	AC DC	90-95 (lower value est.)	80-90 (est.)

While the ubiquitous placement of level 3 EVSE would ensure BEVs have access to fast charging throughout the day, this approach may be cost-prohibitive. Rather, a more strategic approach is to place chargers in locations where vehicles exhibit the longest dwell periods to maximize charging flexibility and/or key travel corridors with potential fast charging to ensure long-distance trip demands are met [114,198]. Additionally, when building out charging infrastructure it is important to consider which EVSE will allow vehicles to charge within dwell times at reasonable cost [198]. For example, while a small, passenger vehicle may be able to charge fully in 1-2 hours using level 2 charger, it might take an HDV several hours, due to its larger battery capacity and higher travel demands [140]. Depending on the HDV's travel demands, a level 3 charger may be required to ensure the vehicle receives enough energy during its dwell period to meet its next trip(s), especially in the case of vocations where vehicles are expected to travel long routes with short dwell periods between trips, such as public transit [199].

EVSE installation costs can vary based on location and charger rating, see Table 8. Installation costs reported include the cost of the charger, labor and supplies for the installation, permitting, O&M costs, as well as any upgrades that may be needed. Price tends to increase with greater charger ratings and the amount of upgrades required for the local grid to support a vehicle charging [198,200]. For level 3 chargers, a new transformer installation can cost between $10,000-50,000 above the installation cost of the charger [201–204]. Maintenance costs can range in price depending on the set-up and type of charger. The higher the power of the charger and the greater the number of connected vehicles, the more likely there will be additional transmission upgrade costs, especially in residential areas [200]. These costs may be passed on to users that are on non-residential electricity plans through demand charges—fees based on peak electricity use [205].

Table 8. Vehicle EVSE Installation Costs

Charger Rating	Location	Cost per Charger
Level 1 (120 V)	Home	\$0-\$1500 – Plug-in EVs come with charging cable that can be connected to home outlet (120V) [206,207]
Level 2 (240 V)	Home	\$1,000-\$3000 [194]
Level 2 (240 V)	Public	\$1,000 (wall mount)-\$6,000 (Advanced communication features) [207,208]
Level 3 (480 V) DC Fast Charging	Public	\$4,000-\$51,000 [202,207] Some estimates above \$100,000, eg. [209] with large (1000 kVA/480V) transformer upgrades

The charger rating can also influence how grid-connected vehicles participate in grid services. As most electricity markets are currently structured, vehicles need to be aggregated to a set minimum capacity in order to participate formally in grid services. The minimum bid varies by region and by grid service: for example, in Singapore the minimum bid for spinning reserve is 1 MW [210]. Southern California Edison requires a minimum bid of 100 kW for regulation up/regulation down, with a minimum of 500 kW/1 hour charging and/or discharging capability, and bid steps of at least 10 kW [211].

2.2.4.2 Hydrogen Pathways and Fueling Infrastructure for Fuel Cell Electric Vehicles

Understanding hydrogen productions pathways is important in determining grid impacts as well as the net emissions impact of using FCEVs. Hydrogen may be produced through several methods, the most prevalent today being steam methane reformation (SMR) [212]. Conventional SMR has associated GHG emissions and is not renewable, as it converts fossil fuel-based natural gas (CH_4) and oxygen to hydrogen and carbon dioxide [213]. In order to meet California emissions reduction targets, hydrogen must be produced at scale through a renewable pathway. Renewable pathways include electrolysis, thermochemical pathways—

biomass gasification, liquefaction, and pyrolysis—, and biological pathways—anaerobic digestion, fermentation, and metabolic processing [212].

In electrolysis, hydrogen is produced through the electrochemical separation of water into hydrogen and oxygen. This process is considered renewable if the electricity used to separate the water molecules is from a renewable source (eg. solar or wind power). The dominant electrolyzer technologies include alkaline, proton exchange membrane (PEM), and solid oxide (SOEC) electrolyzers, with alkaline electrolyzers being the most mature and SOEC electrolyzers being the least [106,214]. Alkaline and PEM electrolyzers operate at relatively low temperatures 60-80^{o}C, with system efficiencies around 50-70% [215,216]. Both types of electrolyzers have the ability to ramp up and down; studies such as Ursúa et al (2016), Barbir (2005), and Valverde et al (2013) have demonstrated their operation in coordination with variable renewable generation to produce renewable hydrogen [215–217]. PEM electrolyzers generally have lower minimum loads (0-5% of full load) compared to alkaline electrolyzers (10-20%), indicating a greater flexibility in dynamic operation [218]. SOECs, on the other hand, are operated at high temperatures, generally between 500-1000^{o}C, with efficiencies of 70-85% possible [219]. SOECs tend to have a higher minimum production rate compared to alkaline and PEM electrolyzers and are less mature, both in terms of overall technology development and dynamic operation of the SOECs [220]. While SOEC ramping has been demonstrated in simulation and in the laboratory, eg. [221–223], there remains work to be done to bring this technology to full market maturity [220].

Renewable thermochemical pathways require a biomass feedstock, such as switchgrass or agricultural waste [224]. In biomass gasification, the feedstock is transformed into methane and other byproducts, which are then cleaned and reformed into hydrogen [225]. Alternatively, in pyrolysis, biomass is transformed to produce carbon monoxide—along with other byproducts—which is reacted with water to form hydrogen and carbon dioxide [226]. In liquefaction, a slurry is produced combining biomass with water, sometimes a catalyst, and then reacted under pressure to produce an oil, which can then reformed to produce hydrogen [227,228].

Utilizing thermochemical pathways to produce hydrogen has some drawbacks. In general, thermochemical processes require significant energy inputs to break down the feedstock, and specifically, the equipment required for liquefaction currently make it cost-prohibitive [227]. Also, hydrogen production through these pathways can still result in emissions from the growth of the feedstock and processing, which can depend on methods used to remove pollutants during hydrogen production; these emissions are generally much lower than traditional fuels [224,226]. Additionally, hydrogen production rates and purity can vary over time in response to natural changes in feedstock composition [71].

The biological pathways for producing hydrogen are even less mature [229], and therefore, they are not likely to provide a significant percent of hydrogen in the timescale of this study. This analysis will focus on hydrogen from electrolysis to meet FCEV hydrogen demand. Of the mature technologies, only electrolysis results in no additional GHG and criteria emissions in the production of hydrogen if it relies solely on renewable electricity. The potential impact of fuel source diversification will be discussed and a sensitivity analysis will be conducted to determine grid impacts of reducing electrolyzer load.

Unlike vehicle charging infrastructure, which can build on the existing electric grid for the transmission of energy to vehicles, FCEVs require hydrogen production plants, a new network of hydrogen fueling stations, and the method to transport hydrogen from the production site to refueling station (unless hydrogen is made and dispensed on-site) [230]. In order to meet fuel demands, stations should be strategically distributed across the state and sized to match projected fuel demands of the region. Analyses have been conducted in coordination with state agencies to optimize the placement of future refueling stations, such as Kang et al. (2013) where hydrogen refueling stations were sited such that the average distance to a station would be 2.5 minutes [231]. In the proposed roadmap that resulted from this work, researchers estimate that a minimum of 68 stations strategically sited could be sufficient in supporting statewide FCEV deployment [232]. Nicholas and Ogden (2006) looked at regional analysis within California to ascertain which factors affect siting results and found that population density and convenience (measured in time to a station) were the main drivers [233]. Currently, California already has over 40 stations across the state with more than 20 in some stage of planning or construction [234]. This work assumes that fueling stations are adequately distributed across the state to supply fueling demands.

2.2.5 Vehicle-Grid Integration Impacts

A significant amount of research examines light-duty vehicle electrification [32,33,235–238,34,35,44–46,105,114,193]. Researchers have examined LDV electrification from a number of perspectives, examining BEV feasibility and charging strategies, as well as impacts on grid dynamics, and overall grid performance. These studies establish a strong foundation that can be applied to heavy-duty vehicle electrification.

A number of studies have examined the feasibility of battery electric vehicles for light-duty applications [114,239,240]. Zhang, Brown, and Samuelsen (2013) evaluated how many miles traveled by light-duty vehicles could be electrified given different vehicle and infrastructure parameters in California. They found that prioritizing placement of EVSE in locations with the highest dwell periods (home and work for light-duty vehicles) can result in feasibility levels between 80-96% of vehicles, with only home charging at level 2 already satisfying almost 90% of vehicles [114]. Greaves, Backman, and Ellison (2014) investigated the effect of a vehicle's drive cycle on the reported range of the BEV as well as overall BEV feasibility. They also found that around 90% of daily trips could be met with only at-home charging, but electrifying long distance trips would require additional charging options [239]. Dong and Lin (2014) investigated how driver behavior may influence BEV feasibility, allowing for travel modifications in order for drivers to adapt to the constraints of BEVs. They found that if drivers are willing to drive at a very low state-of-charge (SOC) (equivalent to a near-empty tank of gasoline), almost 60% of drivers were able to meet their travel demands with very few days (0-5%) requiring trip modifications, but as the minimum acceptable SOC increases, so does the level of trip modification [240].

In addition to feasibility, studies have explored grid and emissions impacts of integrating zero-emission vehicles, with special emphasis on grid-connected vehicles. In reviewing these works it can be concluded that understanding the timing and scale of vehicle charging is crucial in determining the impact of electrification on the grid as well as overall emissions. Immediate charging of light-duty plug-in electric vehicles (PEVs)—plug-in hybrid vehicles and battery electric vehicles—results in electric load demands that do not align well with renewable generation availability [32]. In the cases that light-duty PEVs can charge at home or at home and work, a majority of the charging demand occurs in the early evening, when electricity demand is already at its peak [114,241]. This can result in increased peak demand during the time that power plants are already ramping up to balance the sharp decline in solar generation that occurs at sunset [31]. Greater ramping and higher peaks may require further transmission and distribution upgrades as well as affect the resource planning policies of electric utilities to ensure they have the capacity and system flexibility to manage vehicle charging [186,241].

Coordinating the timing of PEV charging, whether through a time-of-use or smart charging strategy, can have significant benefits compared to immediate charging including increased renewable utilization, decreased ramping requirements for balance generation, and reduced peak demand [32,35,242]. At low renewable penetration levels, charging vehicles serve as a new electric load, which can increase demand for conventional power generation, but as renewable generation increases, and particularly otherwise curtailed renewable generation increases, there's a greater opportunity for grid-connected vehicles to support renewable integration while offsetting emissions from the transportation sector [31]. Furthermore, Wang et al. (2019) found the reducing emissions by adopting zero-emission vehicles was more cost-effective than stationary energy storage pathways in reducing system GHG emissions [230].

2.3 Zero-Emission Technologies for the Dynamic Support of a 100% Clean Electricity Grid

While the integration of transportation fuel demands onto the grid will provide a significant level of flexible load control, there may remain a need for additional dynamic support technologies to ensure electric demand and generation are balanced at all times and that the state consistently meets its emissions reduction targets. Zero-emission technologies include electric power generators, energy conversion technologies, and/or energy storage technologies that can respond quickly and reliably in order maintain grid performance. Each strategy has different features, with their own benefits and limitations for meeting dynamic support needs. Clearly defining technology capabilities along with grid needs will aid in the development of portfolios that achieve a 100% clean electricity grid. Important technical characteristics of available technologies include response time, ramp rate, efficiency, minimum part load condition [243], and for energy storage technologies: charge/discharge rate, storage duration, and power-to-energy ratios [107,244].

The technical constraints of different technologies can affect how well they are suited for different grid services. Generally, dispatchable power resources can provide flexible generation to balance renewable variability, but are unable to utilize excess renewable electricity directly [51]. Conversely, flexible loads are able to shift demand to use otherwise curtailed renewable generation and avoid times of peak load [35]. Energy storage technologies can respond the renewable variability through charging during over-generation events and discharging during renewable deficits; however, these technologies are limited by their storage capacity and other operational constraints [52].

Within these broad categories, different technologies can have significantly different characteristics. For example, response times range from milliseconds to minutes, depending on the technology. Lithium ion batteries and other batteries with similar chemistries can respond within milliseconds, and have high round-trip efficiencies. However, batteries tend to lose their charge over time (termed “self-discharge”), making them less effective for seasonal or longer-term storage, and are limited to the amount of energy that can be stored [52].

On the other hand, power-to-gas (P2G), which uses electricity to produce gaseous fuel,, in this case, hydrogen, also has no direct emissions, has a lower efficiency than lithium ion batteries when used in the same type of services [245]. Nevertheless, hydrogen, the gas produced, can be stored for longer periods of time and be used in a greater variety of applications, including power generation with stationary fuel cells, fuel for fuel cell vehicles, conversion to other gaseous or liquid fuels, and direct use in industrial processes [246]. Renewable hydrogen can be used directly to produce zero-emission electricity, or it can be stored, potentially for long periods of time either in the natural gas pipeline or a designated hydrogen storage system [247]. Hydrogen is also spatially flexible, since it can be utilized at the site of production or can be transported (by truck or pipeline). Demand for renewable hydrogen may also increase in the future, independent of grid emissions goals as other sectors, like industry, seek to reduce their own carbon footprints [59,246].

The rate at which a technology ramps is also limited by its configuration. For example, compressed air energy storage (CAES) relies on compressed air as the storage medium and requires feeding this compressed air into a turbine [106]. While generation output can ramp up fully under a minute, the compression (“charging”) stage is slower, about 20% of capacity per minute [248]. Fuel cell ramping rates can vary significantly based on the fuel technology. Lower temperature fuel cells (eg. PEMFC) tend to ramp faster than high temperature fuel cells (eg. SOFC) [249]. In comparison, natural gas combined cycle power plants ramp 2-7% per minute, depending on design and part load condition at the time of ramping [248,250].

Another consideration, particularly to dispatchable generation and energy conversion technologies, is minimum load points below which power plants cannot operate. These minimum generation levels affect the flexibility of the resource to respond to variation in the net load [251]. Conventional load-following natural gas power plants have minimum turndown levels around 40-50% (limited by emissions regulations rather than technical constraints) [250,252]. Fuel cells currently deployed operate as baseload generation; however, future fuel cells may provide dynamic, load-following support [249,253–256]. Shaffer et al. (2015) found that lowering the minimum load point of load-following fuel cells increased renewable integration and that deploying load-following fuel cells reduced both GHG and criteria pollutant emissions at moderate renewable penetration levels [256]. In general, lowering minimum load points can increase the ability of dispatchable resources to manage variable renewable generation; however, it will have negative consequences on efficiency, and greater cycling of the power plant in response to increased ramping will increase wear on the power plant [257,258].

Another important distinction is that most dispatchable generation and energy conversion technologies currently deployed in California use natural gas as the input fuel, including load-following power plants, peaker power plants, and fuel cells [258]. In the future, if these resources are to be used, they will either need to switch to a renewable fuel (eg. biogas or hydrogen), capture produced GHG emissions, or be used sparingly, in order to meet GHG emissions reduction goals [259]. In a 100% renewable grid scenario, only the option of switching to a renewable fuel would be permitted. Proton-exchange membrane (PEM) fuel cells already directly use hydrogen in vehicle applications and solid oxide fuel cells (SOFC) have an internal reformation system that converts natural gas to hydrogen [260,261]. Fuel cells can also utilize waste streams directly [262]. Conventional load-following and peaker power plants can be paired with carbon capture technologies, which have shown that up to 90-99% of the carbon dioxide produced at a natural gas power plant can be recovered and stored [252,263,264]; however, this process has a negative impact on system efficiency (about -10%) [263] and system cost (up to 30%) [264], and it would not be considered a renewable resource. These power plants can also be retrofitted to utilize renewable fuels, although it may decrease system efficiency and still may result in some criteria pollutant emissions depending on the fuel and system design [265].

Multiple technologies may be suited technically to provide the same service, and ultimately which technology is deployed is dependent on other considerations such as technology maturity, scalability, and cost [77,266]. This analysis, therefore, will focus on the *type* of services required to achieve 100% clean electricity grid. A portfolio approach will be applied to develop a number of reasonable technology mixes to meet the future grid's flexibility requirements, and the variability in cost between these portfolios will be assessed. This method will allow for a better understanding of the challenges and trade-offs of a high renewable grid versus achieving a 100% clean electricity grid.

2.4 Remaining Gaps in Literature

For California and other parts of the world to move towards 100% renewable, zero-emission grids, complementary technologies to support renewable integration need to be clearly established. Previous studies have examined high renewable penetration up to 100% into different grids and the role of support technologies in achieving high levels of renewable utilization [37,40,50,51,267,268]. A summary of important literature covering these topics is presented in Table 9. However, the studies that identified challenges to high renewable penetration either proposed solutions but did not do an in-depth analysis of those strategies, or focused on a single strategy to overcome challenges that did not include coordinated heavy-duty ZEV integration. The studies examining 100% renewable penetration mainly focus on demonstrating feasibility with (1) a limited exploration of scenarios, and (2) consideration of neither the challenges to renewable integration nor required support technologies [37,40,112]. For example, several studies examined the simultaneous deployment of ZEVs and renewable generation and how ZEV adoption can improve renewable integration; however, most of these studies only investigated moderate ZEV penetration into the transportation sector and not for a 100% renewable grid [31,35,44,269]. A few studies examined the transition to 100% ZEVs under a renewable paradigm, but either focused on only one vehicle type (light-duty vehicles) with a great emphasis on plug-in electric options or applied a methodology that does not measure the impact of vehicle deployment on grid dynamics [75,270]. The studies examining heavy-duty vehicle charging dynamics in detail focus on the deployment of a limited number of vehicles and do not explore the net impact on the electric grid, eg. [140,271].

Furthermore, work examining the combined impact of strategies on both GHG and air pollutant emissions is limited. Most studies on vehicle-grid integration that examine emissions impacts focus on climate, eg. [59,259,272]. These studies found that switching vehicles to zero-emission options is crucial for meeting California's GHG emissions reduction goals. Less in-focus are the subsequent air quality co-benefits. Studies exploring the impact of vehicle-grid integration on air quality find a significant reduction in air pollutant emissions is achievable through zero-emission vehicle adoption [273,274]. Of the studies found that examine air quality and/or GHG emissions benefits of vehicle electrification [152,275], very few explore the distinct benefits of intelligent charging of heavy-duty vehicles [276]. In fact, most emissions reduction studies that include HDV electrification do not quantify BEV feasibility nor do they seek to compare the timing and scale of electricity demand of battery electric HDVs versus LDVs [37,75,152,275]. Heavy-duty BEV feasibility is an emerging area of research. One study by Çabukoglu et al. (2018) modeled BEV feasibility based on known fleet usage in Switzerland and found that given current battery technologies and home-base charging, only between 6–19% of heavy duty vehicles could be electrified; high electrification could only be achieved with multiple battery swaps or significant battery improvements [277]. There remains an opportunity to couple ZEV feasibility constraints with vehicle-grid integration in order to identify trade-offs in pursuing high heavy-duty vehicle electrification.

In addition to the potential environmental benefits of ZEVs, the adoption of zero-emission vehicles will have impacts on the cost of energy, primarily driven by the increase in infrastructure required to support a large-scale deployment of grid-connected vehicles. Much of the work exploring infrastructure costs of zero-emission vehicles have been informed by the current and anticipated demands of light-duty PEVs and FCEVs [26,194]. Heavy-duty vehicles are expected to utilize higher charging rates (level 2 and level 3) than light-duty vehicles due to higher energy demands and greater travel constraints [278]. While costs for level 3 chargers are available [194], the literature on how these costs may influence the future levelized cost of energy is limited, especially at high adoption of heavy-duty BEVs. Wang et al. (2019) found that the cost of greenhouse gas emission reduction ($/tonne GHG reduced) using grid-connected light-duty vehicles increases with higher charging levels, particularly moving from level 2 to level 3 [230]. Investigating potential costs is needed to understand potential trade-offs of installing level 3 chargers—comparing potential increased costs with potential increased grid benefits.

In effect, there remains a need to examine, from a systems perspective, the potential for grid-connected heavy-duty vehicles to provide grid services in order to establish a greater understanding of the challenges and opportunities to transition towards a robust electricity system that seeks to maximize climate and air quality co-benefits. This is the focus of this dissertation.

Table 9. Relevant Literature in the Investigation of Vehicle-Grid Integration Dynamics and Environmental Impacts

Authors	Year	Scope	Heavy Duty Vehicles?	HDV Fuel Mixes E-/H2/Biofuels/Petrol.	Grid Simulation	V2G	GHG	AQ	Cost
Kempton and Tomic [45]	2005	V2G Integration	No	NA	Load Signal	Yes, LDV	No	No	No
Lund and Kempton [44]	2008	V2G Integration	No	NA	Full Grid Model	Yes, LDV	No	No	No
Zhang et al. [34]	2014	Optimal Charging for RE integration	No	NA	Full Grid Model	No	No	No	No
Duran et al. [140]	2014	HDV Travel patterns and charging demand	Light-, Medium-Heavy Duty	Battery Electric Vehicles	No	No	No	No	No
Zhao et al. [276]	2016	V2G Integration	Medium-Heavy Duty	BEVs and Extended Range Electric Vehicles	Price Signal	Yes	Yes	Limited	Yes
Yang et al. [75]	2009	80% Reduction in GHG Emissions	Yes, not dynamically modeled	5/0/95, 23/56/0/21, 53/9/13/25	No	No	Yes	No	No
Williams et al. [279]	2012	80% Reduction in GHG Emissions	Limited	Biofuels	Full Grid Model	No	Yes	No	Yes
Budiscak et al. [36]	2013	Towards 100% Renewables	No	NA	Full Grid Model	Yes, LDV	Limited	No	Yes, Minimized
Wei et al. [59]	2013	80% Reduction in GHG Emissions	Yes	14/0/0/86	Full Grid Model	No	Yes	No	Yes, Minimized
Jacobson and Delucchi [37]	2015	100% Renewables	Yes, travel assumptions not stated	70/30/0/0 (est.)	Full Grid Model	Yes, LDV	Limited	Limited	Yes
Steinberg et al. [152]	2017	80% Reduction in GHG Emissions	Yes	50% BEV, 9% FCEV, 33% Petrol., 8% HEV	Full Grid Model	No	Yes	No	Yes

Chapter 3. Approach

Overall, this work investigates the potential for zero-emission heavy-duty vehicles to provide flexible support to a highly renewable grid, and provides new insights into vehicle-grid integration challenges and opportunities. Task one establishes the foundational understanding of the challenges to high renewable integration and the potential strategies to overcome them from the grid perspective. The second task (Task 2) focuses on the development of a model to simulate heavy-duty vehicle integration onto the electric grid. The third task develops vehicle-grid integration scenarios for the year 2050 given two California goals: an economy-wide reduction in GHG emissions by 80% compared to 1990 levels and a 100% clean electricity grid. These scenarios are then analyzed in Task 4, based on changes to grid balancing requirements, greenhouse gas emissions, air quality, and levelized cost of energy.

Task 1. Develop an understanding of vehicle flexibility to integrate renewable energy and the additional balancing requirements to achieve up to 100% renewable penetration into the California grid.

Task 1.1 Literature review for barriers to 100% renewable electric grid

Task 1.2 Literature review for vehicle energy demand, travel behavior, zero-emission vehicle options, and vehicle charging strategies

Task 1.3 Literature review for zero-emission technology portfolio options for dynamic support to accommodate variable renewable electricity generation to achieve 100% renewable electricity generation

The disparity between the timing of variable renewable power generation and electric load demand presents an impediment to achieving 100% renewable integration without additional strategies to balance the grid. In this task, a literature review was conducted to characterize the types of events that lead to under-utilization of available renewable generation. Common as well as grid-dependent challenges were identified and defined. This first investigation informed a second examination of zero GHG emission technology options for mitigating the identified challenges.

Current understanding of large scale ZEV impacts on the electric grid comes primarily from studies focused on transitioning light duty, passenger vehicles to ZEVs [31,35,44,269]. However, heavy duty vehicles, mostly used for commercial activities, have quite different travel patterns and operational constraints compared to light duty passenger vehicles [1,167,173,280], which will influence their suitability to provide grid services. The different charging and fueling constraints of heavy duty vehicles versus light-duty vehicles can provide insight into their varying roles in meeting grid emissions reduction targets and, conversely, the role of the grid to meet transportation emissions reduction targets.

The studies addressing vehicle-grid integration tend to focus on battery electric vehicles and plug-in hybrid electric vehicles [34,46,281]. The potential grid impacts of renewable hydrogen production for fuel cell electric vehicles (FCEVs) are less discussed, despite many projections to 2050 assuming moderate to high utilization of hydrogen as a transportation fuel for both LDVs and HDVs [37,75,152,282]. Renewable hydrogen production from electrolysis in many cases can serve as a more flexible load than plug-in vehicles due to the decoupling of fuel production and travel demand [31]. Additionally, the future potential for large-scale hydrogen storage means that hydrogen may ultimately be stored months before use, essentially shifting renewable use across seasons [283]. The advance of HDVs towards zero-emission options renews the need to understand the constraints and opportunities for renewable hydrogen production in terms of impacts on the grid and satisfaction of FCEV demand.

Not all pathways for vehicle-grid integration will result in a robust, 100% renewable grid without additional support technologies. Therefore, a portfolio of technologies which complement vehicle-grid integration will be explored. Technologies to be considered must have the following characteristics: 1) have the potential to maintain a 100% clean electric grid, 2) be a flexible, dispatchable resource, and 3) emit low to zero criteria pollutants. Given these constraints, the following preliminary technologies have been identified: stationary energy storage (battery energy storage, flow batteries, pumped hydro), power to gas, and stationary fuel cells [53,106,256]. The results of this task are presented as an expanded background section in Chapter 2, preceding this chapter.

Task 2. Simulate electricity and hydrogen demand to achieve transformation of the heavy-duty vehicle sector to zero-emission vehicles.

Task 2.1 Characterize HDV integration with probable charging/fueling strategies

Task 2.2 Develop HDV module

Task 2.3 Conduct a sensitivity analysis for battery electric vehicle feasibility

A range of vehicle types are projected to transition to zero-emission alternatives. These new vehicles will either have a direct impact on electric load profiles due to plug-in charging on the grid or an indirect impact through the increased demand for renewable fuel production, most likely dominated by hydrogen production. A light-duty vehicle module was previously developed by Zhang (2014) [115] and demonstrated in several applications [31,32,34,46]. These previous studies illustrate the capability of this module to simulate BEV, PHEV, and FCEV deployment scenarios. This work draws from this established capability to simulate both plug-in electric and fuel cell electric LDV deployments at levels projected by the ARB for 2050 [282]. The objective of this task is to develop a similar module for heavy duty vehicles as feasible given available data on vehicle travel patterns and vehicle parameters. The travel data were collected from existing datasets [160,169,284] and vehicle parameters were determined from literature as well as the California Air Resources Board's mobile source emission inventory (EMFAC) and Vision Scenario Planning model [1,2].

The characterization of the heavy-duty vehicle fleet required the identification and classification of relevant vehicle types and associated travel patterns. Dwell time, and consequently charging availability, were extrapolated from the established characteristic travel profiles. The HDV vehicle module was validated against existing California data. Charging behavior was simulated based on travel demands, charging intelligence, and available charging infrastructure, including electric vehicle supply equipment (EVSE) and charging location. The charging model was integrated into the modeling platform, the Holistic Grid Resource Integration and Deployment tool (HiGRID), in order to simulate the impact of electric vehicle charging and the production of hydrogen for fuel cell vehicles on the grid.

HiGRID was developed by the Advanced Power and Energy Program (APEP) at the University of California, Irvine and will used to simulate the vehicle-grid scenarios [49]. HiGRID is a temporally-resolved platform that simulates the dispatch of defined grid resources to meet the electric load profile. The structure of this multi-module platform is outlined in Figure 16 [285].

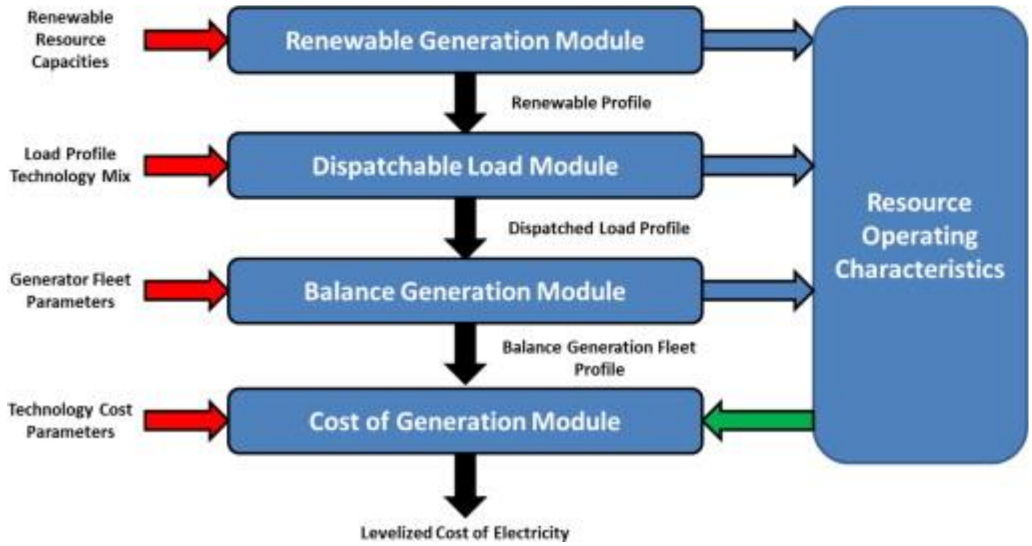


Figure 16. HiGRID Flow Chart, reproduced from [281] *with permission from Elsevier*

The flexible structure of this tool allows for new and advanced technologies to be evaluated for their impact on the grid, including changes to grid operations and the dynamic dispatch of balancing generation resources. This makes it especially valuable in answering questions regarding the complete integration of renewable generation to achieve a robust zero-emission grid. Previously, this model has been applied to related research questions, such as examining the impact of deploying renewable generation on grid GHG emissions, the role of hydropower for helping to integrate renewable generation, the GHG emissions impact of vehicle integration, and the air quality impacts of stationary fuel cells [31,256,286].

The heavy duty module built as a part of this work has been designed to provide insight into the potential of grid-connected vehicles to balance variable renewable generation. Factors affecting vehicle flexibility to balance the grid include: vehicle state of charge, EVSE charging rate, dwell time, charging intelligence, and travel constraints [287,288].

Task 3. Develop strategies that achieve a) 80% reduction in GHG emissions from the electric grid and b) a 100% clean electric grid with vehicle-grid integration.

> **Task 3.1** Project vehicle populations to 2050 and determine zero-emission vehicle deployment strategies for 80% reduction in GHG emissions from the transportation sector and the electric grid
>
> **Task 3.2** Determine additional balancing requirements to achieve a 100% renewable grid given vehicle strategies
>
> **Task 3.3** Identify viable technology mixes to meet emissions targets and grid balancing requirements for a 100% clean electric grid

By framing this analysis around a 100% clean electric grid, it provides the opportunity to explore the marginal increases in cost and capacity investments as the grid moves towards 100% renewable integration in comparison to the emissions benefits returned. To that end, this task identifies new challenges and opportunities for renewable integration with the coordination of battery electric vehicle (BEV) charging and hydrogen fuel production for fuel cell electric vehicles (FCEVs). It evaluates the potential for transportation to integrate variable renewable generation with particular focus on the feasibility of heavy-duty vehicles to provide grid support. This was achieved through the development of vehicle deployment scenarios set in the year 2050.

Using the existing LDV module and the new HDV module, the deployment of ZEVs on the grid was simulated with HiGRID. Vehicle populations and corresponding vehicle miles traveled were scaled to the year 2050 based on EMFAC assumptions and E3 PATHWAYS scenarios [1,150]. Fuel economy assumptions reflect reasonable efficiency improvements informed by current tests of new vehicle technologies and supported by literature [289–291]. Both battery electric and fuel cell vehicles were deployed to simulate different ZEV deployment scenarios. The scope of strategies explored include: a) relatively low ZEV adoption that meets

California’s State Implementation Plan (SIP) targets [2,292], b) significant adoption of ZEVs with an emphasis on electrifying short trips, and c) maximized transformation of heavy-duty vehicles to electricity and hydrogen use, as limited by assumed vehicle range constraints. These strategies aim to explore the sensitivity of grid services to the level of vehicle penetration and fuel/charging assumptions.

Strategies to achieve a 100% clean electric grid should not only eliminate grid GHG emissions but also ensure grid performance. In scenarios where vehicle deployment is insufficient to meet grid firming demands, additional strategies were deployed to balance demand. Viable strategies were informed by Task 1, and include power-to gas pathways, stationary energy storage, and stationary fuel cells.

Task 4. Evaluate the impact of zero-emission vehicle integration on grid balancing requirements, GHG emissions, air quality, and levelized cost of energy.

Task 4.1 Evaluate the impact on grid balancing requirements of zero-emission vehicle integration for a) a grid that meets an 80% reduction in GHG emissions and b) a 100% clean grid.

Task 4.2 Evaluate the impact on grid and transportation emissions of zero-emission vehicle integration at a) an 80% reduction in grid GHG emissions and b) a 100% clean grid.

Task 4.3 Evaluate the impact on statewide air quality of zero-emission vehicle integration at a) an 80% reduction in grid GHG emissions and b) a 100% clean grid.

Task 4.4 Evaluate the impact on levelized cost of energy of zero-emission vehicle integration at a) an 80% reduction in grid GHG emissions and b) a 100% clean grid.

Task 4 evaluates the scenarios developed in Task 3. Metrics used for evaluation include grid balancing requirements (Section 4.1), reduction in GHG emissions (Section 4.2), change in criteria pollutant emissions (Section 4.3), and levelized cost of energy (Section 4.4). Grid flexibility has been identified as a key requirement of high renewable systems [51,53,293].

Although a consensus on how flexibility requirements will translate to reserve capacity requirements under high renewable utilization has not been reached, an understanding of how new grid-connected vehicles may serve as flexible loads to balance renewable variability can inform reserve capacity discussions. Additionally, examining the flexibility of deployed resources around high renewable utilization provides insight into how these technologies may provide additional support to other sectors as they implement their own strategies to reduce emissions [10]. GHG emissions reductions are evaluated for the transportation sector. The vehicle emissions for each vehicle deployment scenario is presented as CO_2e emissions for the following categories: light-duty, bus, and heavy-duty vehicles. Grid GHG emissions changes will be determined based on the results of the vehicle-grid analyses conducted in HiGRID and are presented as a change in emissions from the “Current Policy Reference” (CPR) base case.

The air quality analysis was conducted using the Community Multiscale Air Quality Modeling system version 5.2 (CMAQv5.2) (CMAQ) from the U.S. Environmental Protection Agency [294]. CMAQ simulates the spatial and temporal emission and dispersal of pollutants as well as the non-linear reactions in the atmosphere that result in formation of secondary pollutants, most notably ozone. Model inputs include: meteorological conditions, emissions (anthropogenic, biogenic), initial conditions, and boundary conditions [294]. While CMAQ is most frequently applied for the year 2035, it recently has been applied for projections out to the year 2050 [274].

In order to simulate air quality for the year 2050, emissions for the base year 2012 were first established using EMFAC, the California Air Resources Board (CARB)’s statewide emissions inventory [1]. The baseline emissions were projected to the year 2035 using CARB’s CEPAM:

2016 SIP - Standard Emission Tool, assuming growth of emissions as well as implementation of control measures in line with the State Implementation Plan (SIP) [295]. 2035 emissions were further projected to the year 2050 using the current policy reference assumptions in E3's PATHWAYS model [65]. Emissions factors were temporally and spatially allocated across the state using the Sparse Matrix Operator Kernel Emissions tool (SMOKE) [168]. The output of SMOKE was then applied to CMAQ to derive the spatial and temporal impact of emissions changes on criteria pollutant concentrations. For this analysis, the criteria pollutant emissions of interest are PM2.5 and ozone. Primary and secondary PM2.5 are incorporated. Air quality impacts are presented for the heavy-duty zero-emission vehicle scenarios as the change in concentration between each deployment scenario and the CPR base case.

The levelized cost of energy (LCOE) was calculated using the HiGRID Cost of Generation module, previously applied in [49,296], see Figure 17. As a part of this work, costs associated with integrating vehicles include the cost of EVSE equipment, hydrogen fueling stations, and transmission upgrades. The cost of battery degradation and potential revenue for providing grid services are not evaluated.

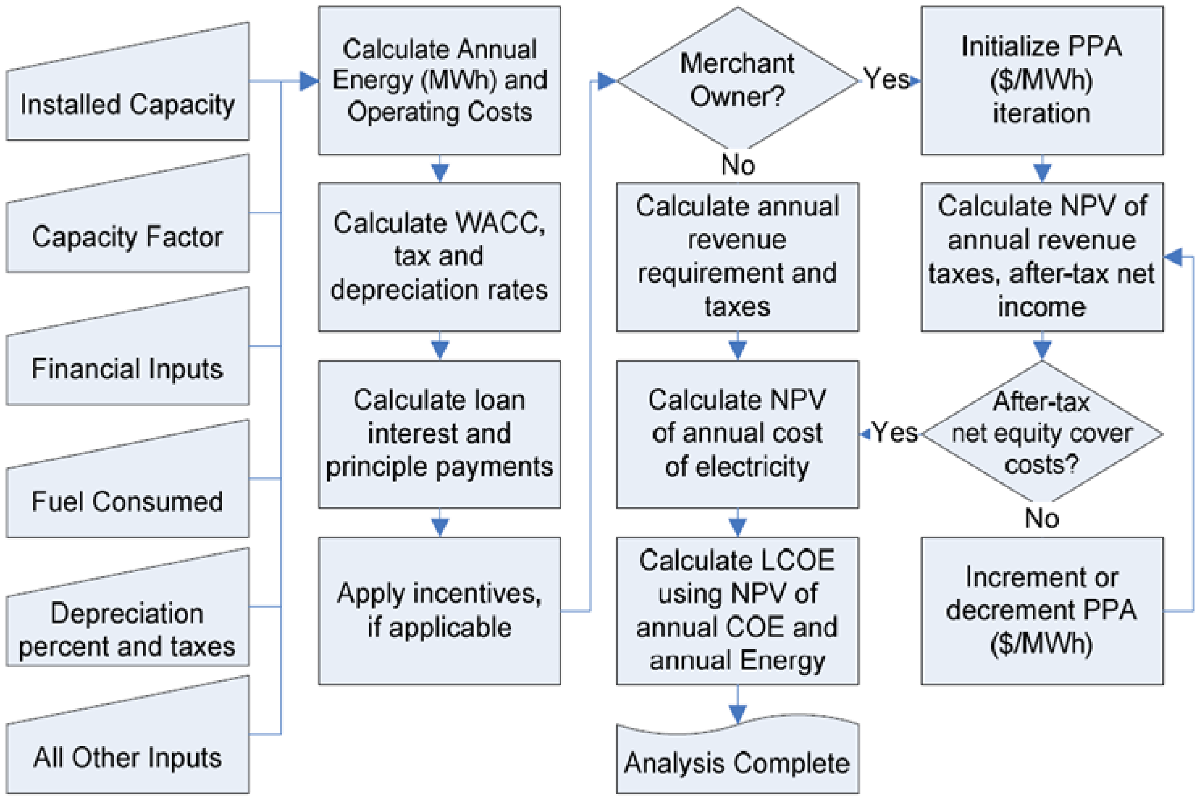


Figure 17. Cost of Generation Model Flow Chart, reproduced from [297] *with permission from Elsevier*

Chapter 4. Electricity and Hydrogen Demand to Achieve Transformation of the Heavy Duty Vehicle Sector to Zero-Emission Vehicles

This chapter focuses on developing a model to simulate the electricity demands of zero-emission heavy-duty vehicles onto the future California electric grid. The steps to meet this task are: 1) Characterize heavy-duty vehicle integration with probable charging and fuel strategies based on the literature review, 2) develop a heavy duty vehicle charging module, and 3) conduct a sensitivity analysis to assess the impact of vehicle and infrastructure assumptions on BEV feasibility.

4.1 Characterization of Zero-Emission Heavy-Duty Vehicle Integration onto the Grid with Probable Charging and Fueling Strategies

The heavy-duty vehicle population is a diverse collection of vehicles ranging in weight (8,501 – 33,000+ lbs.) and use (agriculture to public transit to work-site operations). The first task of this chapter is to define how heavy-duty vehicles will be categorized. Based on this categorization, a dataset of vehicle trips will be developed that is representative of the overall HDV travel profile at the state level. The dataset should encompass the range of operational diversity to sufficiently capture overall HDV travel constraints that influence BEV adoptability.

Previous work investigating heavy-duty vehicle activity have employed a range of methods for grouping HDVs into different categories and characterizing their activities. The California Air Resources Board has supported research into characterizing both heavy-duty vehicles by weight class and, for class 7 and 8, by specific vocations [160,167]. Caltrans, in its commercial vehicle models, separates HDVs by trip distance (0-50 miles and 50+ miles) as well as by region within the state. In the Caltrans long distance commercial vehicle model, vehicles are further characterized by their commodity type [117]. In its heavy-duty vehicle model, SCAG models trips based on whether they are internal (local), external (crossing through multiple regions), or port-related. Within each model, vehicles are sorted by region, commodity, and weight category: light-heavy, medium-heavy, and heavy-heavy [162], consistent with the ARB's weight class delineation. For the U.S. EPA model Motor Vehicle Emission Simulator (MOVES), heavy-duty vehicles are classified into the following categories based on activity patterns: single unit short-haul trucks, single unit long-haul trucks, combination short-haul trucks, combination long-haul trucks, refuse trucks, and three types of buses: intercity, transit, and school [171]. For the purpose of producing emissions rates, these activity profiles are re-categorized into the following regulatory classes: light-heavy (class 2b with 4 tires, 8,501-10,000 lbs.), light-heavy (Class 2b with 6+ tires and Class 3, 8,501-14,000 lbs.), light-heavy (14,001-19,500 lbs.), medium-heavy (19,500 lbs. to 33,000 lbs.), heavy-heavy (>33,000 lbs.), and urban buses (>33,000 lbs.) [171]. The CalHEAT study, funded by the California Energy Commission, subdivided heavy-duty trucks into six categories: Class 2B/3 (1. pickups/vans), class 3-8 vocational work trucks (2. urban, 3. rural/intra-city, 4. work site support), and class 7/8 tractors (5. over the road, 6. short haul/regional) [116]. Lastly, in the E3 PATHWAYS model, heavy-duty vehicles (weight 8,501-33,000+ lbs.) are categorized as medium duty (8,501-33,000 lbs.), heavy duty only includes vehicles greater than 33,000 lbs., and buses are their own category [150]. In general, most previous categorization methods take into consideration gross vehicle weight, with some methods including additional classifications by distance traveled and/or vocation.

For this study, multiple methods of classification were investigated based on available data to create a representative dataset and validation it. While there have been a few studies characterizing activities by vocation, eg. [118,160], only limited statistical trends on behavior were available and did not include sufficient information on the location and dwell periods of vehicles needed to establish potential charging profiles nor validate profiles generated from other sources. Instead, three categories were devised in line with the California Air Resources Board's general categories: light-heavy (8,501-14,000 lbs.), medium-heavy (14,001-33,000 lbs.), and heavy-heavy (>33,000 lbs.), Table 10. Buses span the weight range of heavy duty vehicles from Type A school buses (<10,000 lbs.) [298] to transit buses that can weigh over 60,000 lbs. at full capacity [299]. The sample data applied in this study had limited bus data (less than 10 vehicles of varying bus types) and therefore these vehicle trips were removed and the resulting dataset accounts only for trucks (straight and tractor configurations).

Table 10. Vehicle Weight Classifications Including Current Study

<table>
<tr><th rowspan="2">Gross Vehicle Weight Rating (lbs.)</th><th colspan="5">Vehicle Classifications</th></tr>
<tr><th>Class</th><th colspan="2">California ARB (EMFAC2011) [1]</th><th>U.S. FHWA [300]</th><th>Current Study</th></tr>
<tr><td>0-6,000</td><td>1</td><td>Light-duty cars and trucks (LDA, LDT1, LDT2)</td><td rowspan="2"></td><td rowspan="2">Light truck</td><td rowspan="2">Light duty vehicles</td></tr>
<tr><td>6,001 – 8,500</td><td>2a</td><td>Medium-duty cars and trucks (MDV)</td></tr>
<tr><td>8,501-10,000</td><td>2B</td><td>Light-heavy duty trucks (LHD1)</td><td rowspan="8">Buses (SBUS, Motor Coach, UBUS, OBUS, All Other Buses)</td><td>Light/Medium duty truck</td><td rowspan="2">Light-heavy duty</td></tr>
<tr><td>10,001 – 14,000</td><td>3</td><td>Light-heavy duty trucks (LHD2)</td><td rowspan="4">Medium Duty Truck</td></tr>
<tr><td>14,001 – 16,000</td><td>4</td><td rowspan="3">Medium-heavy duty trucks (T6 Small)</td><td rowspan="4">Medium-heavy duty</td></tr>
<tr><td>16,001 – 19,500</td><td>5</td></tr>
<tr><td>19,501 – 26,000</td><td>6</td></tr>
<tr><td>26,001 – 33,000</td><td>7</td><td>Medium-heavy duty trucks (T6 Heavy)</td><td rowspan="3">Heavy Duty Truck</td></tr>
<tr><td>33,001 – 60,000</td><td>8a</td><td rowspan="2">Heavy-heavy duty trucks (T7)</td><td rowspan="2">Heavy-heavy duty</td></tr>
<tr><td>>60,000</td><td>8b</td></tr>
</table>

Based on information on dwell periods of heavy-duty vehicles, there are two general categories of locations that vehicles can charge at: home base and other (not home base) locations. Charging at home base would require fleet owners to install EVSE equipment at their home base location(s). Charging at other locations would require private and/or public installation of EVSE across a diverse set of locations accessible to heavy-duty vehicles along their routes. If the focus of implementation is to maximize the number of trips that can be met with BEVs, widespread EVSE placement may be reasonable. However, if heavy-duty vehicles are also planning to provide grid services, it may be more desirable to coordinate charging events during home base dwell periods, because the vehicles dwell there longer and more consistently, allowing for greater flexibility in grid participation. Additionally, non-home base dwell locations may vary from day to day, making it harder to plan grid participation at these sites. The impact of charging at home base versus everywhere will be explored in later sections.

In addition to the three weight classifications, it is important to clarify that the heavy duty vehicle charging model developed for this study is intended to represent statewide travel by heavy-duty vehicles registered and traveling within California. It is assumed that vehicles registered within the state are subject to California regulations and will be the first to be converted to zero-emission vehicles. According to the 2017 CA-VIUS, this encompasses roughly 95% of all light-heavy and medium-heavy duty VMT within California and 72% of heavy-heavy duty. The survey also found that in-state registration also indicates an in-state home base location [161]. Home base location is critical in the deployment and operation of battery electric vehicles, as well as grid impacts of electrification.

Another consideration is that HDVs may be transitioned to fuel cell electric vehicles operating on renewable hydrogen. Whereas BEVs require a direct connection to the grid to charge, the decoupling of hydrogen production and FCEV hydrogen use provides an opportunity to produce hydrogen when most beneficial to the grid and keep it stored for later fueling demands. The constraints for FCEV feasibility are fuel tank capacity of the vehicle and the availability of refueling stations.

While there are limited data on current heavy-duty FCEV models, Kast et al. (2017) simulated potential vehicle configurations for various vocations given known drive cycle behavior; a summary of the heavy-duty FCEV results is presented in Figure 18 [291].

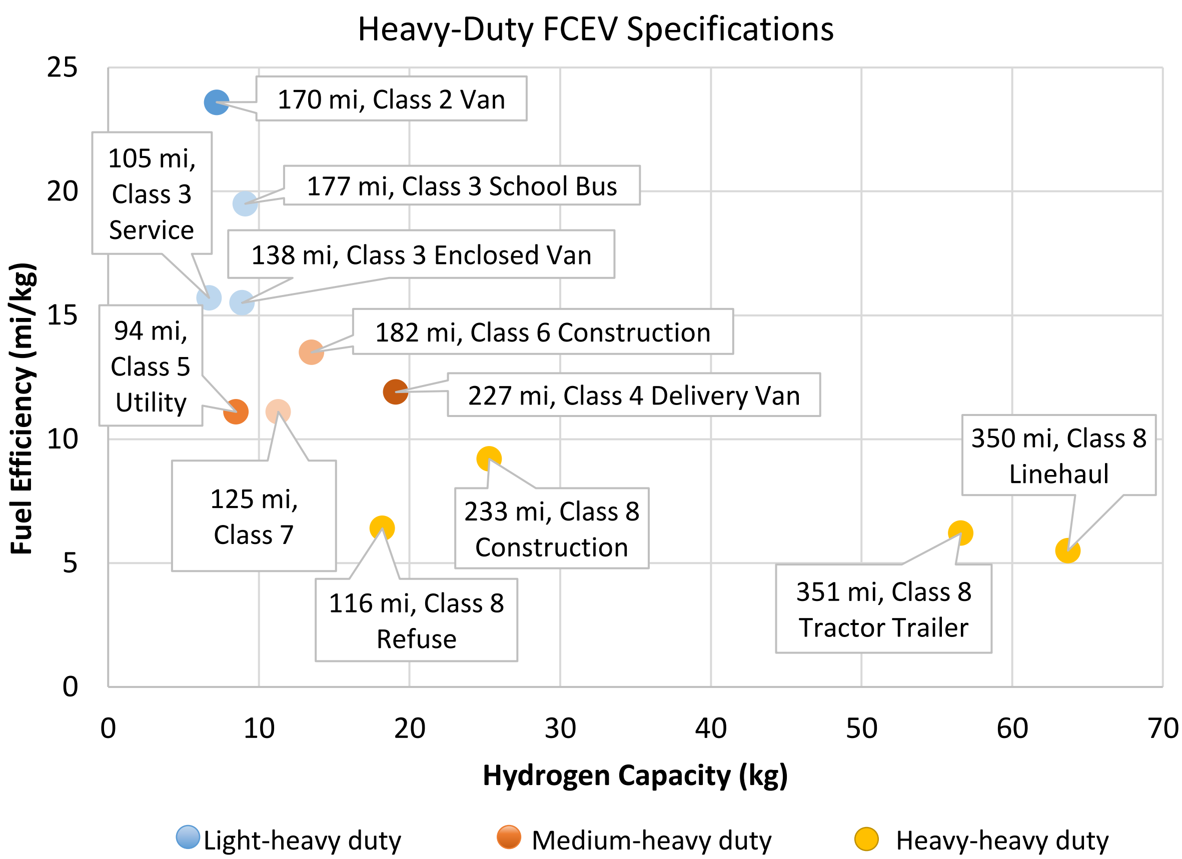


Figure 18. Heavy-Duty Fuel Cell Electric Vehicle Specifications for Heavy-Duty Vehicles Calculated in Kast et al. (2017) [291]

These vehicle results indicate that fuel efficiency is dependent on both a vehicle's gross vehicle weight rating and vocation, and for the purposes of this study a general average for vehicle category (light-heavy, medium-heavy, and heavy-heavy) can be determined. Additionally, Kast et al. (2017) calculated that on-board hydrogen capacity can meet 40% - 100% travel demands of the given vocations [291], based on the travel data used [118].

In the case that a vehicle's daily miles traveled exceeds its range, it will need to refuel, potentially multiple times a day depending on demand versus range. This work assumes that hydrogen refueling stations are readily available by the year 2050, and hydrogen is produced on-site through electrolysis and stored in tanks to provide on-demand hydrogen. Of the hydrogen refueling stations in California, a few already have on-site production of hydrogen, including the stations in Anaheim and at Cal State Los Angeles [301]. While refueling can be accomplished in a matter of minutes, multiple refueling events in a day can be burdensome to the driver and may begin to affect operational feasibility. For the sensitivity analysis conducted in Section 4.3, the number of refueling events for different FCEV configuration assumptions will be evaluated.

4.2 Heavy-Duty Vehicle Model

4.2.1 Model Source Data and Validation

Several datasets and previous models were considered for application in this study. The following travel information is required to sufficiently model the electric vehicle charging demand at the state level: data from a sufficient number and diversity of vehicles to encompass trip variability by purpose, time, and length; and, for each vehicle: trip start and end times, location types, trip lengths, dwell times, and vehicle weight. Studies with detailed trip data available tend to be narrow in scope, looking at more detail characteristics of select vehicle vocations, e.g. [118]. Data from these studies cannot be expanded to represent sufficiently state-level behavior. Additionally, most heavy-duty studies tend to be focused more on the operational characteristics of the vehicles and less on dwelling periods or vehicle locations throughout the day [116,160,302], limiting their application in a study where dwell times and locations are critical for evaluating EVSE infrastructure requirements and potential electric grid impacts.

While there have been a few previous studies that have collected California-specific statewide travel data, most recently and relevantly the 2017 CA-VIUS survey, data from these studies are confidential, and therefore, unavailable for use. Additionally, Caltrans has developed two models, Short Distance Commercial Vehicle Model and Long Distance Commercial Vehicle Model, to represent commercial truck travel throughout the state. Of the two models, only the SDCVM trip data were available, as the long-distance (trips >50 mi) model for Caltrans is currently under revision. A complete and representative dataset for all trip lengths, therefore, could not be aggregated from the Caltrans models.

After reviewing available datasets, the trip data from the 2007/2008 Texas Commercial Vehicle Survey, provided by the Transportation Planning and Programming Division of the Texas Department of Transportation, were selected to be used as the base input for this study, to be calibrated to align with known California statistics on heavy-duty vehicle travel. A similar methodology was previously applied by Caltrans for the development of its CSTDM model, when it calibrated survey data from Canada to align with California vehicle statistics [117]. The Texas dataset was selected, as it is the only available dataset with the required detailed trip tables. Additionally, this dataset provides the largest sample of vehicles from a wide range of vocations encompassing over 20 regions, varying in city size and economic activity [169].

As previously discussed, hourly profiles can vary by region depending on a number of factors including traffic patterns, share of truck vocations, and proportion of local versus long-distance travel. Therefore, the truck dataset was filtered to select regions with similar hourly VMT distributions compared to accepted California trends. The filtering process was as follows: the vehicle trip data for each city region were sorted into the categories: light-duty, light-heavy duty, medium-heavy duty, and heavy-heavy duty. The light-duty category was excluded from this study as HiGRID already has a validated California-specific light-duty vehicle model. For the three remaining categories, the normalized hourly VMT distribution for each vehicle sub-sample was calculated. These hourly distributions were compared to the established CARB heavy-duty vehicle activity profiles for weekday and weekend days that are integrated into the U.S. EPA's Sparse Matrix Operator Kernel Emissions (SMOKE) Modeling System [168], see Figure 19.

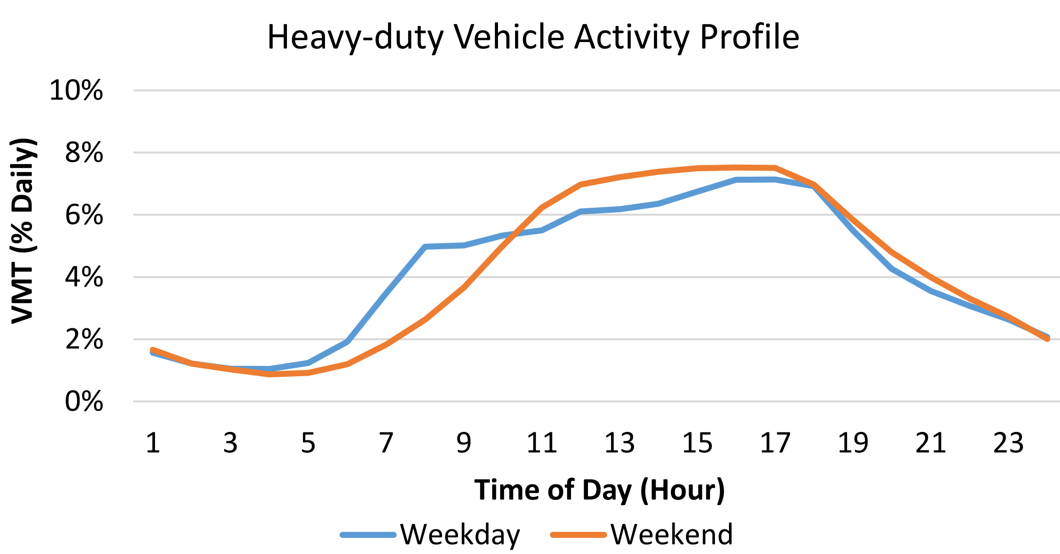


Figure 19. CARB Heavy-duty Vehicle Activity Profiles used for Air Quality Simulations [1]

The root mean square error (RMSE) (in percent daily VMT) between the calculated profiles and the established profiles was calculated by region and category to determine how well each regional sample aligned with California trends and identify subsets that align well:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

The subsets whose RMSE was 2.5% or less were selected and included in the final datasets in order to select profiles that best-aligned with the established profile. The 2.5% variation is approximately the same as the range of values observed in [167,173], presented in Figure 14.

The aggregated datasets for each vehicle category (light-heavy, medium-heavy, and heavy-heavy) were then evaluated based on trip length frequencies, given the importance of trip length in determining overall BEV feasibility. It was found that the initial trip length frequencies for all categories were skewed towards trips under 50 miles, having an underrepresentation of long distance trips. Therefore, an additional calibration step was implemented in order to have the model dataset match the newest information on trip length frequencies. First, trip data in the model dataset were sorted by vehicle into one of five categories: 0-50 mi, >50-100 mi, >100-150 mi, >150-500 mi, and >500 mi trip lengths, based on the majority of trips. Each category was then scaled to match the corresponding distribution frequency reported in the CA-VIUS results. The trip distribution frequencies reported in the CA-VIUS results, calculated for the initial model, and calibrated for the final model are presented in Table 11.

Table 11. Trip Length Frequencies Model Calibration

LHDV				
Trip Range	**Model Initial (% of vehicles)**	**Difference from observed**	**Model Adjusted (% of vehicles)**	**Difference from observed**
0-50	82.0%	49%	55.0%	0.0%
>50-100	9.0%	-67%	26.3%	-2.4%
>100-150	3.6%	-64%	9.7%	-2.6%
>150-500	4.5%	-25%	5.9%	-1.7%
>500	0.4%	-87%	3.0%	-0.0%
Totals	100%		100%	
MHDV				
Trip Range	**Model Initial (% of vehicles)**	**difference**	**Model Adjusted (% of vehicles)**	**difference**
0-50	80.0%	57%	50.7%	-0.6%
>50-100	10.3%	-63%	27.9%	-0.4%
>100-150	3.9%	-68%	12.3%	2.3%
>150-500	5.5%	-31%	8.2%	2.0%
>500	0.4%	-61%	1.0%	-3.0%
Totals	100%		100%	
HHDV				
Trip Range	**Model Initial (% of vehicles)**	**difference**	**Model Adjusted (% of vehicles)**	**difference**
0-50	42.1%	56%	26.7%	-1.0%
>50-100	21.8%	9%	19.5%	-2.4%
>100-150	12.5%	-10%	14.0%	-0.1%
>150-500	19.8%	-24%	25.8%	-0.7%
>500	3.7%	-73%	14.0%	-0.4%
Totals	100%		100%	

The calibration of trip data resulted in an increase in VMT per vehicle per day, compared to the initial model, see Table 12.

Table 12. Vehicle Miles Traveled per Vehicle per Day Comparisons

Vehicle Category	HDV Model Initial	HDV Model Adjusted	EMFAC 2017	CalHEAT [116]	
Light-Heavy	36	72	36	57	94 (avg for all 3)
Medium-Heavy	37	74	50	--	
Heavy-Heavy	113	186	122	150-233	

The calculated VMT/vehicle/day for LHDVs increased to 72 miles/vehicle/day. This value is higher than EMFAC. The discrepancy may be due to a couple of factors:

- *The scope of vehicles that were considered:* the 2002 VIUS survey included both commercial and private vehicles, whereas the 2017 CA-VIUS survey focused on commercial vehicles. CalHEAT also focused on commercial vehicles, but relies on different vehicle categories for its analysis, and so a direct comparison for the light-heavy category (classes 2B and 3) is challenging. Doubly challenging is that private vehicles may be used in commercial applications, so the distinction between private and commercial vehicles is not exact. Private class 2B and 3 vehicles not used for commercial purposes may have travel patterns more similar to light-duty vehicles, however, this is not definite. Additionally, the portion of class 2B and 3 vehicles that are operated as private versus commercial vehicles within California is not well-defined. Birky et al. (2017) surveyed stakeholders and provided a preliminary estimation that about 50% of class 2B vehicles and 90% of class 3 vehicles are used for commercial applications. They also highlighted the need for additional research into the distinct travel behavior of these vehicles [303].
- *The assumed number of operating days in the year and/or the percent of the population active each day:* distance traveled is commonly reported in terms of annual VMT, and therefore, scaling down annual VMT to daily values requires an understanding of the average days per year vehicles operate. EMFAC assumes different operating days for each of its vehicle categories: 327 days for light-heavy duty vehicles and either 312 or 327 days for medium- and heavy-duty vehicles depending on the subcategory [1].

- *The underestimation of long-distance travel in previous studies*: The scope of most vehicle surveys is at the regional level, due to their application in regional planning. A challenge of these studies is accurately capturing vehicle trips that originate outside of the area of interest. How the study is designed and what resources are utilized to count trips may result in the exclusion of vehicles involved in inter-regional travel.

For MHDVs, the calculated VMT per vehicle per day also increased (up to 74 miles/vehicle/day), again greater than the average reported in EMFAC, but within the range of in-state vocations included in EMFAC. CalHEAT did not have a specific category for classes 4-7, so a direct comparison to that study could not be drawn for MHDVs. However, the three categories including MHDVs (class 3-8: urban, rural/intra-city, and work site support) have daily VMT ranging from 36 to 96 miles, assuming miles spread evenly across the year [116]. Lastly, the new average for HHDVs, 186 mi/vehicle/day, while greater than EMFAC's average for that category, falls within the range of values reported in CalHEAT's survey.

The average dwell times for home base and other locations for each vehicle category are in Figure 20. Vehicles dwell significantly longer at home base locations compared to other locations. Vehicles tend to leave home base at the beginning of their route, take several trips, and then return to home base, where they dwell until the start of their next tour. The average dwell time for non-home base locations is about three-fourths of an hour for all categories. The average dwell time for home base locations ranges from about 11-13 hours, depending on the category.

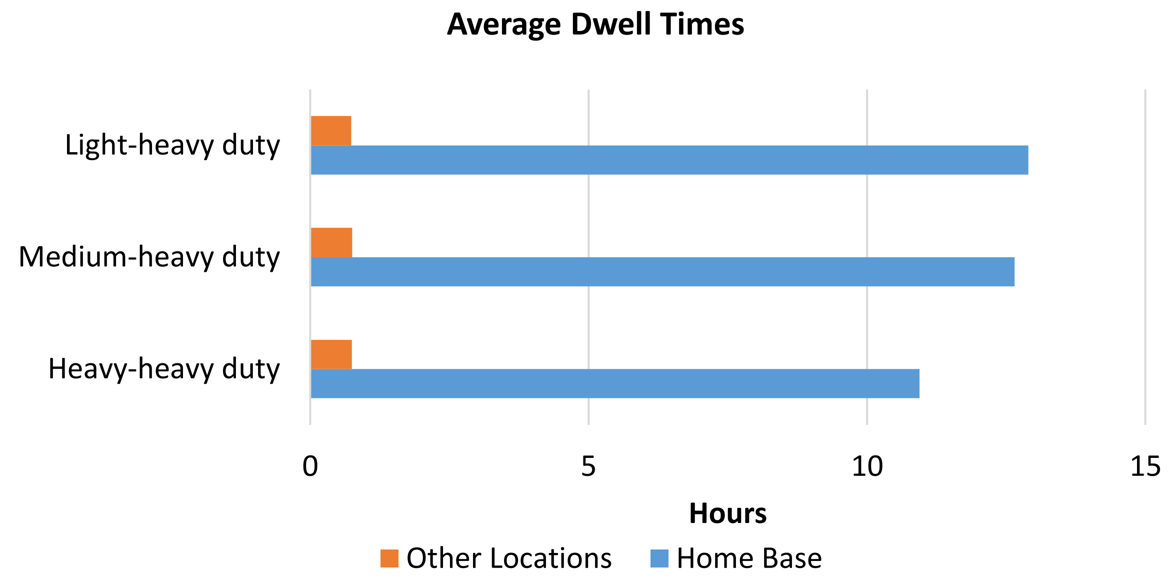


Figure 20. Average Dwell Times for Location Types for Each Vehicle Category

The calibration of the trip length frequency also modified the hourly VMT profile, increasing the number of evening and overnight trips and reducing the relative daily peak, see Figure 21.

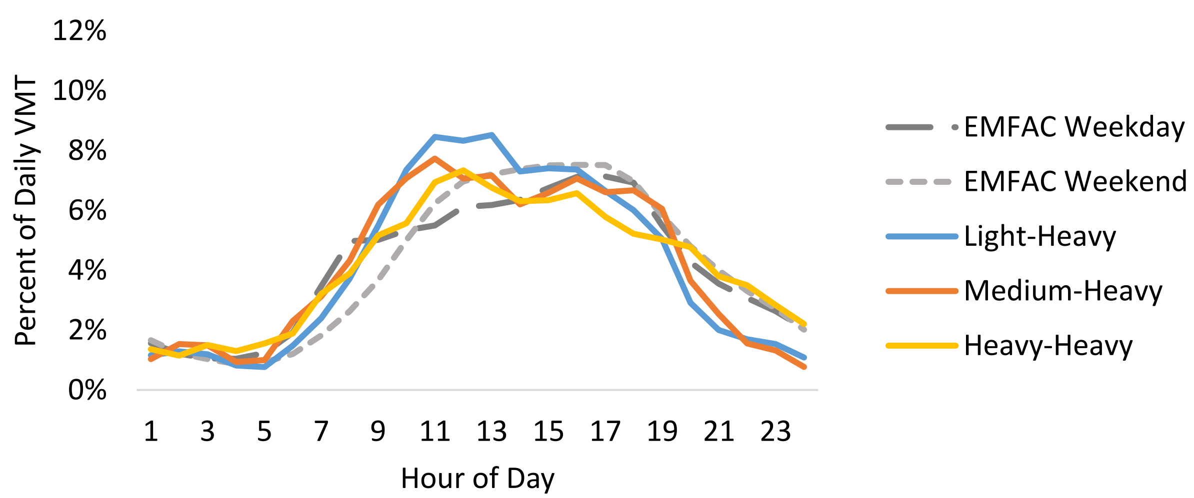


Figure 21. VMT Distribution after Trip Length Calibration

The RMSE for all categories were reduced compared to the uncalibrated data. The final RMSE for each category compared to the weekday and weekend profiles are in Table 13. The difference in hourly VMT between the dataset and the reference profiles are within the range of variation observed in the previous surveys and models.

Table 13. RMSE for Final Calibrated Data

Vehicle Category	Weekday Profile	Weekend Profile
Light-heavy duty	1.3%	1.2%
Medium-heavy duty	0.92%	1.2%
Heavy-heavy duty	0.70%	0.88%

There are several challenges in determining the potential BEV feasibility of out-of-state vehicles and their impact on the California electric grid given the available datasets. First, the 2017 CA-VIUS recorded trip distance as a measurement from home base. However, it is unclear how frequently these vehicles return to home base as a representative group. Following the assumption that registration state correlates strongly with home base state, few to none of the out-of-state vehicles will have access to charging within the state if EVSE equipment is constrained to home base locations. Since this analysis is focused on California grid impacts, out-of-state vehicles charging at out-of-state home bases would not impact the California grid. Due to the far distances these vehicles travel from home base, sometimes across multiple states, it follows that, in order for a significant portion of out-of-state vehicles to be electrified, they must have access to publically available charging stations. The establishment of publically available charging stations or battery swapping locations, as mentioned by [277], would take the coordination of multiple stakeholders including trucking companies as well as local and state governments.

4.2.2 Battery Electric Vehicle Charging Model

The heavy-duty vehicle charging model developed for this work generates an aggregated, scaled charging profile that will be applied within the Holistic Grid Resource and Deployment Tool to determine the impact of vehicle charging on the electric grid. The heavy-duty vehicle charging algorithms for immediate and smart charging are from the previous centralized electric vehicle charging model developed by Zhang (2014) [115]. The vehicle-to-grid charging model algorithm is from Tarroja (2016) [105]. Whereas light-duty vehicle applications of this algorithm had the equality constraint be applied for a 24-hour period, this analysis used a 72-hour period to account for the multiday travel of some heavy-duty vehicles. The **cost function** is as follows [115]:

$$min\left(\sum_{j=1}^{q} f_j \times x_j\right) \tag{2}$$

where, f is electricity cost per kWh, x is charging rate (kW), j is dwell segment, and q is total number of dwell segments.

Equality constraint is:

$$\sum_{j=1}^{q} x_j + \sum_{i=1}^{m} y_i = 0 \tag{3}$$

where, i is trip number, y is discharged energy (kWh), and m is total number of trips.

Inequality Constraints are:

$$y_1 > -c \tag{4}$$

$$y_1 + \sum_{j=1}^{q} x_{1j} + y_2 + \cdots + \sum_{j=1}^{m-1} x_{(m-1)j} + y_m > -c \tag{5}$$

where, c is battery energy capacity.

Bounds on the variables are:

$$(smart)\ 0 \leq x_j \leq p_j \times \Delta t_{ij} \times \eta \tag{6}$$

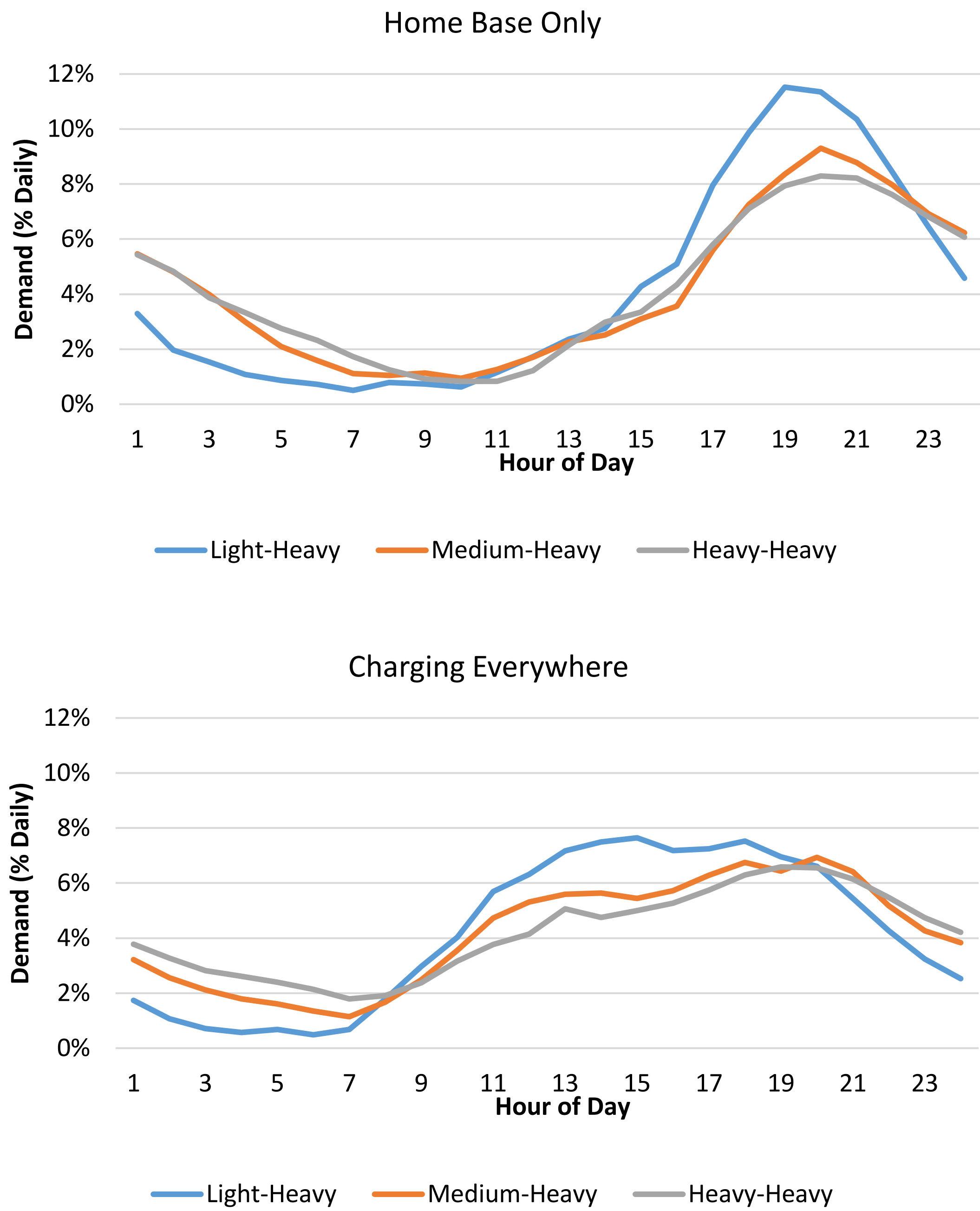
$$(V2G)\ -p_j \times \Delta t_j \times \eta \leq x_{ij} \leq p_j \times \Delta t_j \times \eta \tag{7}$$

where, η = charging efficiency and p is rated power capacity (kW) of EVSE.

The hourly net load profile entering the energy storage model serves as a proxy for "electricity price" for smart and V2G charging algorithms. Selecting for the least cost periods to charge will result in valley-filling of the net load, and V2G discharging during peak cost periods will result in peak shaving. The new load profile, including vehicle charging and discharging, is then applied to the next module: the hydrogen demand model.

The heavy-duty vehicle electric load demands generated by the vehicle charging module depend on the vehicle, EVSE parameters, and charging intelligence set for the model. Selecting home base charging versus everywhere charging will result in vehicles charging at different periods of the day, see Figure 22. Home base only charging with immediate charging results in a peak load demand around 7-9 pm, depending on the heavy-duty vehicle category. The minimum charging load demand occurs between 9 am and noon. This indicates that the heavy-duty vehicle charging profile with home base only charging does not align well with solar electricity generation.

The differences in the peak load demand for each of the vehicle categories is a function of the differences in VMT distribution (both in terms of trip distance and hourly distribution) as well as home base return patterns versus dwell periods in other locations. They are also dependent on the vehicle range assumed for the BEVs deployed. If it is assumed that the BEVs for each category can travel 100 miles before recharging, only vehicles with trips totaling 100 miles or less before returning to home base will be selected. Increasing the vehicle range means that more heavy-duty vehicles with longer trip demands can be converted to BEVs. Electrification of vehicles with higher travel demands results in a greater portion of the BEVs charging into the evening and overnight (These vehicles need to charge longer to meet their higher energy demand.), see Figure 23. The number of vehicles electrified at different vehicle ranges is dependent on the trip distribution patterns for each category. Greater vehicle electrification will increase overall electricity demand, but this demand will be more distributed across the day, so that the relative peak decreases. In general, peak vehicle demand for home base only charging occurs when peak electricity demand from stationary loads occurs, see Figure 24. The simultaneous occurrence of vehicle and stationary peak loads can result in increased demand for fossil fuel generation capacity and increased ramping demands.



(a)

(b)

Figure 22. Charging Profiles for: a) at Home Base Only Charging and b) Charging Everywhere

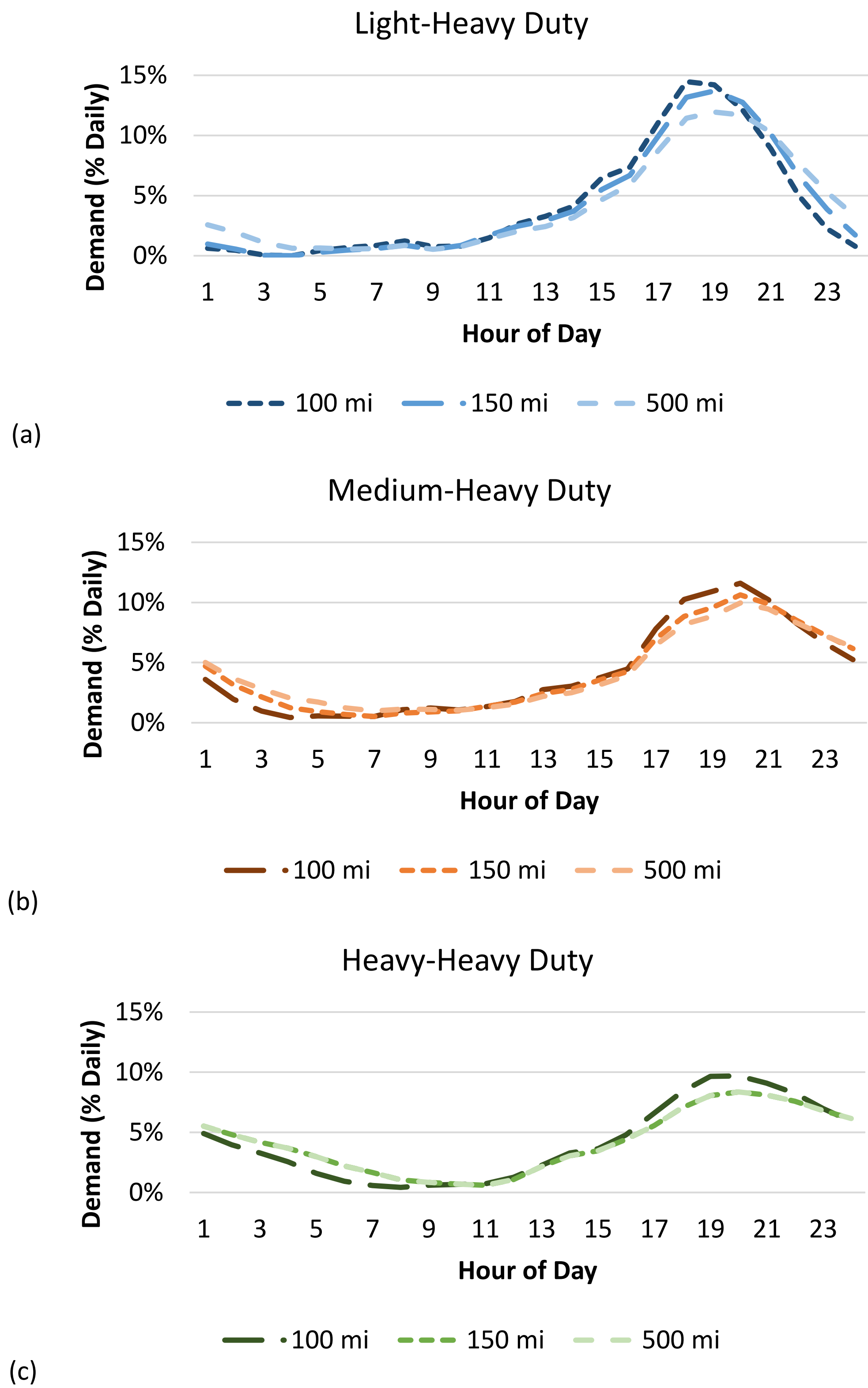


Figure 23. Charging Profiles for Each Vehicle Category with Increasing Vehicle Range: a) Light-Heavy Duty, b) Medium-Heavy Duty, and c) Heavy-Heavy Duty Vehicles

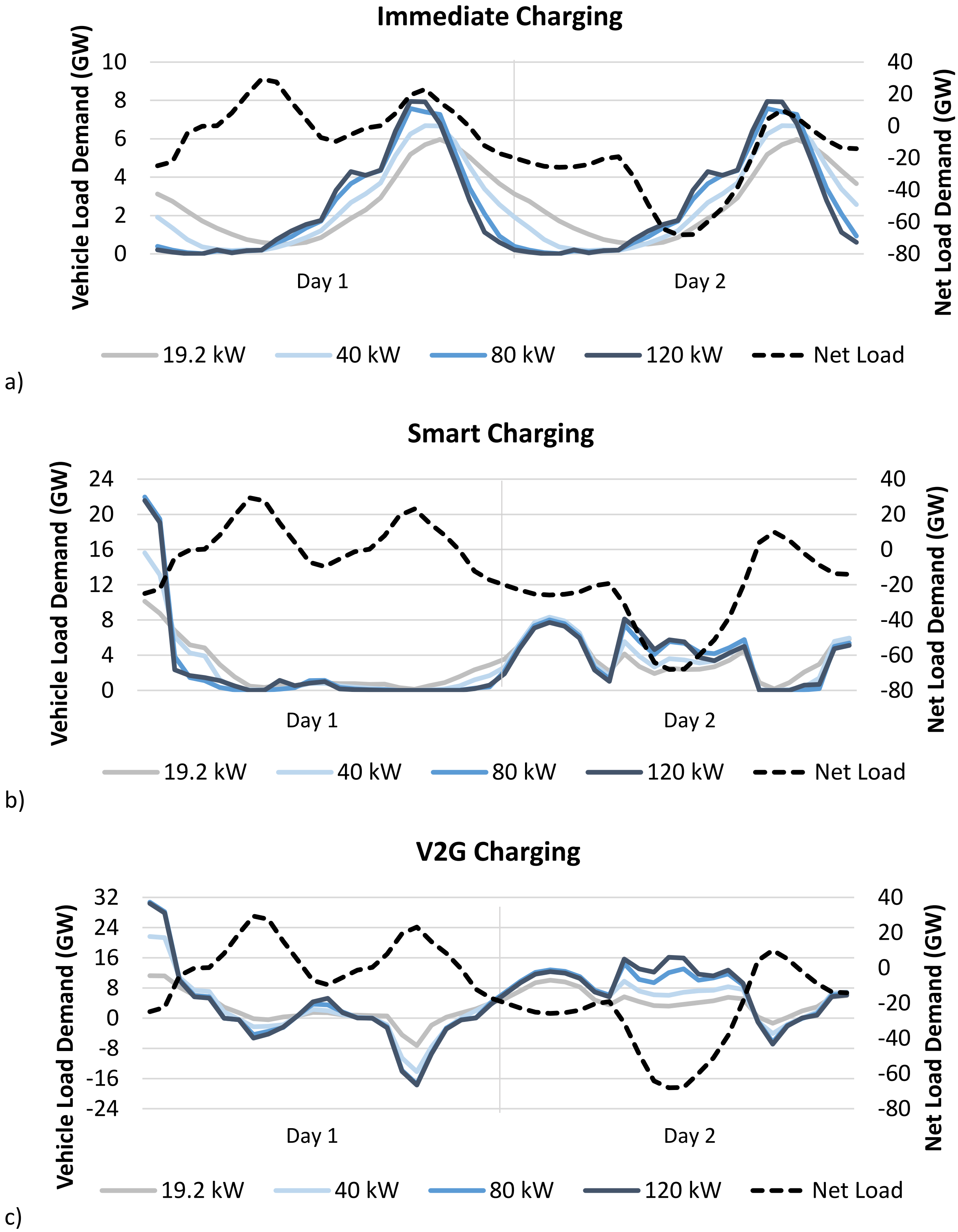
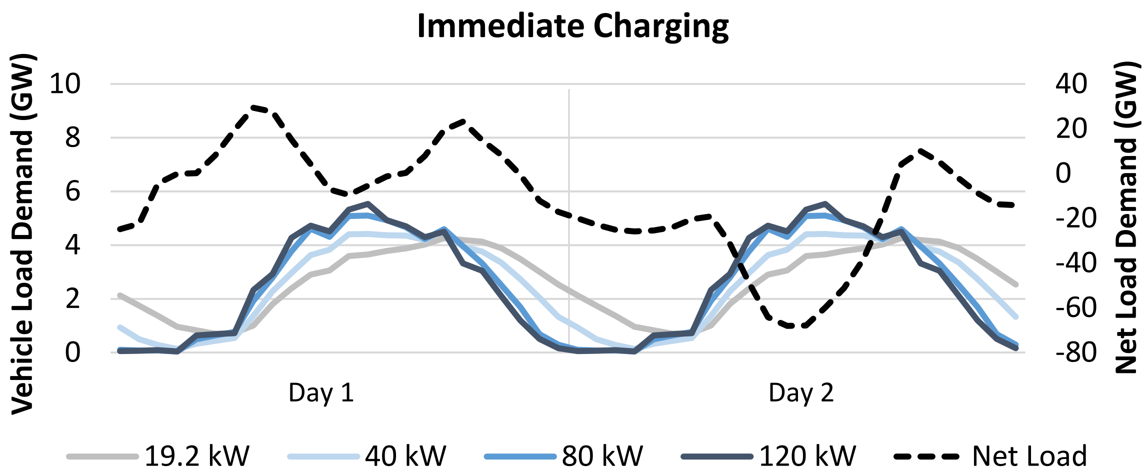


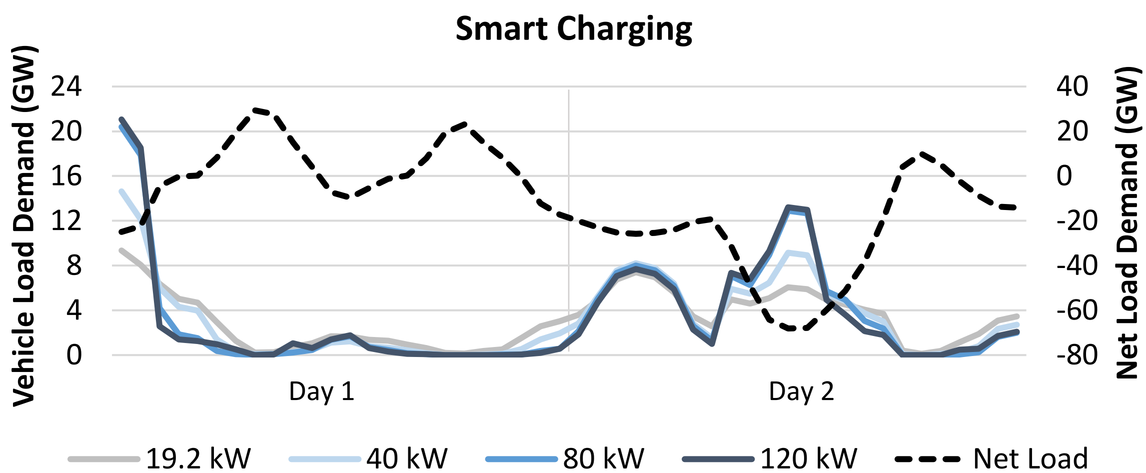
Figure 24. Cumulative Charging Profile for at Home Base Charging with Increased Charging Rate: a) Immediate, b) Smart, and c) V2G Charging Strategies

Heavy-duty BEV load demand is also dependent on the assumed EVSE charging rate. With immediate charging, higher charging rates result in faster charging of the vehicles, which in turn increases the peak demand and reduces overnight charging. Increasing charging rate with intelligent charging strategies also results in increased peak vehicle load demand, however, with intelligent charging these peaks are coordinated with “valleys” in the net load. The result is improved load smoothing. Increasing the charging rate for V2G-enabled vehicles increases the peak vehicle load and the peak vehicle discharge power, resulting in a greater capture and shifting of renewable energy.

Comparing the immediate charging with home base charging versus everywhere charging, by allowing vehicles to charge along their daily routes increases daytime charging and shifts the vehicle electricity demand to earlier in the day, especially for light-heavy duty vehicles, see Figure 25. The peak charging demand also decreases, as the vehicle load is spread more evenly across the day. In addition, everywhere charging increases charging (and discharging) flexibility for vehicles with intelligent charging. For the smart charging cases, everywhere charging is more effective in filling the midday valley compared to home base only charging due to the low percentage of HDVs that return to home base throughout the day. More common is vehicles dwelling at different locations along their route. A majority of vehicles dwell overnight, making home base only charging effective in filling overnight valleys that occur.



a)



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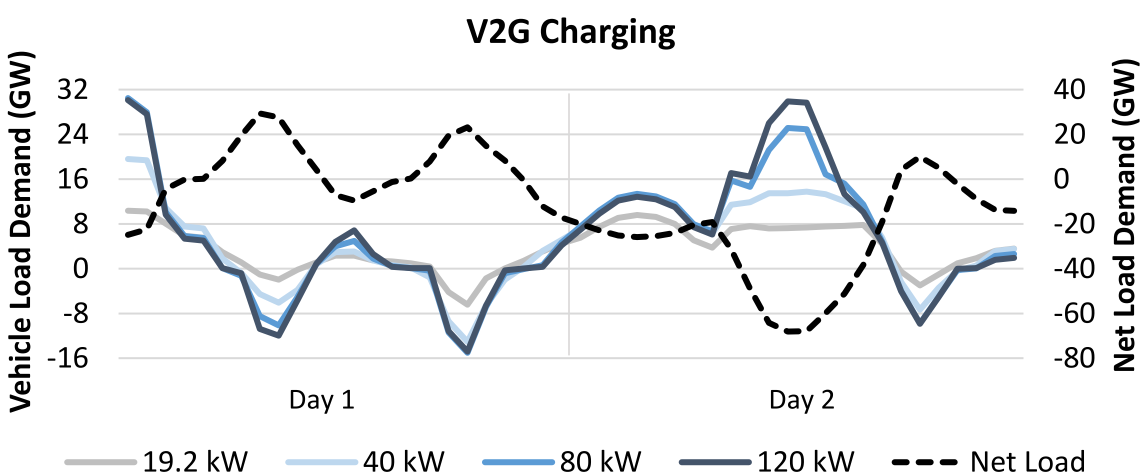


c)

Figure 25. Cumulative Charging Profile for at Charging Everywhere with Increased Charging Rate: a) Immediate, b) Smart, and c) V2G Charging Strategies

4.2.3 Hydrogen Demand Model

For this study, hydrogen production and refueling performance are modeled using the existing hydrogen module in HiGRID. This module was developed by Tarroja et al (2015) [31] and has most recently been employed in Wang et al. (2019) [230], where it was expanded to include updated costs to represent a suite of different electrolyzer technologies and distribution methods for hydrogen use in FCEVs. For this analysis, alkaline electrolyzers are used to produce hydrogen on-site at refueling stations.

The hourly hydrogen demand in Figure 26 is derived from available data on hydrogen and gasoline fueling stations as well as overall gasoline demand trends [304–306]. Hydrogen demand is expected to follow closely with gasoline demand behavior due to the similarity in vehicle characteristics and refueling experience [304]. The demand profile includes both light-duty and heavy-duty vehicles, which is appropriate, since this analysis incorporates hydrogen demand for both vehicle categories.

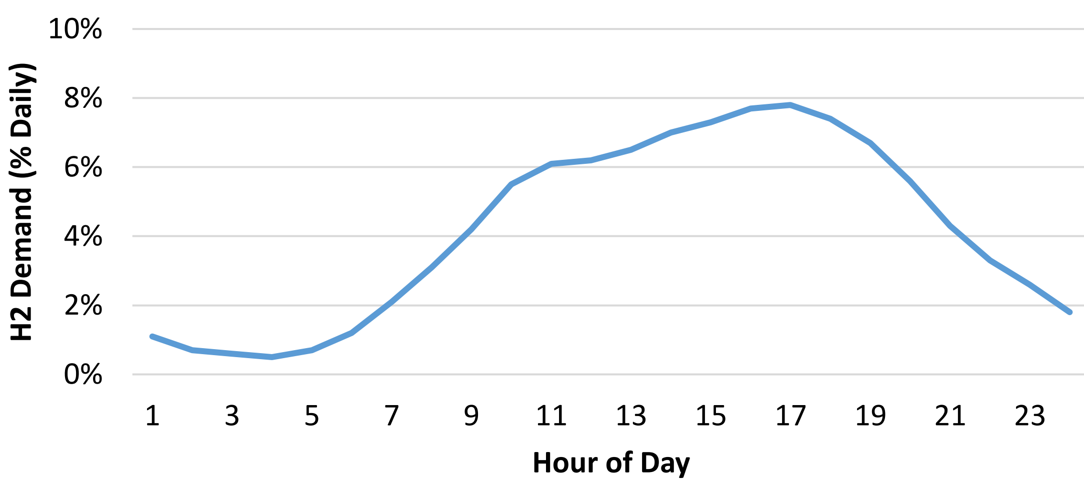


Figure 26. Hourly Hydrogen Refueling Demand

The hydrogen demand profile serves as a constraint within the model: hydrogen must be produced at a rate equal or greater than refueling demand dictates. Hydrogen production rate is not constrained by whether vehicles are driving or dwelling at the time. Hydrogen production is optimized for lowest cost, similar to the BEV charging model; the hydrogen demand model uses the modified net load as the cost function to determine least cost periods to produce hydrogen. Figure 27 demonstrates the hydrogen load demand output of the model.

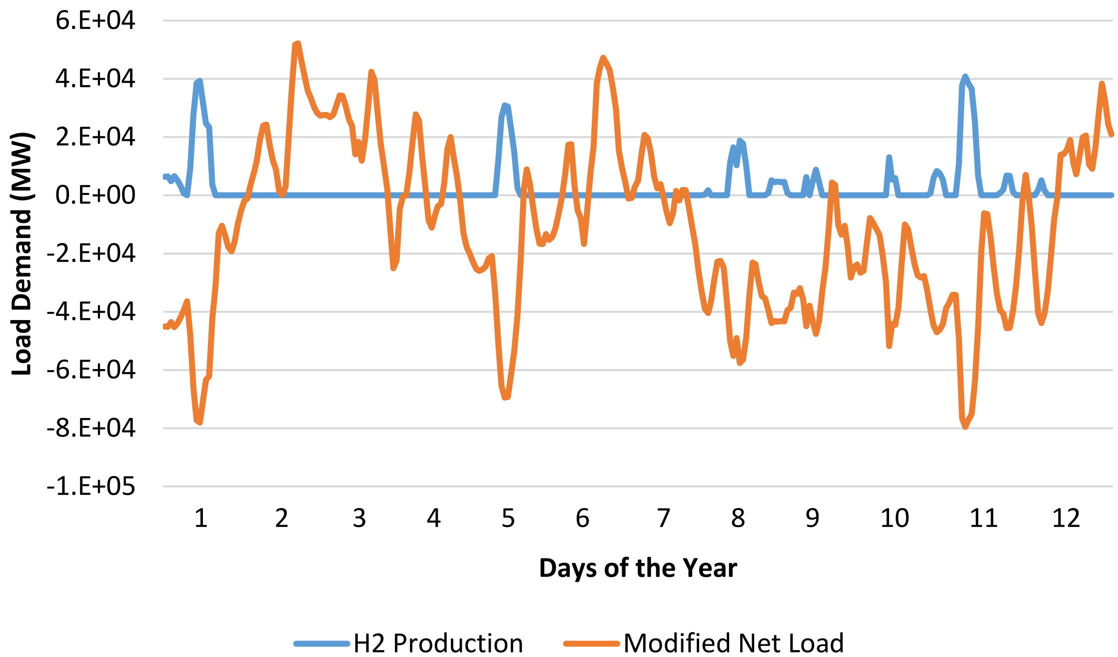


Figure 27. Hydrogen Load Demand Based on a Modified Net Load Input

The hydrogen storage level for the same period of time is in Figure 28. Increases in the hydrogen storage level are the result of hydrogen production exceeding use by vehicles. Conversely, hydrogen storage decreases when vehicle hydrogen demand exceeds production. Because hydrogen demand constraints are aggregated to a total VMT demand within the model, it is important to consider how this demand translates to individual vehicles. This is explored in Section 4.3.2.

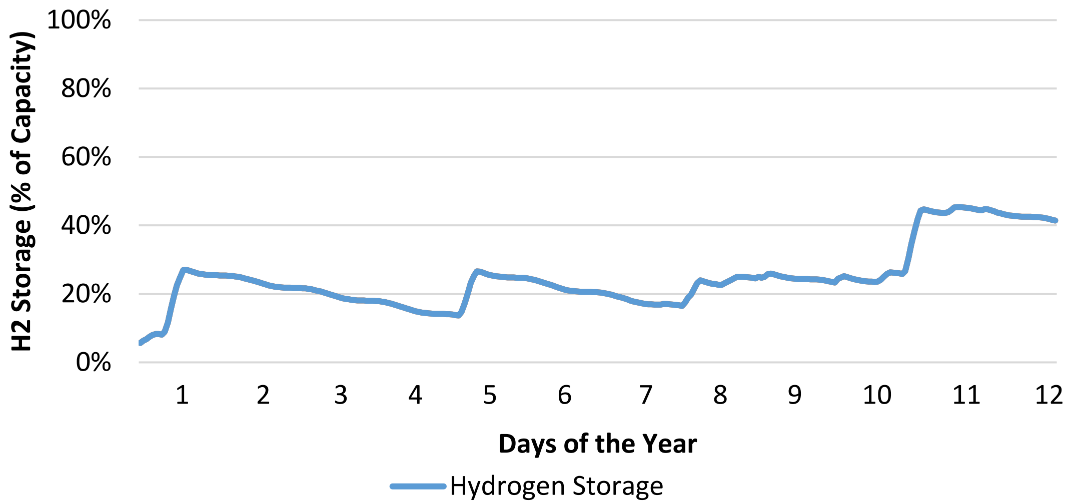


Figure 28. Hydrogen Storage Based on Production and Vehicle Consumption Rates

4.3 Sensitivity Analyses for Zero-Emission Vehicle Feasibility

Sensitivity analyses were performed for both types of zero-emission vehicles examined in this work: Battery electric vehicles and fuel cell electric vehicles. The impact of vehicle and infrastructure assumptions are assessed. This work assumes that vehicles are able to meet the peak power and acceleration demands of all vehicle applications and therefore are not limiting factors in feasibility. The results of these analyses will inform the strategies developed in Chapter 5.

4.3.1 Sensitivity Analysis for Battery Electric Vehicle Feasibility

A sensitivity analysis was conducted to examine the impact of fuel efficiency, vehicle range, and EVSE assumptions on BEV feasibility. BEV feasibility can be measured in terms of the percent of VMT that can be met by a specific BEV/EVSE configuration without modifying vehicle travel patterns. Another, equivalent measurement is the percent of vehicles that can be operated as BEVs under the same assumptions. The values presented in the analysis are percent of VMT and vehicle population for in-state vehicles. Out-of-state vehicles are not accounted for in total percentages. As previously stated, out-of-state vehicles account for 5% of light-heavy and medium-heavy duty vehicle miles traveled in California and 28% of heavy-heavy duty vehicle miles traveled in California.

A reasonable range of current and near future fuel efficiencies is presented in Table 14 based on literature values as well as assumptions made in the Vision model and E3 Pathways study [2,57]. It is important to note that some values gathered are based on laboratory tests or simulations versus on-road driving. The values from on-road tests are noted in Table 2. Additionally, fuel economy is affected by payload carried. The scenarios developed in Chapter 5 will use the average fleet values calculated in previous work that take into account payload and varying fuel economy based on drive cycle [2,150].

Table 14. Fuel Efficiencies and Vehicle Ranges Reported in Literature and Future Projections

Vehicle Category	Current/Near Future Range Reported (mi)*	Current Fuel Efficiency Reported (kWh/mi)*	Vision Individual and Fleet Average Values [2]	E3 Pathways Values [150]	
			Year 2050	Year 2030	Year 2050
Light-Duty	100 – 310	0.25 – 0.51	0.16 – 0.58 Avg. 0.20	0.22 (auto), 0.30 (truck)	0.17 (auto), 0.24 (truck)
Light-Heavy	25 – 145	0.55 – 0.74	0.76 – 1.37 Avg. 0.95	1.03 (combined), 1.85 (buses)	0.97 (combined), 1.45 (buses)
Medium-Heavy	80 – 300	1.34 – 1.90	1.62 – 2.09 Avg. 1.80		
Heavy-Heavy	102 – 500	1.97 – 2.47	2.11 – 6.61 Avg. 2.42	2.06	1.96

Conversion assumptions for table are: 1 kWh = 0.030 Gallons Gasoline Equivalent (GGE), 1 Diesel Gallon = 1.155 GGE, 1 GGE = 0.112 MMBTU, 1 kWh = 0.026 Diesel Gallon [307]
* From Table 2

This analysis calculates the upper and lower bound for BEV feasibility, given the range of projected fuel efficiency values for a selection of vehicle range and EVSE assumptions. BEV feasibility is calculated as a percent of in-state vehicles only. The different configurations are listed in Table 15. Charging efficiency is assumed to be 0.9 for level 2 charging (<= 19.2 kW) and 0.95 for level 3 charging (>19.2 kW). Level 1 charging is not considered. The results of the sensitivity analysis are summarized in Figure 29 and Figure 30.

Table 15. Parameters for BEV Sensitivity Analysis

Vehicle Category	Low Fuel Efficiency (kWh/mi)	High Fuel Efficiency (kWh/mi)	Charging Locations	Charging Rates (kW)	Vehicle Range
Light-heavy	1.37	0.55	Home base, Everywhere	**Level 2:** 3.3, 6.6, 9.6, 19.2 **Level 3:** 25, 80, 120, 350	100, 200, 500
Medium-heavy	2.09	1.34	Home base, Everywhere	**Level 2:** 3.3, 6.6, 9.6, 19.2 **Level 3:** 25, 80, 120, 350	100, 200, 500
Heavy-heavy	6.61	1.97	Home base, Everywhere	**Level 2:** 3.3, 6.6, 9.6, 19.2 **Level 3:** 25, 80, 120, 350	100, 200, 500

As demonstrated in this feasibility analysis, BEV feasibility is strongly dependent on travel patterns, vehicle range, fuel efficiency achieved, and EVSE available. In general, BEV feasibility increases with greater vehicle range, higher charging rates, and increased access to EVSE—home base versus everywhere (all dwell locations). As charging rate increases, the difference between high and low fuel efficiency decreases; trip distance becomes a limiting factor in BEV feasibility. For this reason, increasing the charging rate to higher level 3 capacities does not always yield improved feasibility. For at home charging, there are only marginal improvements in BEV feasibility after level 2 – 19.2 kW with a vehicle range of 100 miles and after level 3 – 80 kW with a 200 to 500 mile range except for least efficient heavy-heavy duty vehicles with a 500 mile range, which see similar levels of improvement up to the maximum charging rate tested of 350 kW. For the EVSE parameters presented here, maximum BEV feasibilities for 100-mile light-heavy duty, medium-heavy duty, and heavy-heavy duty, respectively, as a percent of daily VMT, are: 40%, 36%, and 8%; for 200-mile vehicles: 63%, 62%, and 24%; and for 500-mile vehicles: 72%, 75%, and 48%.

Once route distance becomes a limit to BEV deployment, charging other locations beyond home base are required to increase BEV feasibility. Allowing heavy-duty vehicles to charging anywhere they dwell for 15 minutes or longer increased the BEV feasibility of all vehicle categories, with level 3 charging rates up to 350 kW continuing to increase the percent of VMT electrified, especially for heavy-heavy duty vehicles. Charging everywhere increased the maximum BEV feasibility most significantly compared to home base charging for short range vehicles. Comparing the two different charging location strategies—home base only and everywhere—the increased access to charging stations with everywhere charging results in an increase in BEV feasibility. For vehicles with a range of 100 miles, LHDVs had a 50% increase in VMT electrified with everywhere charging compared to home base only charging, MHDVs, a 64% increase, and HHDVs, a 175-238% increase depending on fuel efficiency. There remains to be a benefit to charging everywhere in terms of BEV feasibility at higher vehicle ranges, but there are diminishing returns. For vehicles with a range of 500 miles, the increase in VMT electrified for LHDVs is 17%, for MHDVs, 12-24%, and HHDVs 6-21%.

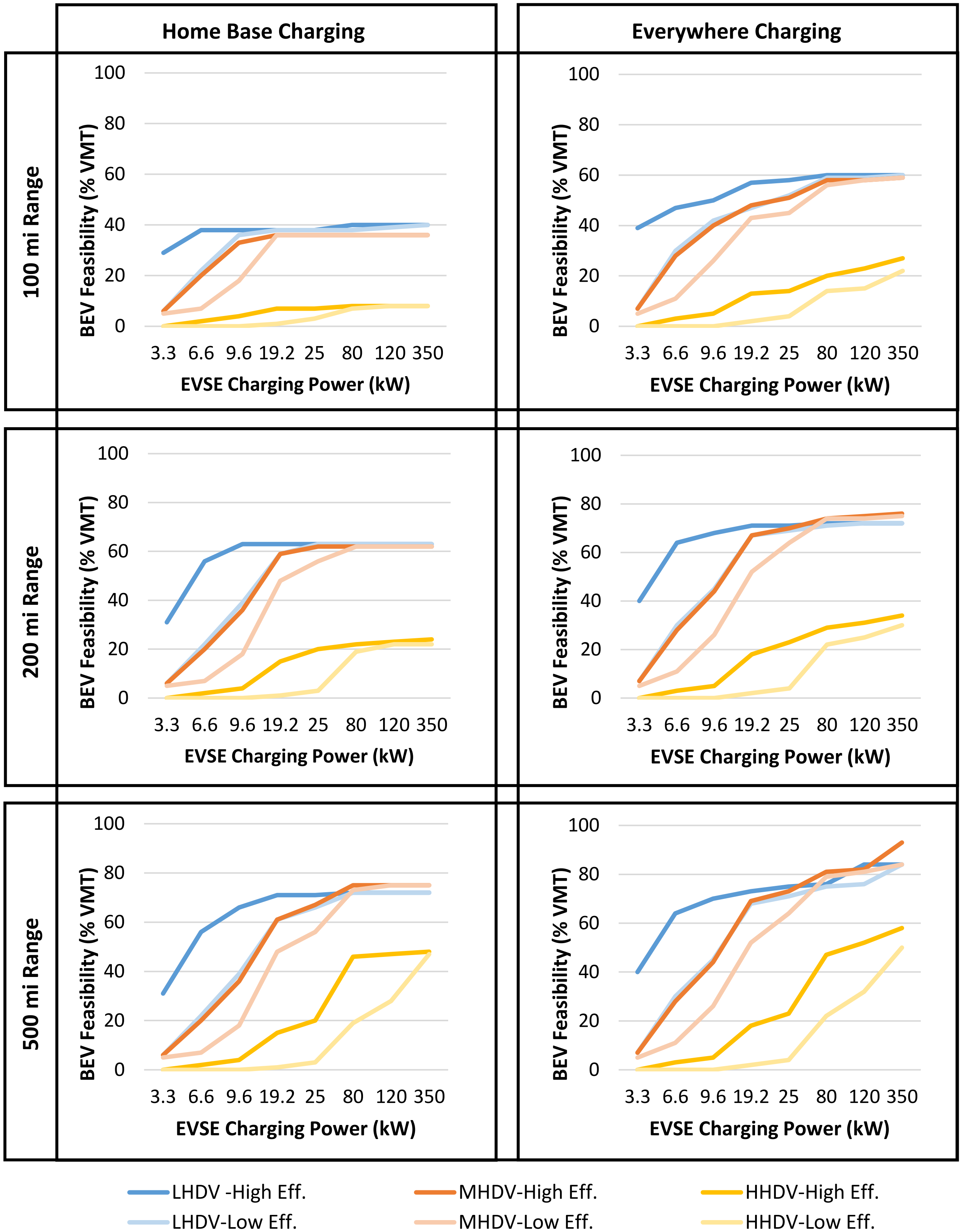


Figure 29. BEV Feasibility by HDV Category as a Percent of daily VMT

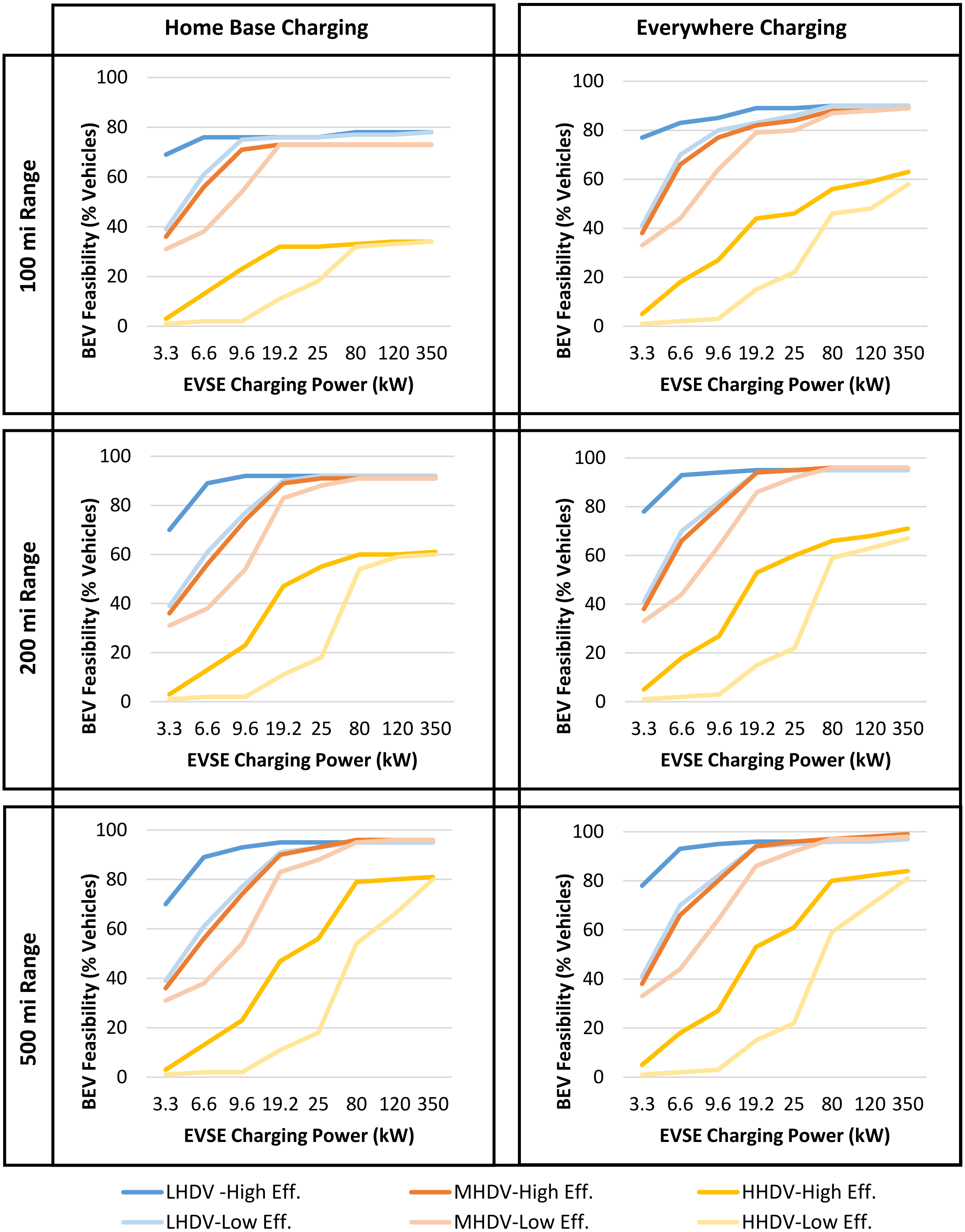


Figure 30. BEV Feasibility by HDV Category as a Percent of Vehicle Population

Comparing the different vehicle categories, the trip distribution for each vehicle category drives what the maximum BEV feasibilities are for different vehicle range configurations. Despite an overlap in fuel efficiency values between low efficiency MHDV and high efficiency HHDV categories, HHDVs have much lower BEV feasibility compared to MHDVs. This difference is the direct result of HHDVs having a much greater percentage of long-distance trips compared to MHDVs. Conversely, LHDVs and MHDVs also have overlap between their lower and upper bounds of fuel efficiency, respectively, and at lower ranges and charging rates, have very similar levels of BEV feasibility. This is due to their similar proportion of trips under 200 miles from home base. This trend shifts at higher vehicle ranges and charging rates. In fact, despite a greater energy demand per mile, because MHDVs have a smaller percentage of long-distance trips (>500 miles from home base) (1% versus 3% for LHDVs), MHDVs have a higher BEV feasibility than LHDVs under certain configurations with higher level 3 charging rates.

Examining BEV feasibility in terms of percentage of vehicles converted to BEVs shows that a relatively large percentage of vehicles can be electrified with vehicle ranges of 100-200 miles and home base charging. However, these vehicles are the ones traveling short distances and therefore, they make up a smaller percent in terms of total VMT, for example: 76% of the light-heavy duty vehicle population can be electrified with 100-mile range BEVs with home base charging at a peak level 2 rate, but this encompasses only 40% of the VMT from in-state vehicles.

4.3.2 Sensitivity Analysis for Fuel Cell Electric Vehicle Refueling Demand

Fuel cell electric vehicle refueling frequency depends on vehicle technical specifications assumed. Refueling frequency depends on vehicle miles traveled. In the cases that a trip distance exceeds the vehicle's range, it may be assumed that the vehicle cannot be a FCEV. This assumption is to maintain the same operational constraints as for the BEV sensitivity analysis. For this sensitivity analysis, it is assumed that the vehicle is able to refuel during a dwell period if it is 15 minutes or more. The FCEV parameters for the sensitivity analysis are in Table 16.

Table 16. Parameters for FCEV Sensitivity Analysis

Vehicle Category	Low Fuel Efficiency (mi/kg H_2)	High Fuel Efficiency (mi/kg H_2)	Vehicle H_2 Capacity (kg)
Light-heavy	15**	23.6*	5, 10, 20, 40, 70
Medium-heavy	11.1*	15**	5, 10, 20, 40, 70
Heavy-heavy	4.79+	11.2**	5, 10, 20, 40, 70

* Values from Kast et al. (2017) [291], ** Values from E3 PATHWAYS [150], + Value from Chandler and Eudy (2008) [148]

The results of the sensitivity analysis are in Figure 31. A 100 mile range is equivalent to a tank capacity of 4.2 – 6.7 kg H_2 for light-heavy duty vehicles, 6.7 – 9 kg H_2 for medium-heavy duty vehicles, and 8.9 – 20.9 kg H_2 for heavy-heavy duty vehicles. The wide span of potential hydrogen capacity requirements for heavy-heavy duty vehicles is due to the wide range in fuel efficiency values found in the literature. A 200 mile range is equivalent to doubling the tank size of the 100 mile range results, and a 500 mile range is equivalent to increasing the 100-mi tank size 5x.

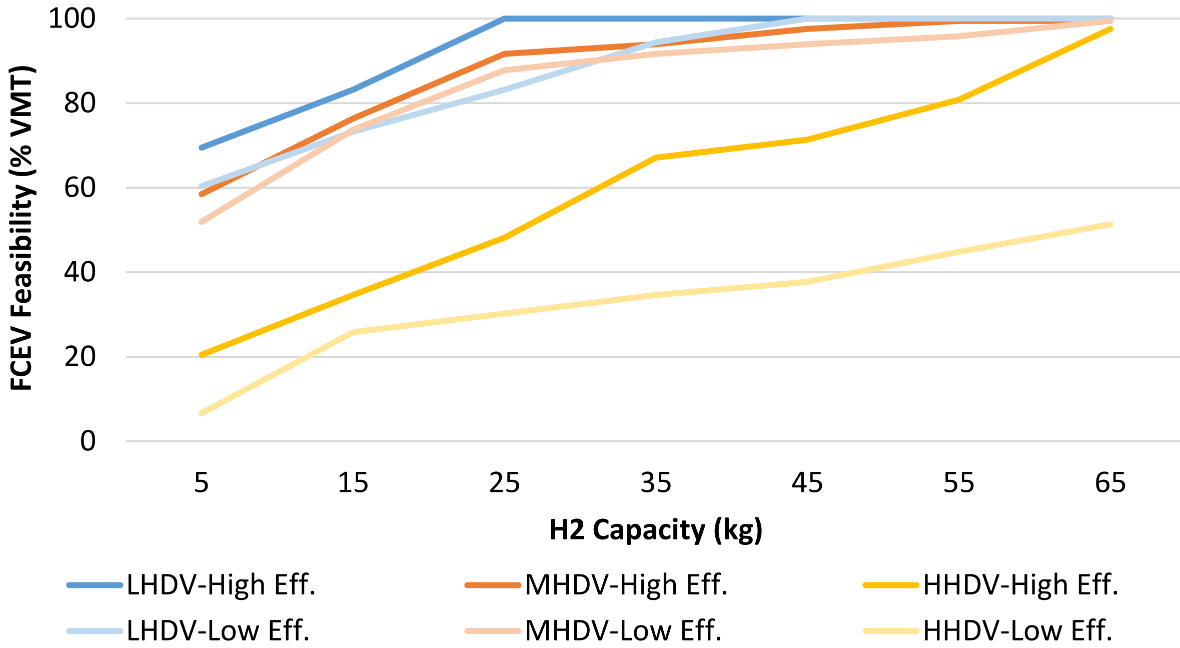


Figure 31. FCEV Feasibility Assuming No Trip Interruption for Different H_2 Capacities

Similar to the results for BEV feasibility, medium-heavy duty vehicles see an increase in FCEV feasibility as a percent of total VMT compared to low-efficiency light-heavy duty vehicles. Again, this is driven by the varying trip distributions for each vehicle category. Medium-heavy duty vehicles have fewer long trips (+500 miles from home base) compared to light-heavy duty vehicles. Fewer longer distance trips which cannot met by short-range ZEVs results in a greater percent of total VMT met.

The number of refilling events per vehicle for a 24-hour period at different vehicle ranges can also be calculated. It is assumed that trips cannot be interrupted to refuel. The refueling frequency for light-heavy duty vehicles is in Figure 32, for medium-heavy duty, Figure 33, and for heavy-heavy duty, Figure 34. "NA" refers to vehicles that cannot be FCEVs based on the vehicle range specified.

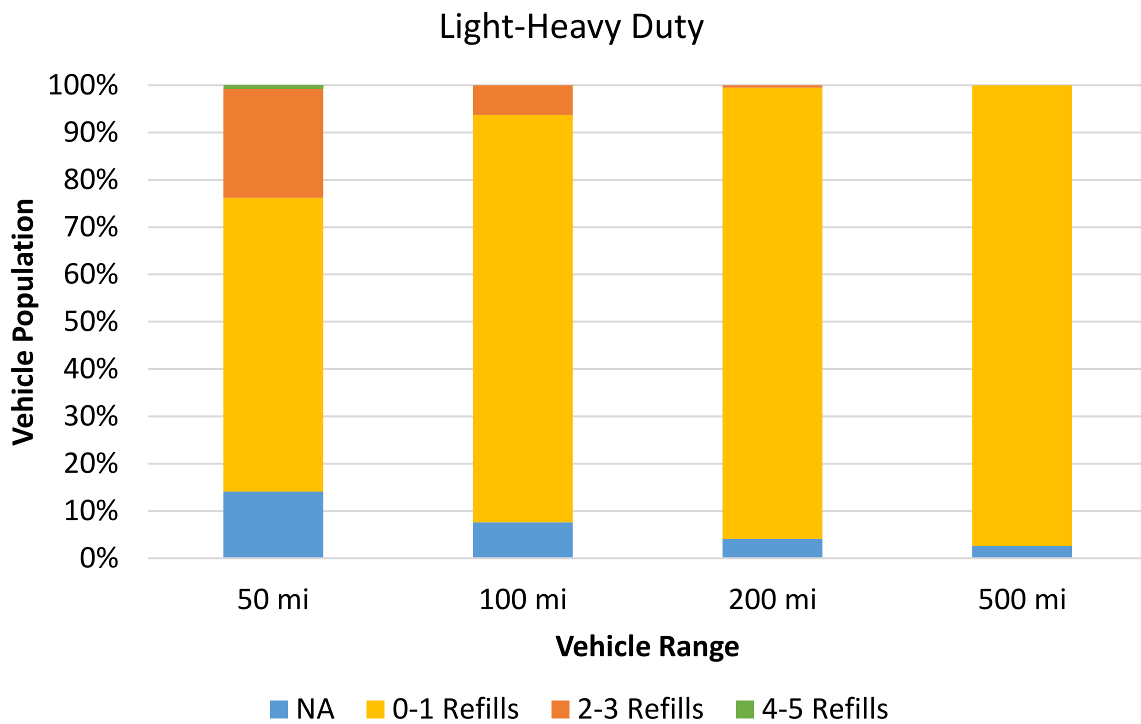


Figure 32. Refueling Frequency of Light-Heavy Duty FCEVs for Different Vehicle Ranges

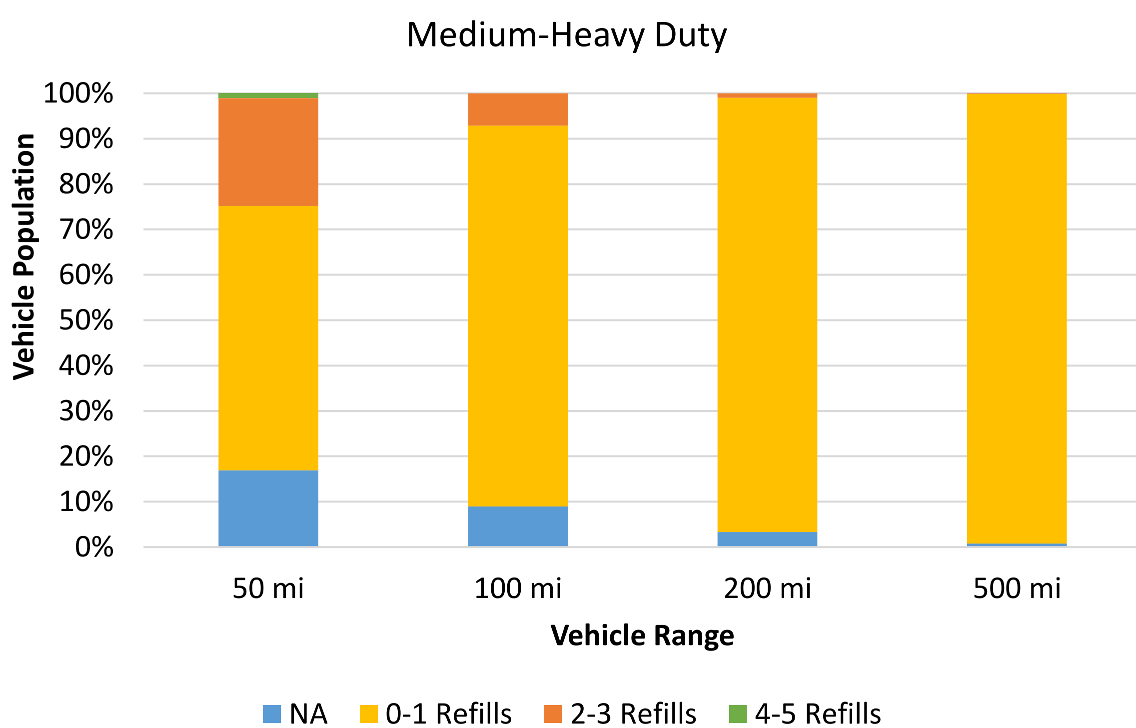


Figure 33. Refueling Frequency of Medium-Heavy Duty FCEVs for Different Vehicle Ranges

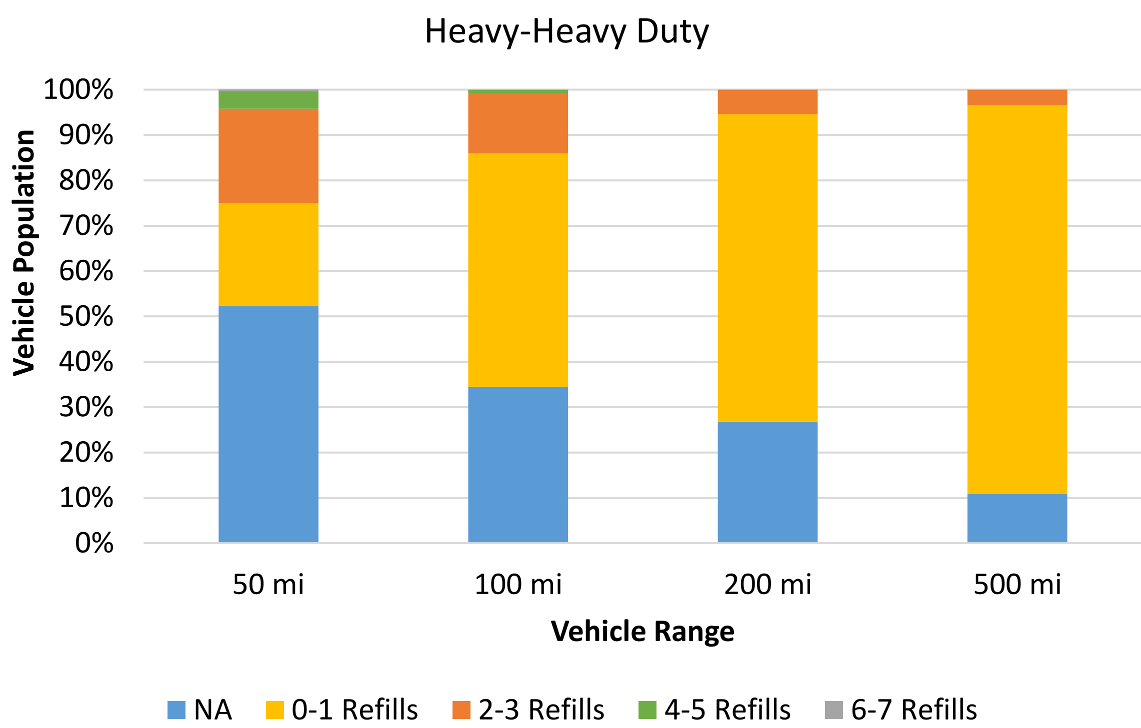


Figure 34. Refueling Frequency of Heavy-Heavy Duty FCEVs for Different Vehicle Ranges

Light-heavy and medium-heavy duty vehicles have similar trends in refueling frequency. Light-heavy duty vehicles have a greater portion of the population that takes trips over 500 miles, resulting in lower feasibility with 500 mi range FCEVs. Most light-heavy and medium-heavy duty vehicles are able to meet travel demands with one or less refills per day. Heavy-heavy duty vehicles require more refueling events per day for all vehicle ranges due to their longer trips. 100-mile range FCEVs would require some HHDVs to refuel 4-5 times a day to meet demand. While multiple refills per day is feasible, a high refill frequency may make operation inconvenient or unreasonable.

A comparison of ZEV feasibility for different vehicle range assumptions is presented in Table 17. Home base only charging is denoted “H” and everywhere charging, “E”. FCEVs are able to meet a greater percent of VMT for all range assumptions compared to BEVs for the three heavy-duty vehicle categories. For the configurations examined, the 100-mi BEVs with home base charging have the lowest feasibility in terms of VMT electrified. As the BEV range increases, the percent of VMT captured increases both in absolute terms and as a percent compared to FCEVs. However, in order for BEV and FCEVs to support equivalent VMT levels, the BEVs need a 500 mile range and charge at 350 kW.

Table 17. Comparison of Feasibility (% VMT) for FCEVs and BEVs at Maximum Charging Rate

	100 mi Range			**200 mi Range**			**500 mi Range**		
	FCEV	**BEV (H)**	**BEV (E)**	**FCEV**	**BEV (H)**	**BEV (E)**	**FCEV**	**BEV (H)**	**BEV (E)**
Light-heavy	65%	40%	60%	73%	62%	72%	84%	72%	84%
Medium-heavy	63%	36%	59%	76%	61%	75%	94%	75%	93%
Heavy-heavy	29%	8%	27%	38%	23%	34%	71%	48%	58%

4.4 Chapter Summary and Conclusions

This chapter assessed the feasibility of two types of zero-emission vehicles—battery electric vehicles (BEVs) and fuel cell electric vehicles (FCEVs)—for the heavy-duty vehicle sector. It first categorized heavy-duty vehicles and defined methods for integrating zero-emission vehicles onto the grid. Next, it presented a heavy-duty vehicle charging model that incorporates validated heavy-duty vehicle data and applies intelligent (smart/V2G) vehicle charging algorithms to determine future heavy-duty BEV charging behavior on the electric grid. The feasibility of BEVs for the heavy-duty sector was assessed for a range of potential future vehicle and infrastructure configurations. Lastly, renewable hydrogen production dynamics were presented and the feasibility of FCEVs to meet HDV demand was evaluated based on projected vehicle parameters. Based on the results of this chapter, the following conclusions can be drawn:

1. **Heavy-duty BEVs require significantly greater charging rates and battery capacities compared to light-duty vehicles in order to meet travel demands.** From a technical standpoint, more than half of Class 3-7 VMT can be met with heavy-duty BEV models in development today without trip modification, but further increasing electrification will require level 3 charging at locations other than home base. Class 8 trucks have a much lower BEV feasibility for the same vehicle configurations due to their lower fuel efficiency and longer trip distances. Overall, BEV feasibility can increase with improvements to batteries and vehicle designs, as well as with the expanded availability of EVSE beyond home base locations. Meeting a high percentage of VMT with BEVs may require multiple charging events per day at different locations throughout their routes.
2. **FCEV feasibility is dependent on achievable range.** Due to the fast refueling times of FCEVs, they are able to meet a greater percentage of VMT compared to BEVs with home base charging as well as most everywhere charging cases except those with high level 3 charging. Unlike BEVs, FCEVs are not constrained by refueling times. Rather, they are limited in their ability to meet VMT demands by their range – tied to tank size and fuel efficiency.
3. **The future maximum zero-emission vehicle feasibility for heavy-duty vehicles will depend on vehicle improvements.** Heavy-duty ZEV models are still in development, with estimates on fuel efficiency and maximum battery capacity in flux. Converting some HDVs, especially for vocations with longer travel and more challenging drive

cycles, will require increased battery capacity compared to current models. The increased weight of the battery may reduce the payload weight that can be added to the truck. Increased battery weight can also reduce the fuel efficiency of the vehicle as well as the achieved range. Reducing vehicle weight through vehicle redesigns and battery improvements can help counter these issues and increase ZEV utilization.

4. **The ability of vehicles to support renewable integration is dependent on the scale of BEV deployment and charging location assumptions.** Vehicles charging only at home base may not capture solar generation, whereas, vehicles charging along their routes during the day have a greater ability to directly charge with solar generation. Vehicles with home base charging are able to utilize wind generation and can still provide valley-filling during evening decreases in demand.
5. **Everywhere charging increases renewable utilization for immediate charging of heavy-duty vehicles.** By allowing vehicles to charge along their routes, more of their electricity demand occurs during the middle of the day when peak solar occurs. Additionally, because the vehicles have been charging throughout the day, they charge less when returning to home base, reducing the vehicles' impact on the grid during peak demand periods when natural gas power plants are operating.

Chapter 5. Strategies that Achieve a) a 80% Reduction in GHG Emissions and b) a 100% Clean Electric Grid with Vehicle-Grid Integration

This chapter presents a series of heavy-duty zero-emission vehicle deployment scenarios for the year 2050. The first set of scenarios starts with a current policy reference (CPR) scenario that incorporates all vehicle and grid emissions policies to date. While the grid parameters established in the CPR base case meet the 80% reduction in GHG emissions target, the vehicle parameters do not. Following the CPR base case is a series of expanded ZEV deployment scenarios, exploring the potential growth in light-duty to heavy-duty ZEVs, starting with the target of an 80% reduction in GHG emissions from these vehicle categories and then further reducing their emissions. The expanded ZEV scenarios maintain the same stationary load assumptions from the CPR base case so that changes in GHG emissions between scenarios is solely driven by changes in vehicle composition and vehicle-grid interactions. The role of increased heavy-duty ZEVs for achieving an 80% reduction in GHG emissions is examined in Chapter 6.

Section 5.2 first analyzes a subset of 80% GHG reduction scenarios to evaluate the remaining requirements needed to meet a 100% clean grid under different scales and strategies for vehicle-grid integration. Additional renewable capacity requirements as well as balancing requirements are assessed. This analysis will establish a set of 100% clean electric grid scenarios that will also be analyzed in Chapter 6.

5.1 Strategies for Achieving an 80% Reduction in Grid GHG Emissions with Expanded Zero-Emission Heavy Duty Vehicle Deployment

The basis of the current policy reference (CPR) scenario used here as the base case is directly from the E3 PATHWAYS Project, and it includes the E3 baseline 2050 electric load profile including load demand for light-duty vehicles and buses [150]. The baseline renewable capacity is also assumed, see Table 18.

Table 18. Resource Generation Capacities Applied in Analysis from E3 PATHWAYS [150]

Technology	Capacity (GW)
Rooftop PV	41.5
Solar	66.0
Wind	99.7
Geothermal	4.86
Hydropower	15.1

The expanded heavy-duty ZEV deployment scenarios are also based on scenarios from the same project, taking the zero-emission vehicle VMT from different portfolio scenarios [150]. Each scenario is named based on the average percentage of heavy-duty VMT met by ZEVs. The high BEV and High H2 scenarios assume a near-total conversion to zero-emission options. The High BEV and High H2 scenarios assume the same level of ZEV VMT. The high hydrogen case examines an expanded deployment of FCEVs versus BEVs, completely switching heavy-heavy duty BEVs to FCEVs and switching 66% of percent of the light- and medium-heavy duty vehicle miles previously met through BEVs to FCEVs. A summary of the vehicle scenarios is presented in Table 19.

Table 19. 2050 Zero Emission Vehicle Energy Consumption for Scenarios [150]

	Light-Duty		Light-Heavy Duty*		Medium-Heavy Duty*		Heavy-Heavy Duty**	
	Elec (GWh)	Hyd (MMBTU)	Elec (GWh)	Hyd (MMBTU)	Elec (GWh)	Hyd (MMBTU)	Elec (GWh)	Hyd (MMBTU)
CPR base case	4.74 E+04	1.77 E+07	9.00 E+02	3.54 E+06	1.30 E+03	5.11 E+06	1.87 E+03	7.26 E+06
CPR-Increased BEV^	6.23 E+04	1.04 E+07	9.00 E+02	3.54 E+06	1.30 E+03	5.11 E+06	1.87 E+03	7.26 E+06
40% HD ZEV⁺	6.23 E+04	1.04 E+07	2.74 E+03	0	3.98 E+03	0	1.54 E+04	0
73% HD ZEV⁺	6.23 E+04	1.04 E+07	5.55 E+03	0	8.05 E+03	0	2.51 E+04	4.22 E+07
High BEV	6.23 E+04	1.04 E+07	6.60 E+03	0	9.55 E+03	0	2.75 E+04	1.24 E+08
High Hydrogen	6.23 E+04	1.04 E+07	2.10 E+03	3.54 E+07	3.02 E+03	5.11 E+07	0	2.51 E+08

*Weighted average of LHDV and MHDV BEV = 34.3 mi/GGE (2050); FCEV = 15 mi/GGE (2050) [150]
** HHDV BEV = 17 mi/GGE (2050); HHDV FCEV = 11.2 mi/GGE (2050) [150]
^ The CPR with increased BEVs is a supplemental scenario applied for the grid balancing requirement and air quality analyses to isolate the impact of heavy-duty ZEVs independent from changes in light-duty/bus ZEV assumptions.
⁺ Percentage refers to % annual VMT

The full composition of the light-duty, bus, and heavy-duty vehicle populations in California (including vehicles registered in-state and out-of-state) is presented in Figure 35 and Figure 36. These populations will be applied for calculating the change in GHG emissions and air quality impacts. They also will be applied in the 100% clean electric grid scenarios. The difference between the scenarios presented here and the scenarios presented in Section 5.2 is the deployment of additional support technologies to reduce grid GHG emissions to zero for the 100% clean electric grid scenarios. It is assumed that all heavy-duty BEVS are in-state vehicles, except for the high BEV scenario, in which a small portion of the out-of-state vehicles will need to be electrified in order to achieve the 95% of VMT stated in that scenario. For this case, it is assumed that the out-of-state vehicles electrified follow the same electric load demand patterns as the in-state BEVs. FCEVs may be in-state or out-of-state vehicles. Hydrogen demand for FCEVs are assumed to support the vehicle miles traveled within the state.

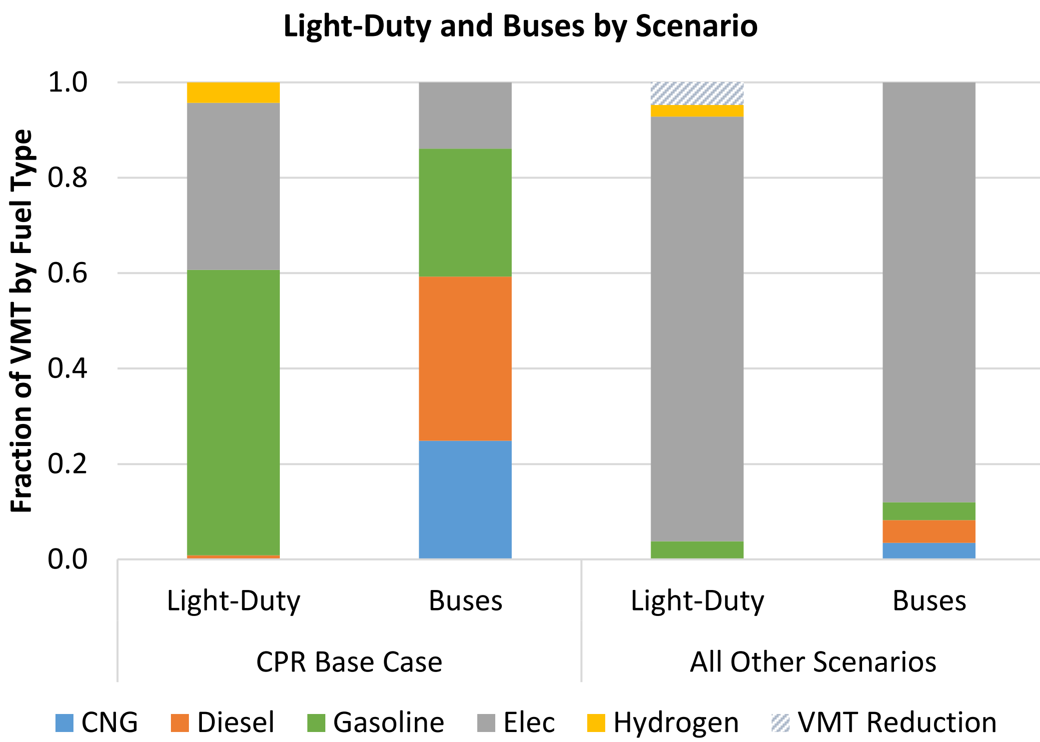
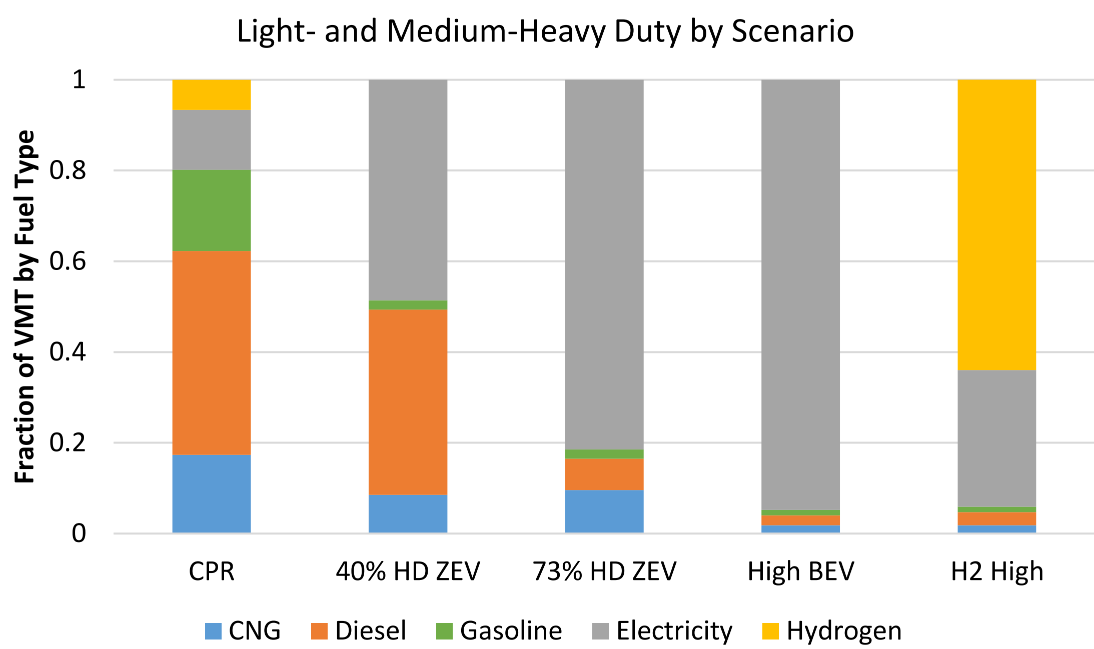


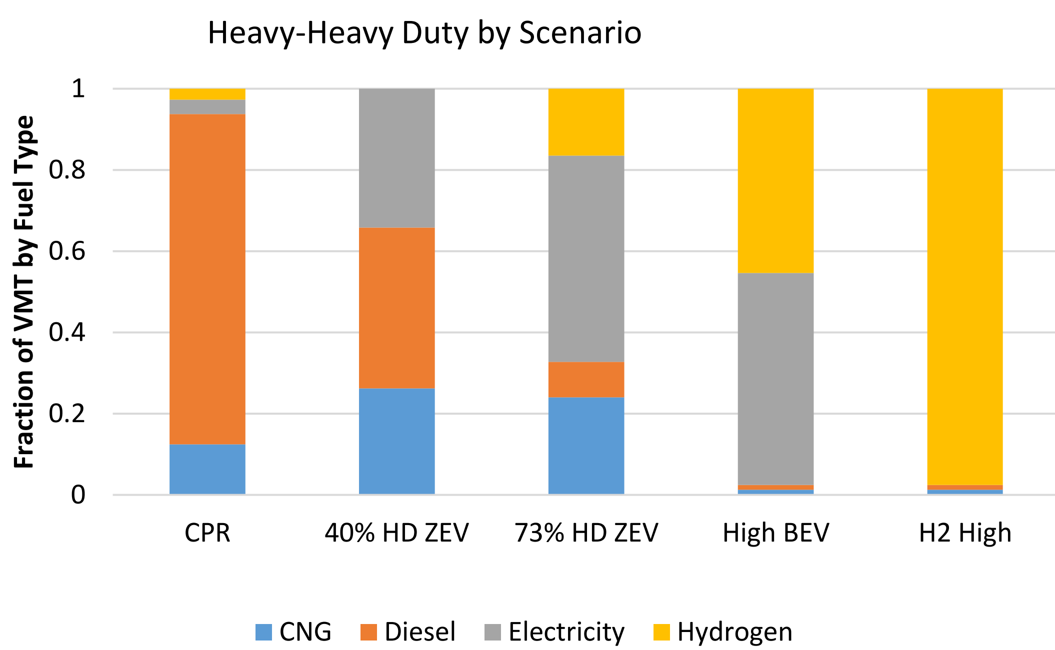
Figure 35. Fraction of VMT met by Different Fuel Types for E3 Scenarios: light-duty and buses

As previously discussed in the introduction of this work, light-duty vehicles encompass a majority of the GHG emissions from the transportation sector. Therefore, in order for the transportation sector to reduce its emissions by 80%, a significant portion of the light-duty vehicle population must be converted to ZEVs. Electrifying light-duty vehicles will introduce a considerable load onto the electric grid and therefore it is incorporated in this analysis. For the CPR base case, the light-duty ZEV population encompasses approximately 37% of light-duty VMT. The expanded ZEV scenarios maintain a consistent penetration of both light-duty and bus

ZEVs, which account for slightly greater than 80% reduction in GHG emissions from both categories of vehicles.



a)



b)

Figure 36. Fraction of VMT met by Different Fuel Types for E3 Scenarios, a) light-heavy and medium-heavy duty vehicles and b) heavy-heavy duty vehicles.

The BEV and EVSE infrastructure assumptions for the scenarios are informed by the sensitivity analysis conducted in Section 4.3. A summary is presented in Table 20. Incorporated into this analysis are the conversion losses applied for both charging and discharging. Transformer losses are applied for discharging back to the grid. Transformer losses on the charging side are already accounted for in the transmission and distribution losses applied on the generation side.

Table 20. BEV Vehicle and Infrastructure Assumptions for Year 2050

Scenario	**Vehicle Range (mi)**	**Vehicle Charging Rate (kW)**	**Charging Locations**	**Charging/Discharging Efficiency (%)**
CPR base case	200	120	Home base	0.95/0.85
40% HD ZEV	200	120	Home base	0.95/0.85
73% HD ZEV	500 (LHDV/MHDV) 400 (HHDV)	120	Everywhere	0.95/0.85
High BEV	600	350	Everywhere	0.95/0.85
High H_2	100	19.2	Home base	0.90/0.85

The modest heavy-duty ZEV adoption in the CPR base case can be achieved with either level 2 or level 3 charging rates and vehicle ranges as low as 100 miles. Spanning the possible variations in BEV and EVSE configurations for the CPR base case has minimal impacts on grid emissions and cost, due to the relatively low level of deployment. Therefore, a vehicle range of 200 miles with a 120 kW charging rate for at home base charging only was selected. These parameters are in line with the specifications of heavy-duty BEVs already being deployed, eg. [135,144]. The scenarios with higher BEV deployments require increased vehicle range and higher EVSE charging rates. The highest BEV deployment requires a larger vehicle range as well as a higher charging rate than are currently available. This scenario represents significant improvement in battery technology.

In the high hydrogen scenario, the BEV range and charging rate can both be reduced by concentrating on electrifying short distance trips. Referencing Figure 30, a BEV with a range of 100 miles, charging only at home base at a Level 2 (19.2 kW) charging rate, can meet 39% of the VMT from in-state vehicles. The 100-mi range and 19.2 kW charging rate can be met through existing technologies and would not require significant improvements in vehicle or infrastructure designs.

5.2 Strategies for Achieving a 100% Clean Electric Grid with Vehicle-Grid Integration

There are several complementary strategies for achieving a 100% renewable or clean grid applied in the literature. It is most likely that a portfolio approach will be implemented, combining the most effective, least-cost options first and then applying (if needed) additional technologies and/or management strategies to move the electric grid from near-zero to 100% carbon neutral. Most studies focus on a portfolio of renewable resources (including hydropower) to achieve low emissions from the electric grid, eg. [40,103,272]. To move to a 100% clean, carbon-neutral grid, the most frequently proposed technology strategies include biopower, energy storage, and demand-side management, eg. [36,37,39,43].

This analysis focuses on energy storage utilization to meet 100% clean electric grid, analyzing the changes in energy storage requirements associated with increased zero-emission vehicle charging intelligence. Stationary Energy storage systems (ESS) are promising, because they not only have quick response times, but they can also utilize otherwise wasted electricity generated from renewable resources. However, when considering the deployment of ESS, it is important to determine the scale and the functions they are intended to serve. Tarroja et al. (2018) demonstrated that achieving 100% through energy storage can be challenging and material intensive due to seasonal shifting demands [43]. They also found that even with an overbuilding of renewable capacity, the energy storage fleet will need over 4600 GWh energy capacity, which translates to a battery fleet power capacity of 1095 GW. In comparison, the peak net demand that needs to be met for the 80% GHG reduction CPR base case is only 63.8 GW. This indicates that energy capacity, not power capacity is driving the high level of battery energy storage deployment needed. Energy storage technologies such as lithium ion, lead acid batteries, etc. that are limited to 1-5 hours of dispatch at maximum power would need to be operated in series to fully meet the renewable energy shifting needs to reach a 100% renewable grid. In contrast, ESS such as flow batteries and hydrogen energy storage can have their energy and power capacities independently sized. Therefore, power capacity can be scaled to match maximum charge or discharge demand and energy capacity can be scaled to meet energy shifting requirements, creating a more tailored buildout of capacity to meet grid needs. The trade-off with implementing a hydrogen storage based system is lower round-trip efficiencies compared to some battery energy storage technologies [230].

This work builds upon the previous analysis by Forrest et al. (2016), which found that increasing the charging intelligence of light-duty BEVs can reduce the energy storage capacity needed to reach 80% renewable utilization onto the California grid [32]. Similarly, heavy-duty ZEV deployment may reduce the additional energy storage capacity to meet a 100% clean electric grid. For the 100% clean electric grid scenarios, two of the expanded vehicle cases—

40% HD ZEVs and High H_2—from the 80% reduction scenarios are replicated in order to explore 1) how increased renewable capacity affects vehicle-grid dynamics and 2) how ZEV integration onto the grid affects resource requirements for meeting a 100% clean electric grid. These two scenarios represent the more conservative estimates in terms of vehicle technical improvements.

To meet electric load demand with 100% carbon-neutral energy, additional solar and wind capacity is added compared to the 80% GHG reduction scenarios. The increased renewable capacity is to accommodate energy losses associated with energy storage used to meet the 100% target. The new baseline for the High H_2 scenarios is higher than the 40% HD ZEV scenarios, based on the higher renewable generation requirements to support the increased vehicle load demand. In addition to the 100% clean electric grid baseline capacities, an additional renewable overbuild scenario is developed for each vehicle case in order to evaluate the impact of renewable capacity on balancing requirements to achieve a 100% clean grid. In multiple studies, eg. Budischak et al. (2013) [36] and Tarroja (2018) [43], renewable capacity overbuild has shown to reduce additional resource capacity to meet high renewable penetrations. The renewable capacity assumptions for the 40% HD ZEV-100% clean electric grid scenarios are in Table 21. The renewable capacity assumptions for the High H_2-100% clean electric grid scenarios are in Table 22. Solar and wind capacity is increased for the baseline and overbuild scenarios, and the other renewable resources are kept constant due to the high availability of solar and wind and the limited capacity to expand geothermal and small hydroelectric power plants.

Table 21. Renewable Capacity Expansion for 40% HD ZEV—100% Clean Electric Grid Scenarios

Technology	80% GHG Reduction Baseline Capacity (GW)	100% Clean Electric Grid Baseline Capacity (GW)	100% Clean Electric Grid Overbuild Capacity (GW)
Rooftop PV	41.5	50.8	62.2
Solar	66.0	80.8	99.0
Wind	99.7	122	157
Geothermal	4.86	4.86	4.86
Small Hydro	1.29	1.29	1.29

Table 22. Renewable Capacity Expansion for High H_2—100% Clean Electric Grid Scenarios

Technology	80% GHG Reduction Baseline Capacity (GW)	100% Clean Electric Grid Baseline Capacity (GW)	100% Clean Electric Grid Overbuild Capacity (GW)
Rooftop PV	41.5	62.2	77.8
Solar	66.0	99.0	124
Wind	99.7	157	196
Geothermal	4.86	4.86	4.86
Small Hydro	1.29	1.29	1.29

For each heavy-duty ZEV deployment scenario, a suite of charging scenarios is evaluated, see Figure 37. In addition to HDV immediate, smart, and V2G charging strategies previously applied for the 80% reduction scenarios, a scenario with LDV smart charging with HDV V2G charging is added in order to assess an "optimistic" utilization of intelligent vehicle charging to balance the electric grid. The grid balancing requirements to meet the 100% clean electric grid target are for each charging scenario are assessed and energy storage capacity is spanned to evaluate the power and energy capacities that can meet the identified requirements. While Forrest et al. (2016) spanned the capacity of a single ESS technology [32], this analysis seeks to deploy a portfolio of battery energy storage systems (BESS), eg. Lithium-ion batteries, and H_2 storage such that the benefits of each type of storage can be realized. For each vehicle scenario, two different energy storage cases will be examined: deploying BESS capacity versus the H_2 storage, in order to examine how technology assumptions may affect capacity requirements and the levelized cost of energy for a 100% clean electric grid. The scaling process is described in more detail in Section 6.1.2.

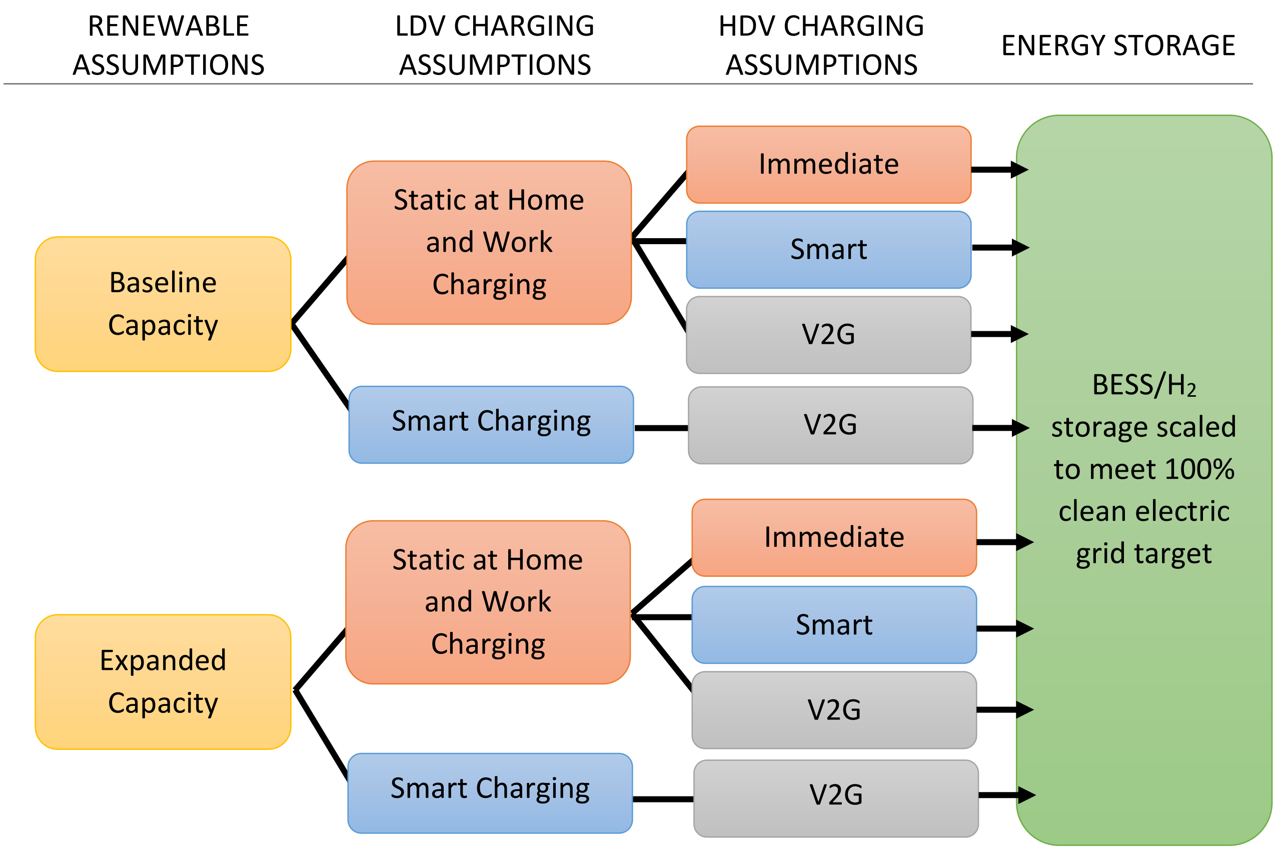


Figure 37. Flowchart for 100% Clean Energy Scenarios

Chapter 6. The Impact of Zero-Emission Vehicle Integration on Grid Balancing Requirements, GHG Emissions, Air Quality, and Levelized Cost of Energy

This chapter analyzes the impact of heavy-duty ZEV deployment for the scenarios developed in Chapter 5. It focuses on the net impacts of heavy-duty ZEV deployment on grid performance, achieving GHG emissions and air pollution reductions, as well as impacts on levelized cost of energy.

6.1 Grid Balancing Requirements

The electrification of vehicle demand can result in an increased need for electricity generation. The misalignment of vehicle demand with renewable availability may negatively impact the grid's balancing requirements: increasing ramping rates, peak demand, and fossil fuel generation. The deployment of zero-emission HDVs with intelligent charging can help mitigate these impacts and potentially provide a net benefit in terms of grid performance. This section investigates the impact of heavy-duty ZEV deployment on grid balancing requirements, such as peak power, ramp rates, and balancing generation.

Grid balancing requirements for the 80% reduction in GHG emission scenarios are calculated from the remaining load unmet by renewables and hydropower generation. The net load must be met by dispatchable generation resources. For the 80% GHG reduction scenarios, natural gas power plants are used to balance the net load. For the 100% clean electricity grid scenarios, different portfolios of energy storage using renewable power are applied.

6.1.1 Grid Balancing Requirements for 80% Reduction in GHG Emissions

The first step to investigating grid balancing requirements for the 80% GHG emissions reduction scenarios is to gauge the changes in the net load profile. The net load duration curves for each vehicle deployment scenario with immediate charging is presented in Figure 38. The net load duration curve shows the portion of the year that has a certain demand or greater. The x-axis spans 0-8760 hours of the year. Values above the zero on the x-axis indicate unmet demand that must be satisfied by the balance generation model. Values below the x-axis indicate the total length of the year with over-generation of renewable electricity.

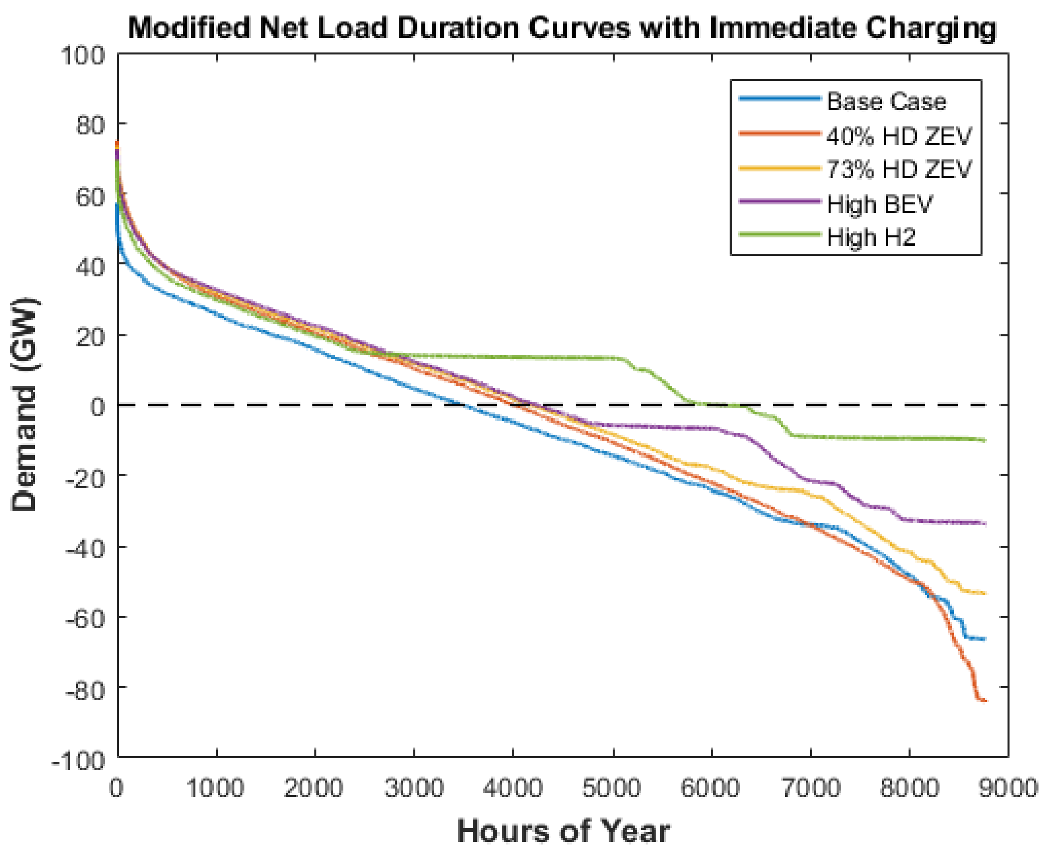


Figure 38. Net Load Duration Curves for 80% GHG reduction Scenarios with Immediate Charging

Overall, the addition of heavy-duty vehicles increases the load, but the net impact on the load duration curve depends on the deployment scenario. There is an increase in peak demand for all scenarios compared to the base case with immediate charging, see Figure 39. The greatest peak is observed for the 40% HD ZEV scenario. Even though there are fewer vehicles being electrified in this scenario, they are short range vehicles with home base charging only, which as shown in Figure 23, can result in higher peak loads compared to longer range vehicles (as in 70% HD ZEV scenario, High BEV scenario) and vehicles that are able to charge everywhere (as in High BEV scenario). The High H_2 scenario with immediate charging has the smallest increase in peak demand. Shifting to smart charging still results in an increased in peak demand compared to the CPR base case, but the new peak values are reduced compared to the same vehicle scenarios with immediate charging. The smart charging scenarios with high BEV deployment (40% HD BEV, 73% HD BEV, and High BEV) are more effective in reducing peak demand compared to the cases with low BEV deployment (CPR Base Case, High H_2).

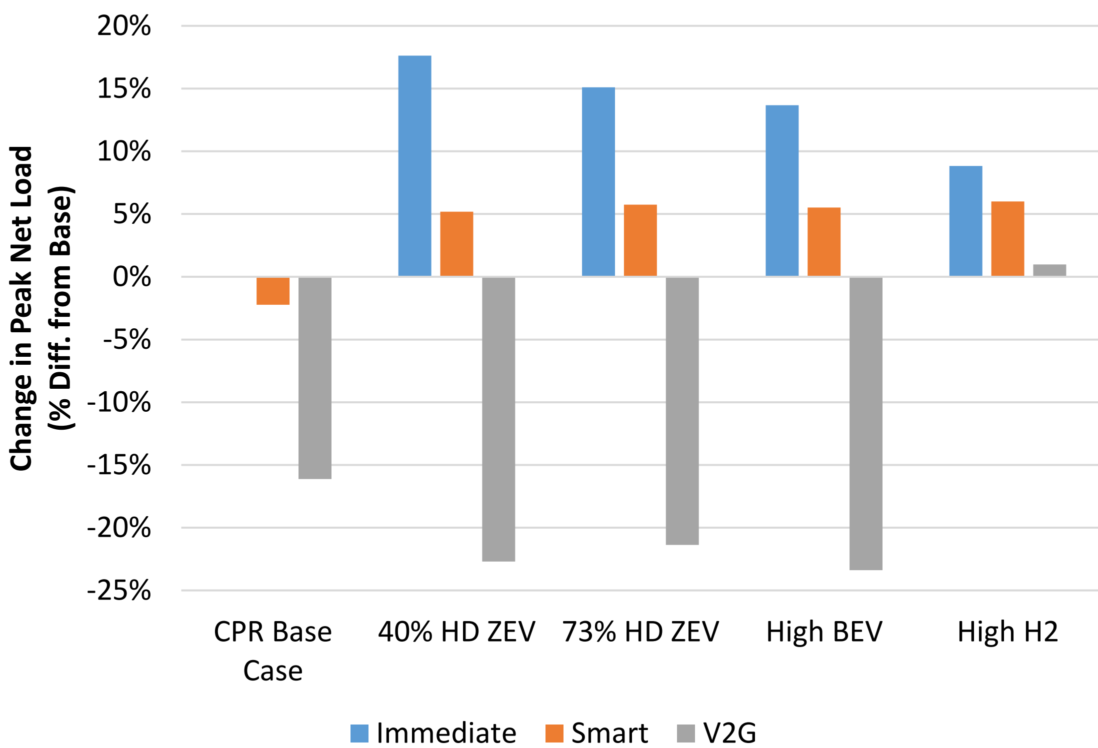


Figure 39. Change in Peak Net Load Demand for All 80% GHG Reduction Scenarios Compared to CPR Base Case with Immediate Charging

In addition to changes in maximum load, there are differences in the minimum load as well. Compared to the base case, the 40% heavy-duty ZEV scenario results in a lower minimum.

This is a direct result of decreasing FCEV hydrogen demand compared to the CPR base case. A comparison between the original CPR base case and the base case with increased light-duty BEVs is presented in Figure 40 to demonstrate how different light-duty vehicle assumptions affect net load dynamics. The 40% HD ZEV curve is included for reference. Immediate charging of BEVs does not align with peak curtailed renewable generation, and so under the 40% HD ZEV, the reduced hydrogen production decreases the amount of peak curtailed renewables that can be captured. At the same time, increasing uncoordinated vehicle load demand on the grid increases peak net demand.

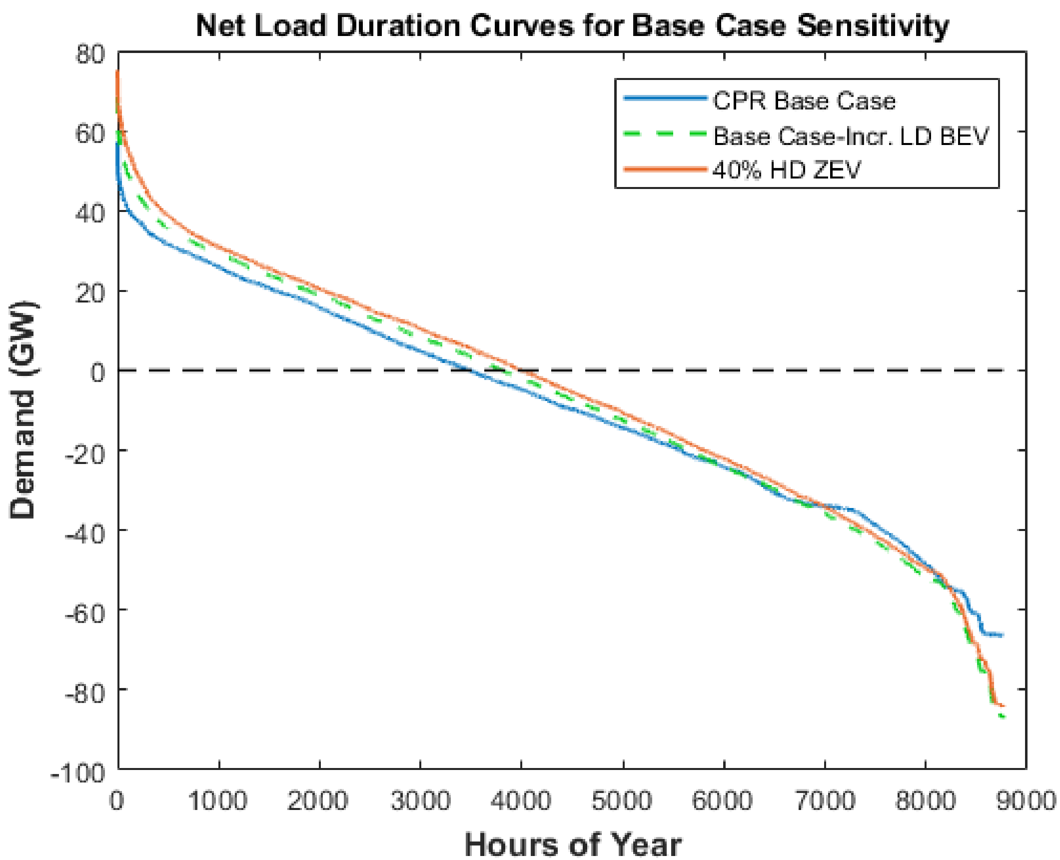


Figure 40. Impact of Increased Light-duty BEV Charging and Reduced FCEV H2 Demand on the Base Case Modified Net Load Duration Curve

Increasing light-duty and heavy-duty ZEV loads on the grid also affects the ramping requirements of the grid. Examining the frequency of different ramp rates in the CPR base case, the median and mode ramp rate for most hours are both zero, see Figure 41. The high number outliers indicates infrequent high ramping events across the year. With immediate charging, ramping requirements are most affected between 4-8 pm (hours 16-20 in Figure 41b). This time period also corresponds to peak electricity demand.

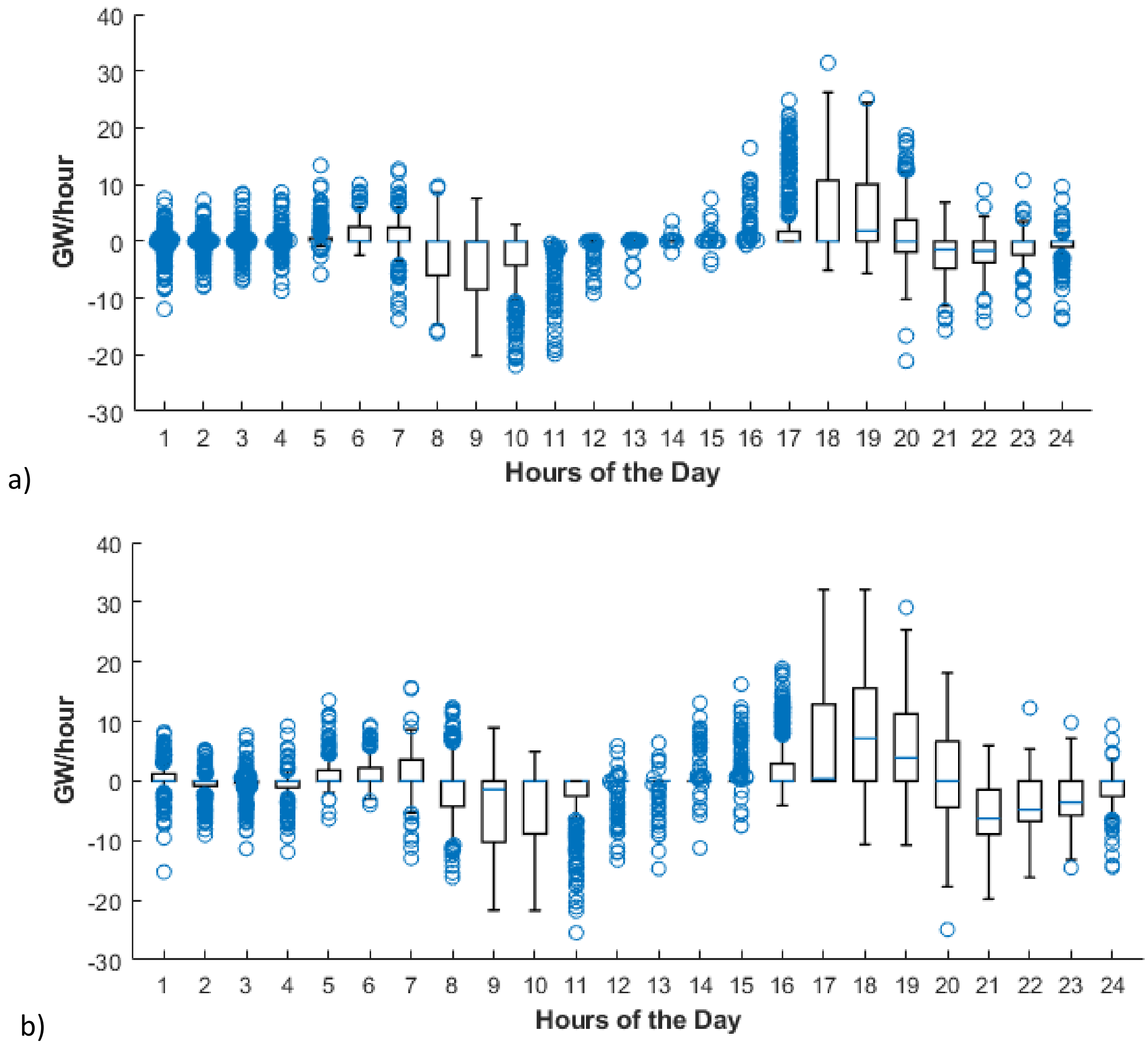


Figure 41. Distribution of Hourly Ramping Requirements for: (a) CPR Base Case with Immediate Charging and (b) High BEV scenario with Immediate Charging

The High BEV scenario with immediate charging represents the scenario with the least flexibility to shift vehicle load demand. The greatest median ramping rate, which occurs between 5-6 pm, is approximately 7 GW/hour. This is equivalent to requiring about half the hydropower plants in the state going from zero to full power in an hour to meet the increase in electricity demand.

Increasing BEV charging intelligence not only results in a reduction in peak demand compared to immediate charging, it can also result in a “flattening” of the net load duration curve, affecting ramping requirements, see Figure 42. A flatter net load duration curve translates to a reduction in demand variability (improved load smoothing), allowing balancing power plants to operate at a steady power output level for longer of the year, which a) improves system efficiency if plants are operated at a high part-load condition and b) reduces demand for fast-ramping peaker plants. Increasing the number of BEVs with V2G charging further increases load smoothing.

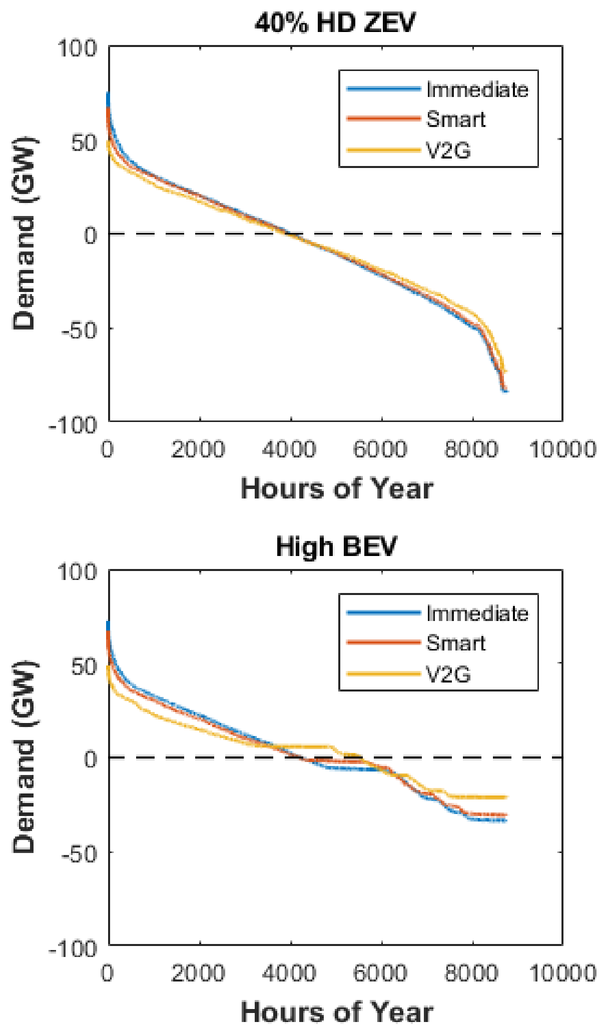


Figure 42. Modified Net Load Duration Curves for All 80% GHG Reduction Scenarios

Comparing the two high ZEV scenarios: High BEVs and High H_2, both net load curves have similar trends in terms of net load smoothing. The higher total load demands for the High H_2 scenarios come from the lower efficiency of hydrogen production versus BEV charging, requiring increased load demand to supply the same number of VMT. The High H_2 scenarios are more effective in smoothing the net load compared to the High BEV scenario with immediate charging, and they result in lower peak net demand. The High BEV scenario with V2G charging is more effective than the High H_2 scenario with V2G charging in reducing the percent of the year with higher load demand values, due to the greater number of BEVs discharging back to the grid compared to the High H_2 scenario.

The difference in dispatch flexibility between these scenarios can be further elaborated on by comparing the hourly modified net load ramp rate distributions (Figure 43). Increasing charging intelligence reduces both the magnitude and frequency of ramping events. The High BEV scenario with smart charging (Figure 43a) has a similar distribution of hourly ramp rates compared to the High H_2 scenario with immediate charging (Figure 43b), with some hours (most distinctly 5 pm) seeing less frequent positive ramping under the High H_2 scenario with V2Gcharging. High BEV scenario with V2G charging (Figure 43c) has the smallest range in hourly ramp rates of all the 80% GHG reduction scenarios. All upper and lower quartiles fall between +4.5 GW/hour and -2.5 GW/hour, respectively. Including outlier day values, the maximum hourly ramp rate + 18 GW/hour between 4-5 pm. In comparison, for the 40% HD ZEV scenario with immediate charging, which has the greatest positive and negative hourly ramping rates, the upper and lower quartiles fall between +17 GW/hour and -9 GW/hour, respectively, and the maximum hourly ramp rate for the year is +34 GW/hour between 4-5 pm.

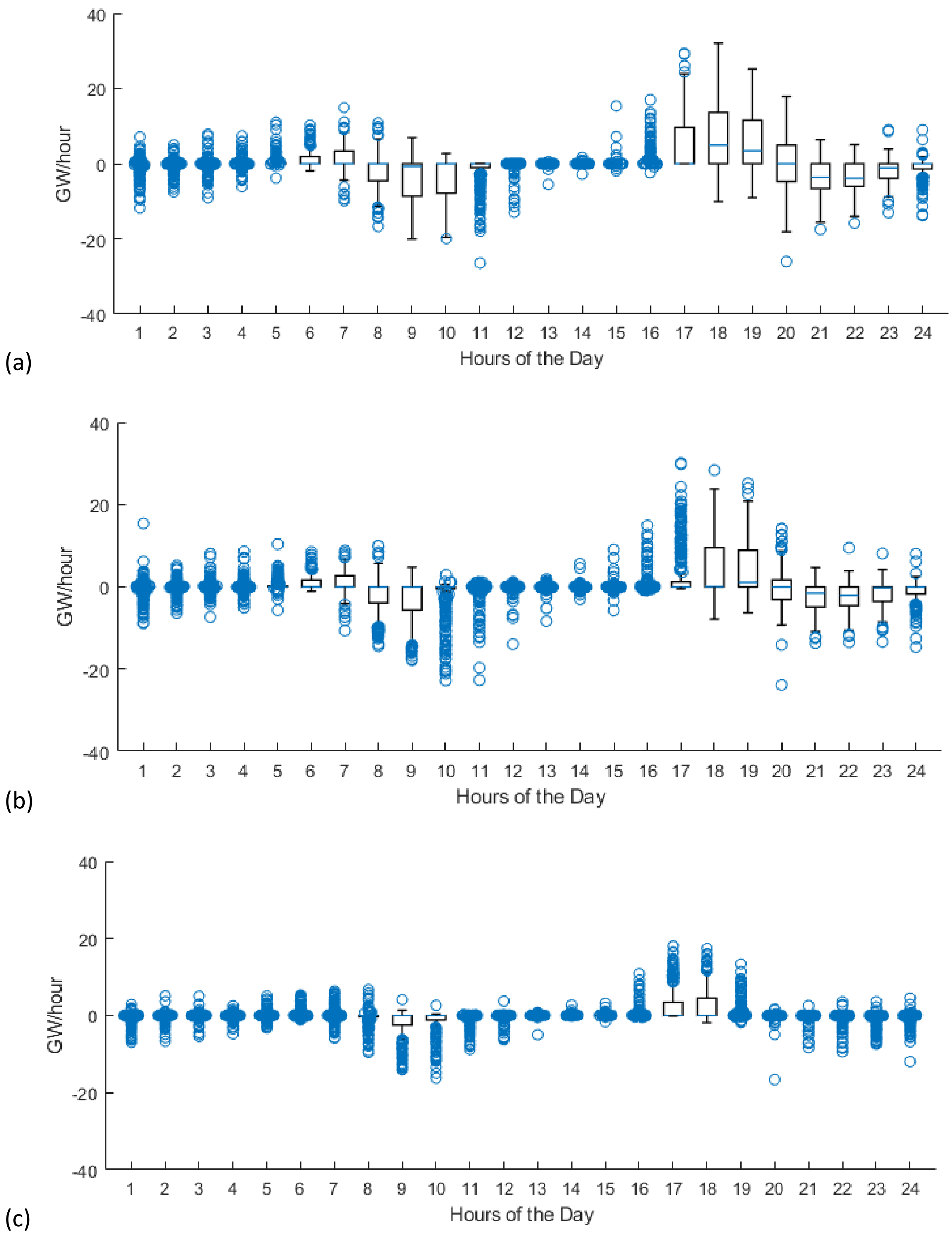


Figure 43. Distribution of Hourly Ramping Requirements for: (a) High BEV Scenario with Smart Charging, (b) High H_2 Scenario with Immediate Charging, and (c) High BEV Scenario with V2G Charging

In addition to the ramping requirements, another important metric for grid performance is the degree to which renewable generation is integrated, measured in terms of total renewable penetration. Renewable penetration is the percent of the electric load demand met by renewable generation either directly or indirectly through energy storage, see Equation 8. The renewable penetration for each scenario, see Figure 44, does not include large hydropower.

$$RE_{pen} = \frac{RE_{total} - RE_{curtailed}}{E_{initial\ load} + E_{vehicle\ load}} * 100 \qquad (8)$$

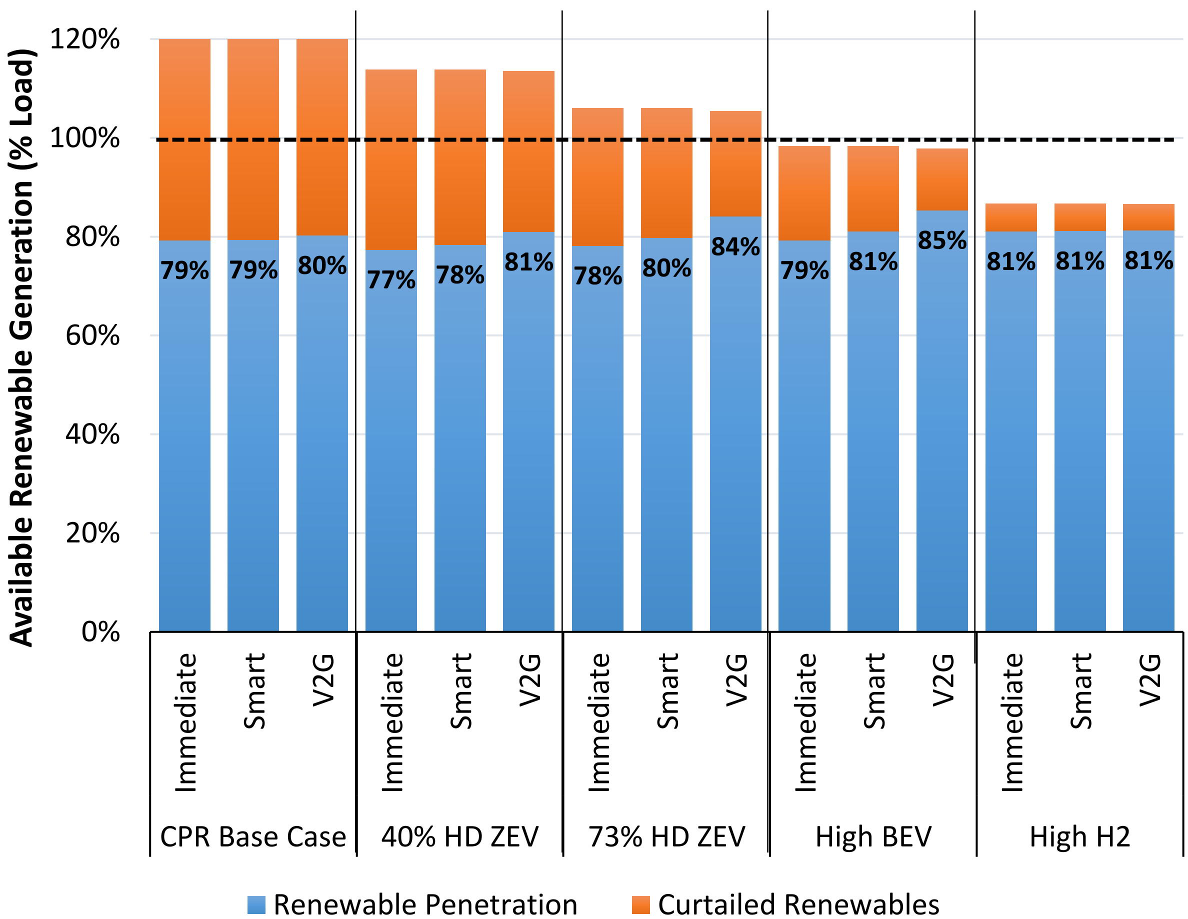


Figure 44. Renewable Penetration and Curtailment for All 80% GHG Reduction Scenarios

As the ZEV population increases, so does the demand for electricity, see Figure 45. Because renewable generation is constant across the scenarios, the maximum potential renewable penetration declines in the expanded ZEV deployment scenarios compared to the CPR base case. The high hydrogen scenarios result in greater absolute renewable usage compared to the other scenarios (see Figure 45), but the lower efficiency of hydrogen production versus BEV charging results in a higher electric load demand. The net impact is a potential renewable penetration of less than 90%.

Increased charging intelligence for each expanded vehicle results in marginal increases in renewable penetration associated with an increase in the percentage of the BEV load met with renewable generation. Increased charging intelligence also decreases the reliance on peaker plants. As demonstrated in Figure 43, smart and V2G charging strategies reduce the hourly ramping rates that balancing generators need to meet, reducing the need for the fast-ramping of peaker plants. Allowing vehicles to discharge back to the grid during peak demand times further reduces the number of periods when peaker plants would have otherwise provided power. In addition to reducing peaker plant generation, the V2G scenarios reduce load following generation, except for the High H_2 scenario with V2G charging. In the High H_2 scenario with V2G charging, peaker plant generation is reduced, but the generation that replaces it is not renewables but rather increased load-following generation. In this scenario, there is a significantly lower availability of excess renewables to utilize compared to the other V2G scenarios, and therefore, load-followers provide additional generation.

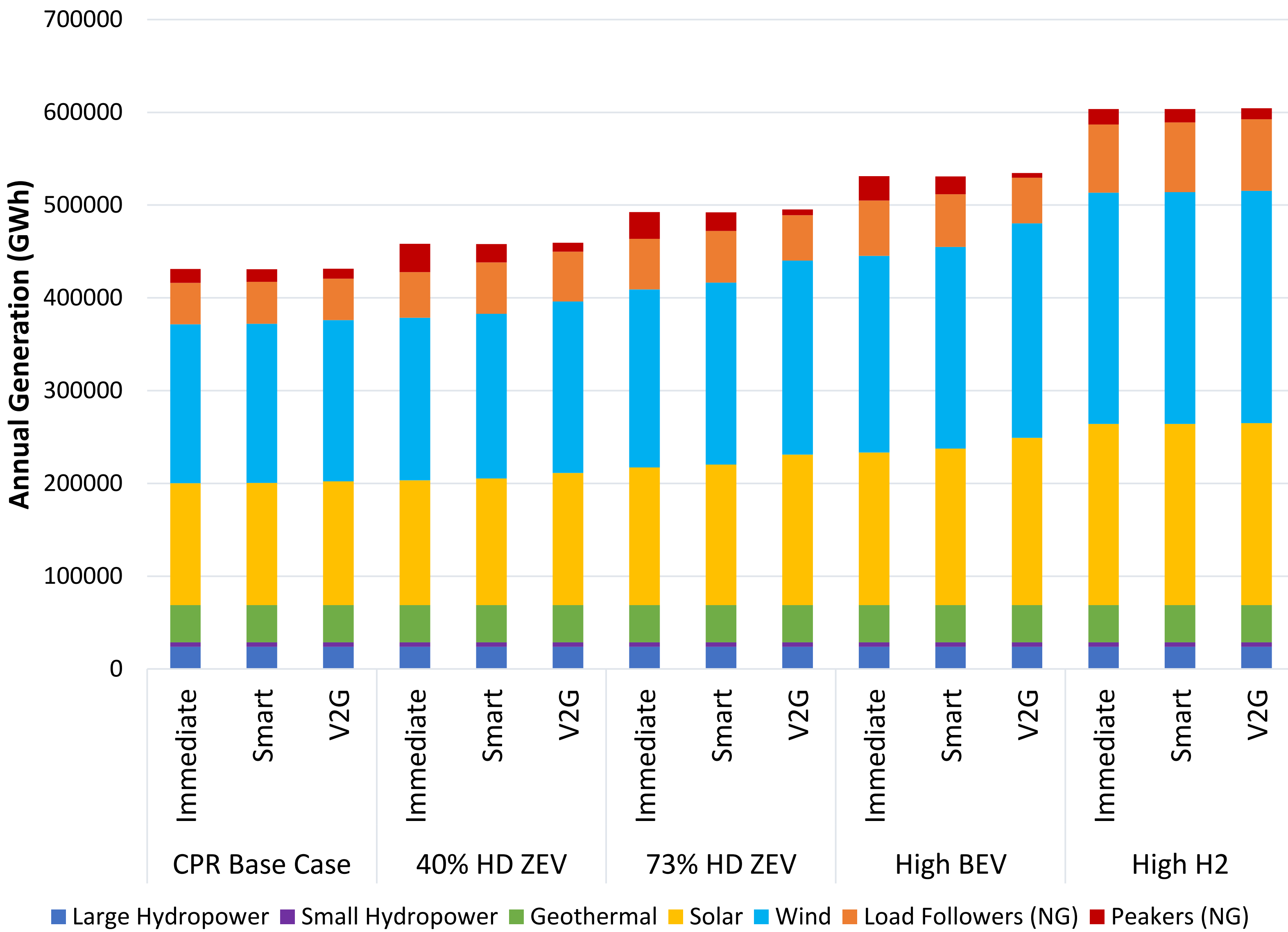


Figure 45. Generation by Resource for All 80% GHG Reduction Scenarios

6.1.2 Grid Balancing Requirements for 100% Clean Electric Grid

Increasing the renewable capacity for the 100% clean electric grid scenarios affects the grid balancing requirements that must be met with energy storage compared to the 80% GHG reduction scenarios. The modified net load duration curves for the baseline and overbuild scenarios demonstrate the impact of greater solar and wind power capacity on the net load and peak demand, see Figure 46 and Figure 47. Increasing variable renewable capacity shifts the modified net load duration curve down, reducing the remaining load demand that needs to be met with energy storage or other dispatchable resources. The trends between immediate, smart, and V2G charging for heavy-duty vehicles remain consistent with the previous 80% GHG reduction scenarios; increasing charging intelligence results in a flattening of the net load duration curve, decreasing curtailed renewable generation as well as peak demand.

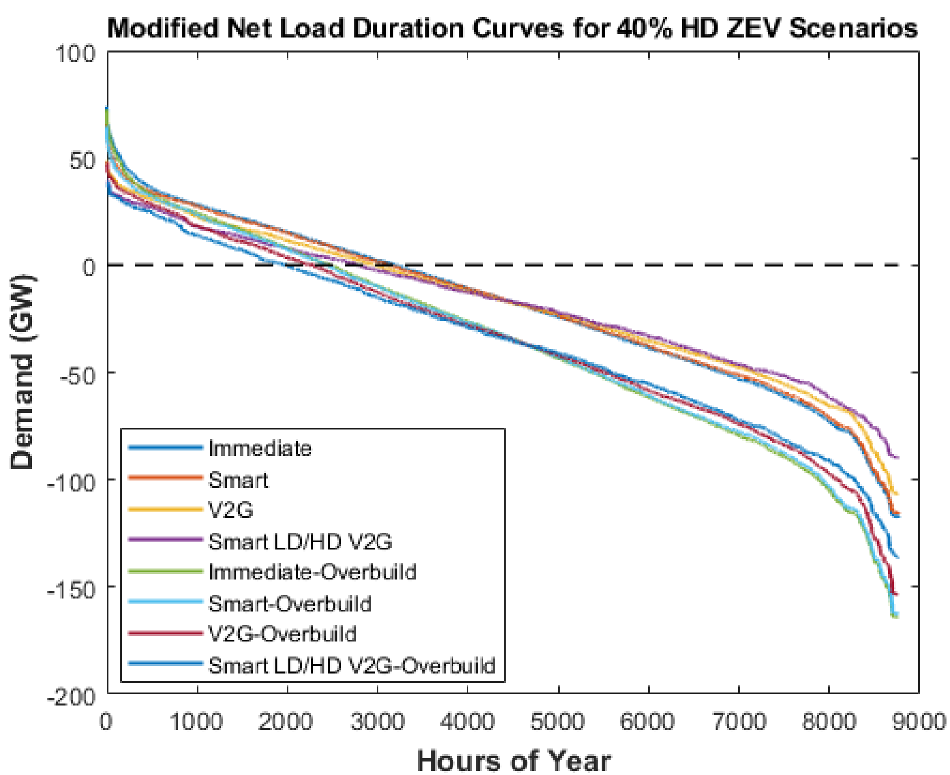


Figure 46. Modified Net Load Duration Curves for 100% Clean Grid: 40% HD ZEV Scenarios

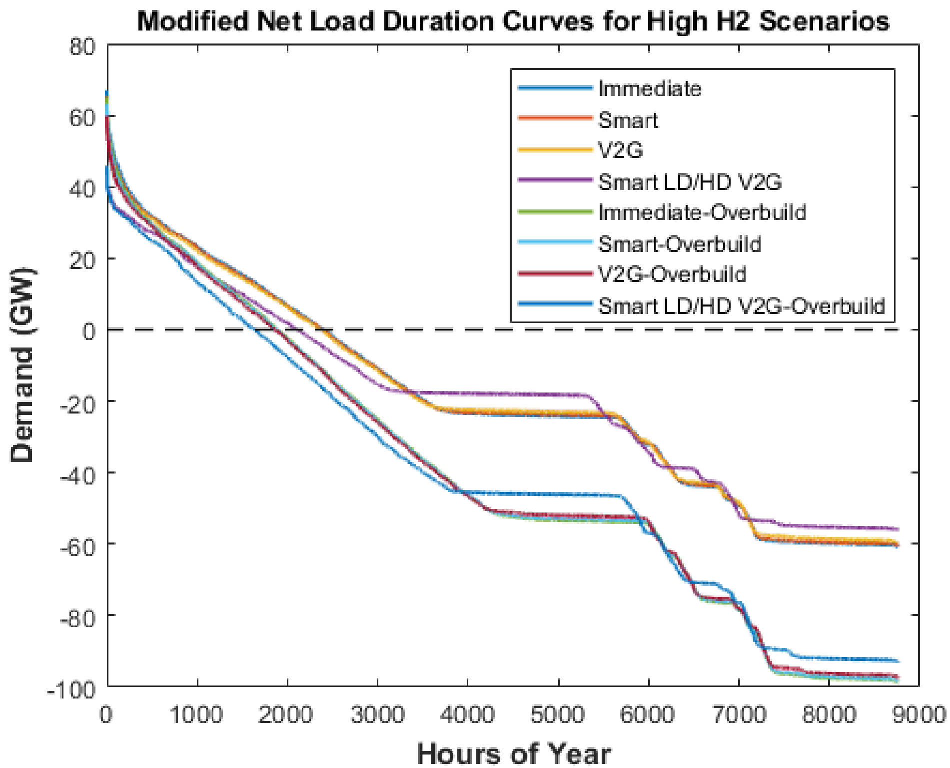


Figure 47. Modified Net Load Duration Curves for 100% Clean Grid: High H_2 Scenarios

The added charging strategy of combining light-duty vehicle smart charging with heavy-duty V2G-enabled charging further reduces peak demand compared to intelligent charging for heavy-duty vehicles only. Figure 48 isolates the High H_2 curves for V2G and Smart LD/HD V2G-enabled charging to highlight the difference between the two strategies. The V2G scenarios for both the baseline and overbuild cases have similar peak net demands despite the increase in renewable availability under the overbuild scenario. Deploying smart charging for light-duty vehicles shifts light-duty vehicle load demand to non-peak periods and more effectively reduces peak net demand compared to overbuilding renewable capacity. This indicates that light-duty vehicles were contributing significantly to peak net demand when relying on immediate charging.

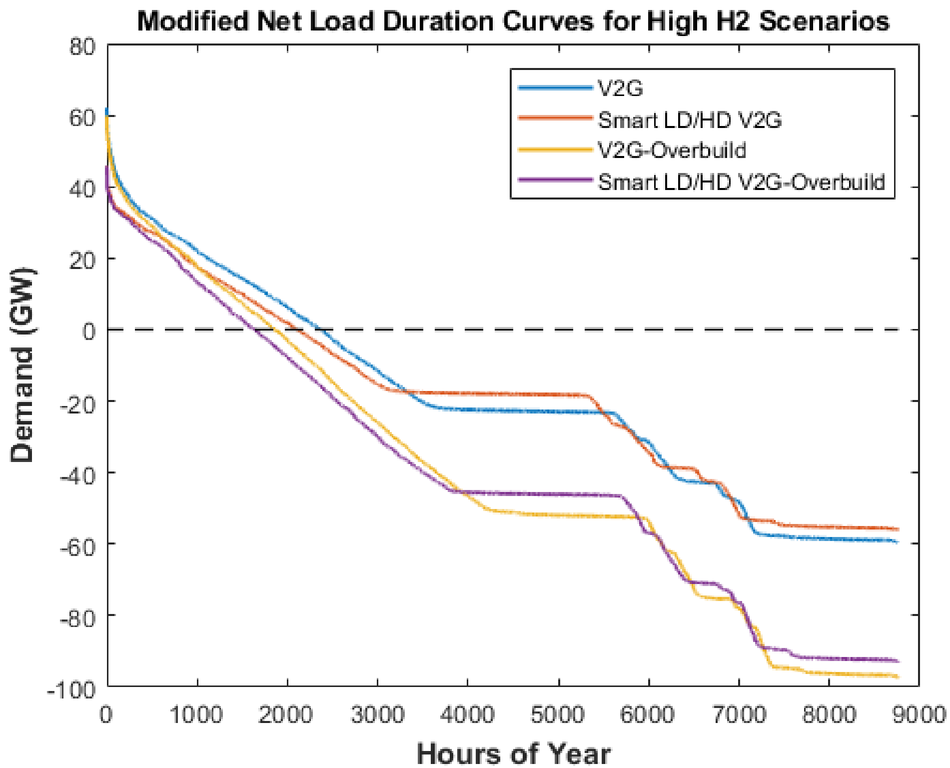


Figure 48. Modified Net Load Duration Curves Comparing Heavy-Duty V2G Only and Added Light-Duty Smart Charging

The decrease in peak net demand for each scenario is presented in Figure 49. For the 40% HD ZEV scenarios, increasing renewable capacity by 20-50% decreases peak net demand by up to 1.2-1.5 GW, and for the High H_2 scenarios, increasing the renewable capacity by 50-90% decreases peak net demand by up to 4.5-4.6 GW. The reduction of up to 4.6 GW in peak demand versus a peak increase in renewable capacity of 80 GW, indicates a low correlation between the timing of added renewable generation and demand. More effective is shifting the loads contributing to the peak net demand: heavy-duty and light-duty vehicles. For the 40% HD ZEV overbuild scenarios, switching from immediate charging to smart light-duty and V2G-enabled heavy-duty vehicles reduces the peak net load demand by 20%. For the High H_2

overbuild scenarios, switching to smart charging light-duty and V2G-enabled heavy-duty vehicles reduces peak net load demand by 24%.

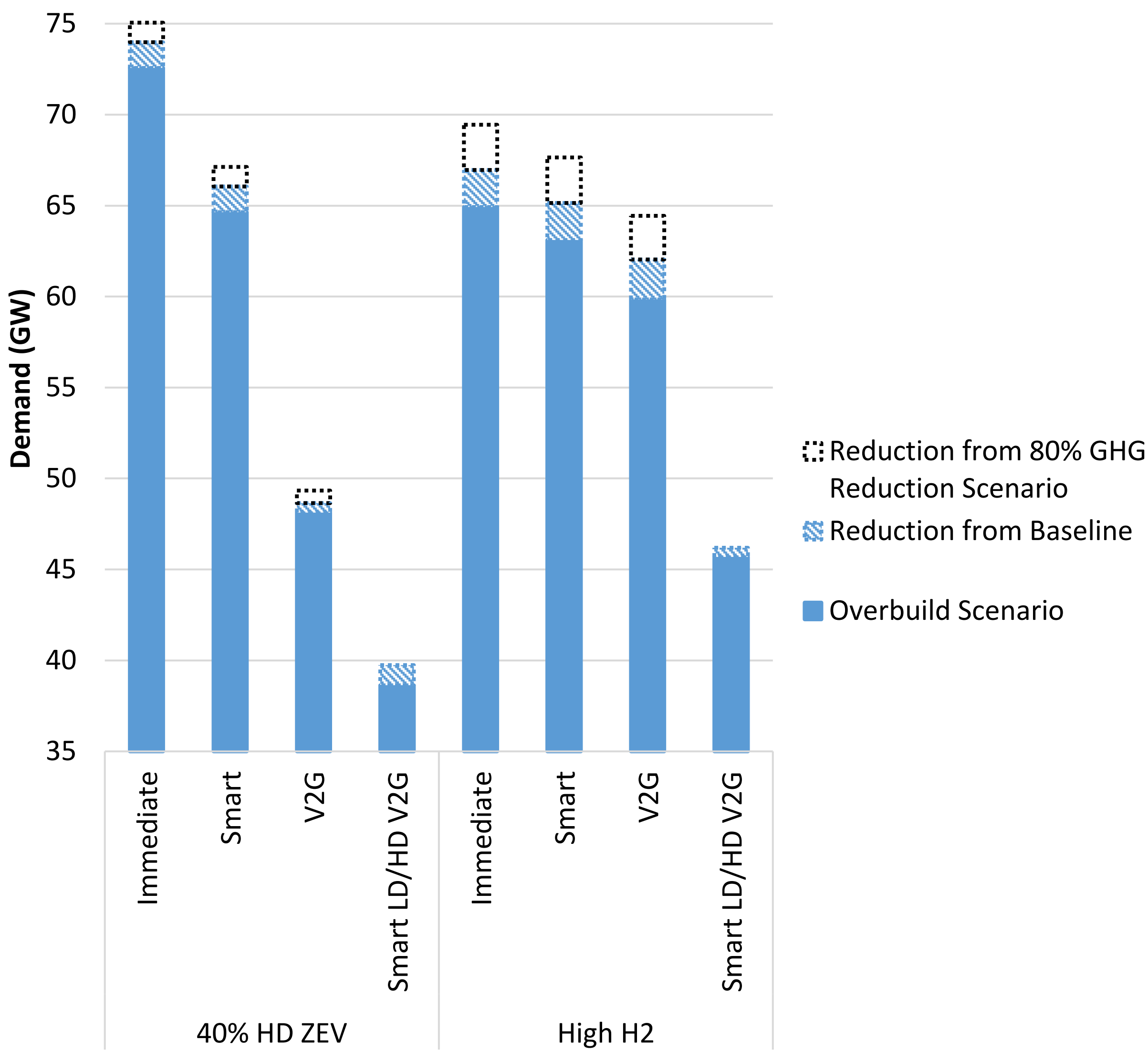


Figure 49. Change in Peak Net Load Demand with Increased Solar and Wind Capacity for 100% Clean Electric Grid Scenarios

The reduction in peak net demand for the heavy-duty intelligent charging scenarios is proportional to the BEV load demand that can be shifted to avoid peak load periods. For example, the High H_2 has about 23% of the heavy-duty BEV load demand compared to the 40% HD ZEV scenarios. Measuring load-shifting flexibility, switching from immediate to V2G charging for heavy-duty vehicles for the same scenarios reduces the peak demand by 7%, which is only 21% of the peak reduction realized for shifting from immediate to V2G-enabled HDV charging in the 40% HD ZEV scenarios.

Increasing renewable capacity also translates to incremental increases in renewable utilization, see Figure 50. In the 80% GHG reduction scenarios, the 40% HD ZEV cases resulted in a renewable penetration between 77% (with immediate charging) and 81% (with V2G-enabled charging). In the 100% clean grid baseline, renewable penetration increases 2-3% for each charging case. Despite increasing renewable capacity by 25% for the overbuild scenario, the resulting increase in renewable penetration is only 1-3%. For the High H_2 scenarios, renewable penetration increases 6-8% between the 80% GHG reduction scenarios and the 100% clean grid baseline. The overbuild scenario increases the renewable penetration another 1-2%. Utilizing smart light-duty vehicles in addition to V2G-enabled heavy-duty vehicles further increases the renewable penetration by 1-2% for all scenarios. The relatively small increase in renewable utilization demonstrates the limit in utilizing connected vehicles to increase renewable penetration. Vehicles are able to smooth the net load and utilize renewable generation, but cannot shift renewable energy across the longer time periods required to meet higher renewable penetration levels.

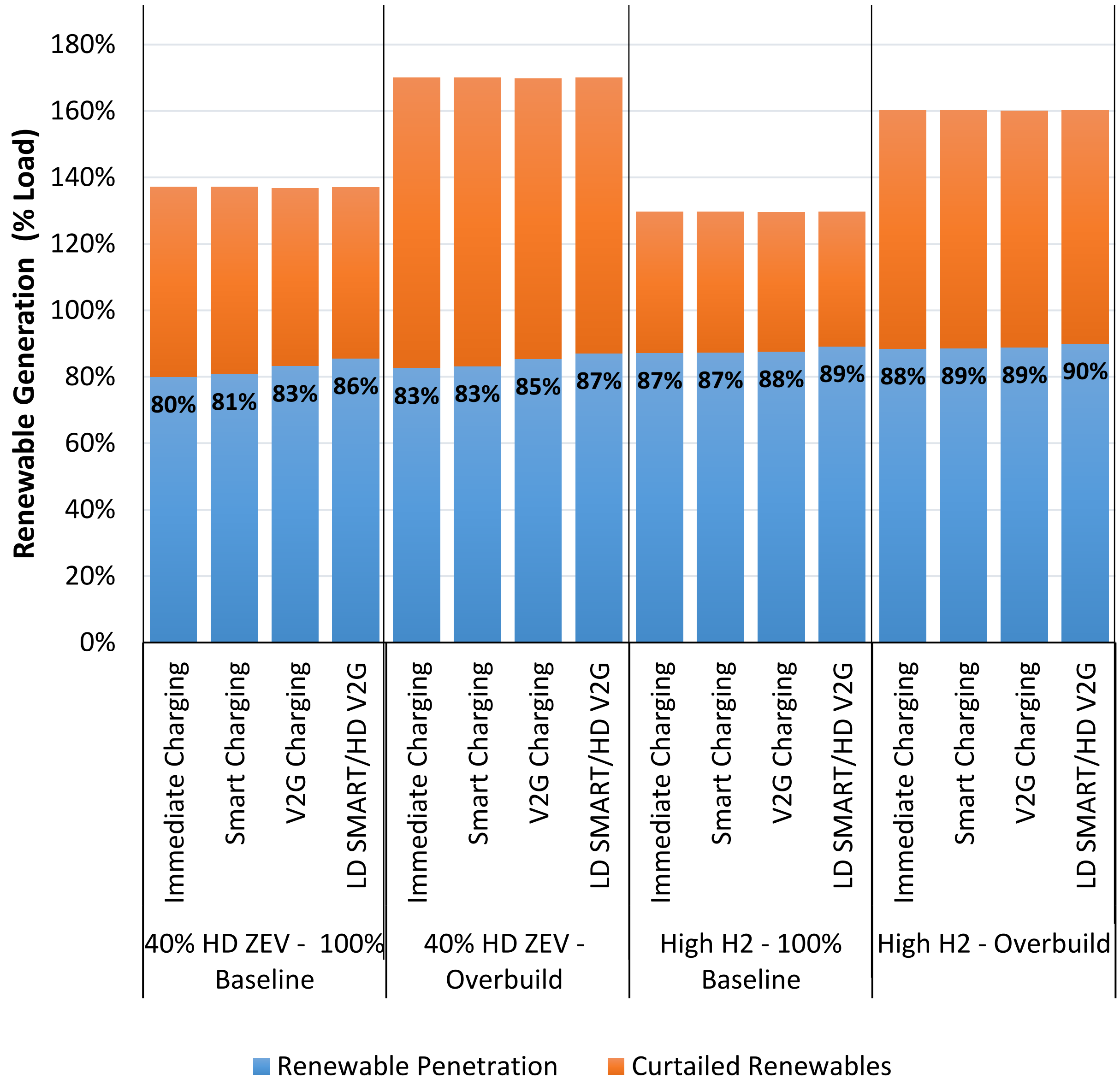


Figure 50. Initial Renewable Penetration for 100% Clean Electric Grid Scenarios before Added Energy Storage Capacity

In addition to changes in peak load demand, increasing renewable capacity and charging intelligence affects ramping requirements that must be met in order to achieve a 100% clean electric grid. The 0.025, 0.25, 0.50, 0.75, and 0.975 quantiles for hourly ramp rates are plotted for the high hydrogen immediate (labeled “Imm.”) and V2G charging scenarios (labeled “V2G”) for the baseline Renewable capacity are in Figure 51. The hourly ramp rates for the 40% HD ZEV immediate and V2G charging scenarios are in Figure 52.

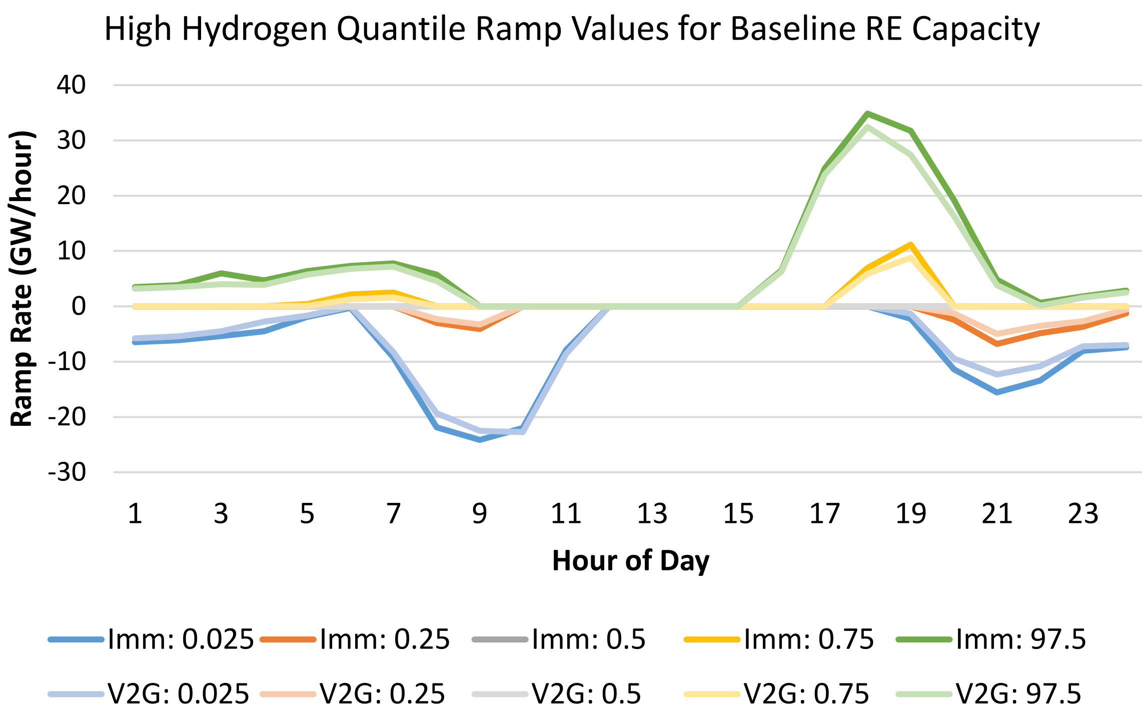
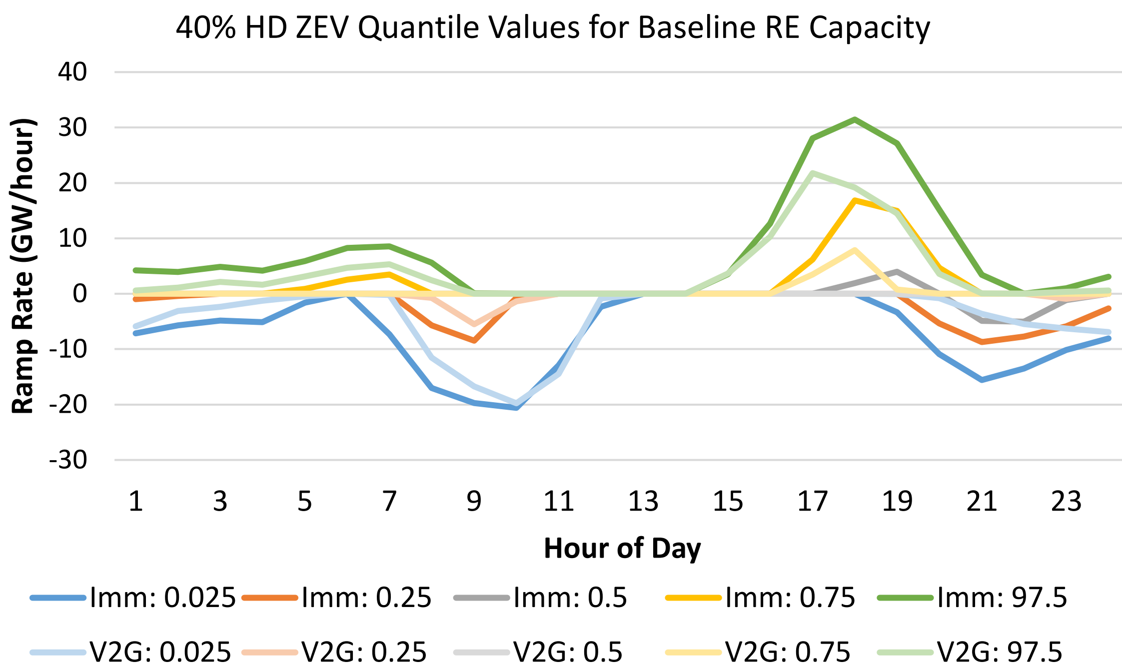


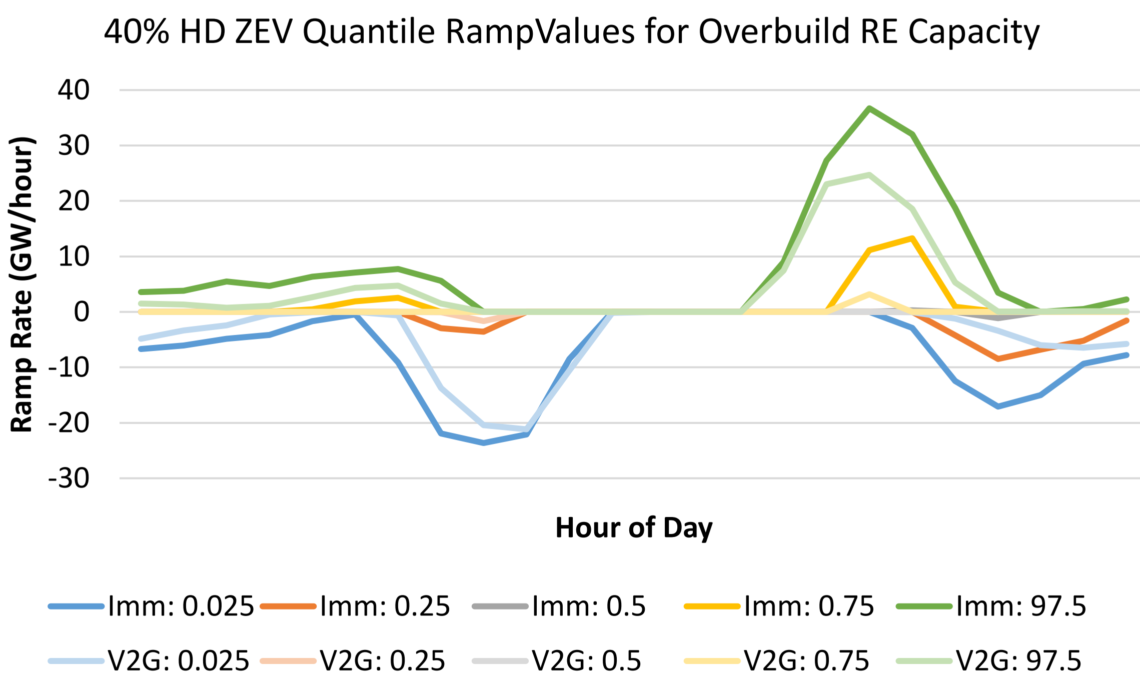
Figure 51. Hourly Ramp Rate Quantile Values for High Hydrogen Scenarios with Increased Renewable Capacity

Increasing renewable capacity for the 40% HD ZEV reduces non-zero median ramp rate magnitudes to zero, but increases the peak magnitudes for the 2.5% and 97.5% percentile (Figure 52b). Increasing charging intelligence reduces the frequency of high magnitude ramping events for both the 40% HD ZEV scenarios and High H_2 scenarios, but as was shown with reduction in peak demand, ramp reductions are dependent on the scale of BEV deployment, see Figure 51 and Figure 52a. Switching from immediate to V2G-enabled charging for the High H_2 scenarios has smaller reductions in ramp rate magnitudes compared to the same switch for the 40% HD ZEV, due to the lower BEV penetration. The higher electrolyzer capacity in the High H_2 scenarios is able to reduce the median ramp rate magnitude to zero for all hours even with

BEV immediate charging, but they do not address the magnitude of outlier peak ramp rate events.



a)



b)

Figure 52. Hourly Ramp Rate Quantile Values for 40% HD ZEV Scenarios with Increased Renewable Capacity, for a) Baseline Renewable Capacity and b) Overbuild Capacity

In order to meet a 100% clean electric grid, additional resources must be incorporated to balance the remaining load. For these scenarios, the combined energy storage capacity must be able to meet the remaining peak net demand and shift otherwise curtailed renewable generation to meet the remaining demand. The minimum amount of curtailed renewable energy that needs to be utilized in order to meet a 100% clean electric grid differs for each scenario. A summary of the renewable energy requirements for each scenario are in Table 23. The calculated percentages do not include round trip energy losses. The average daily energy demand remaining that needs to be met through energy storage for each scenario is in Table 24.

Table 23. Minimum Percent of Curtailed Renewable Energy Required to Meet Remaining Load

	40% HD ZEV – 100% Baseline	40% HD ZEV – Overbuild	High H2 – 100% Baseline	High H2 – Overbuild
Immediate Charging	26%	14%	21%	11%
Smart Charging	25%	13%	21%	10%
V2G Charging	22%	11%	20%	10%
LD SMART/HD V2G	18%	9%	17%	9%

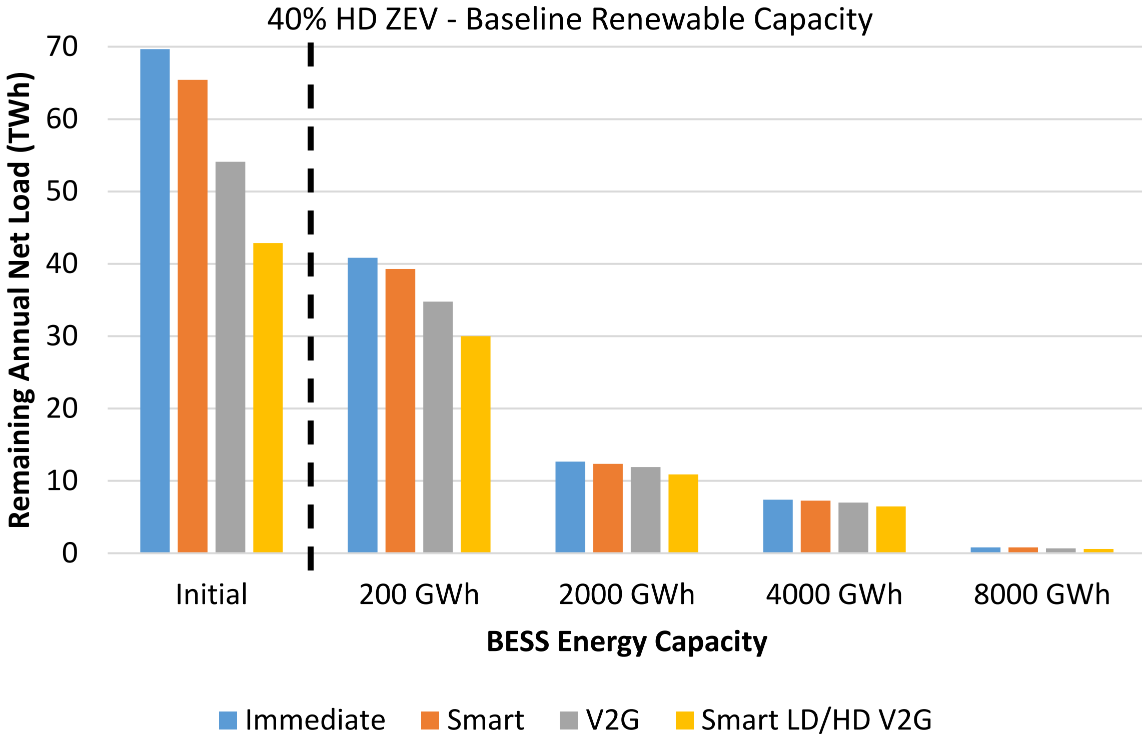
Table 24. Average Daily Energy Demand Remaining

	40% HD ZEV – 100% Baseline	40% HD ZEV – Overbuild	High H2 – 100% Baseline	High H2 – Overbuild
Immediate Charging	191 GWh	147 GWh	138 GWh	109 GWh
Smart Charging	179 GWh	138 GWh	136 GWh	107 GWh
V2G Charging	148 GWh	110 GWh	131 GWh	103 GWh
LD SMART/HD V2G	117 GWh	84.4 GWh	101 GWh	80.2 GWh

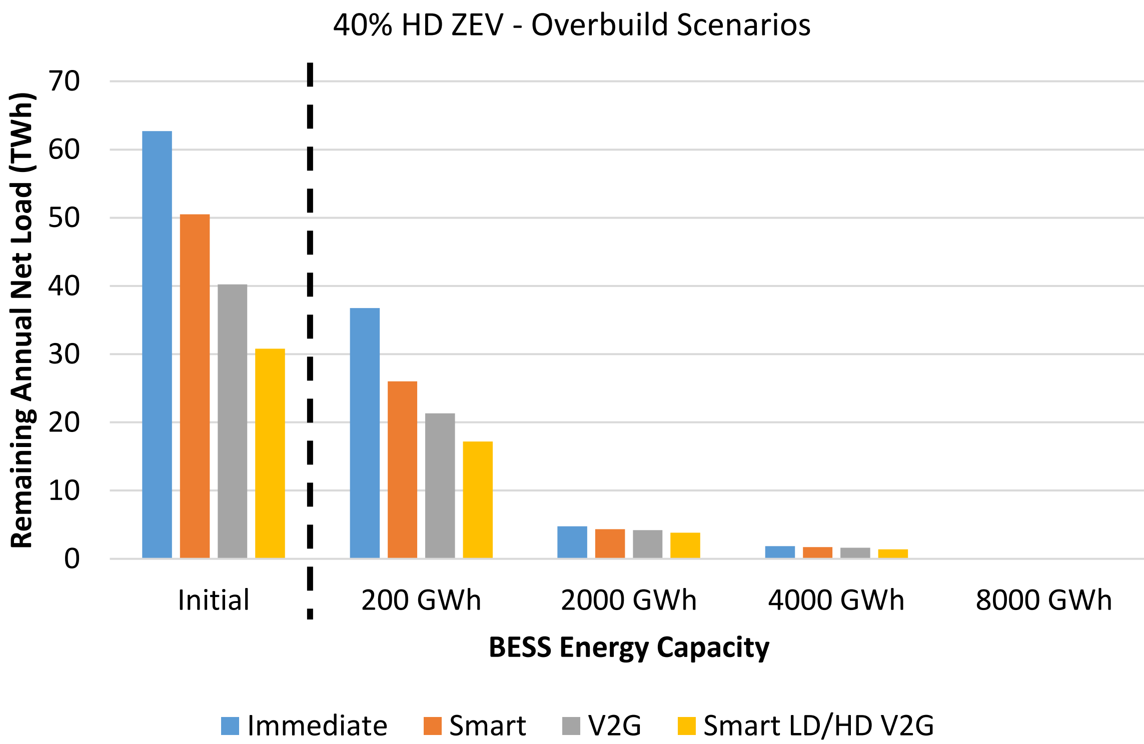
Increasing charging intelligence reduces the average daily energy demand that needs to be met with energy storage to reach a 100% clean electric grid. Switching from immediate to smart charging of heavy-duty BEVs, results in a 1-6% reduction in remaining demand, with the greater reduction achieved through higher heavy-duty BEV penetration. Switching from immediate to V2G, reduces remaining demand by about 25-26% for the 40% HD ZEV scenario, and switching for the High H_2 reduces the demand by 5-6%. The 40% HD ZEV scenario has a greater penetration of heavy-duty BEVs compared to the high H_2 scenario. Introducing smart light-duty BEV charging with V2G-enabled heavy-duty BEV deployment decreases remaining demand by 39-43% compared to immediate charging for the 40% HD ZEV scenario, and 26-27% for the High H_2 scenario.

For this analysis, BESS is assumed to have a round-trip efficiency of 90% and can discharge at maximum power for up to four hours. Hydrogen energy storage is assumed to have a round trip efficiency of 46% and discharge time at maximum power is spanned to meet demand. The maximum feasible discharge time limit is assumed to be one season or 2190 hours. BESS and hydrogen storage are spanned for each scenario to determine the scale of energy storage required to meet a 100% clean electric grid.

The initial spanning results for the BESS cases are presented in Figure 53 and Figure 54.

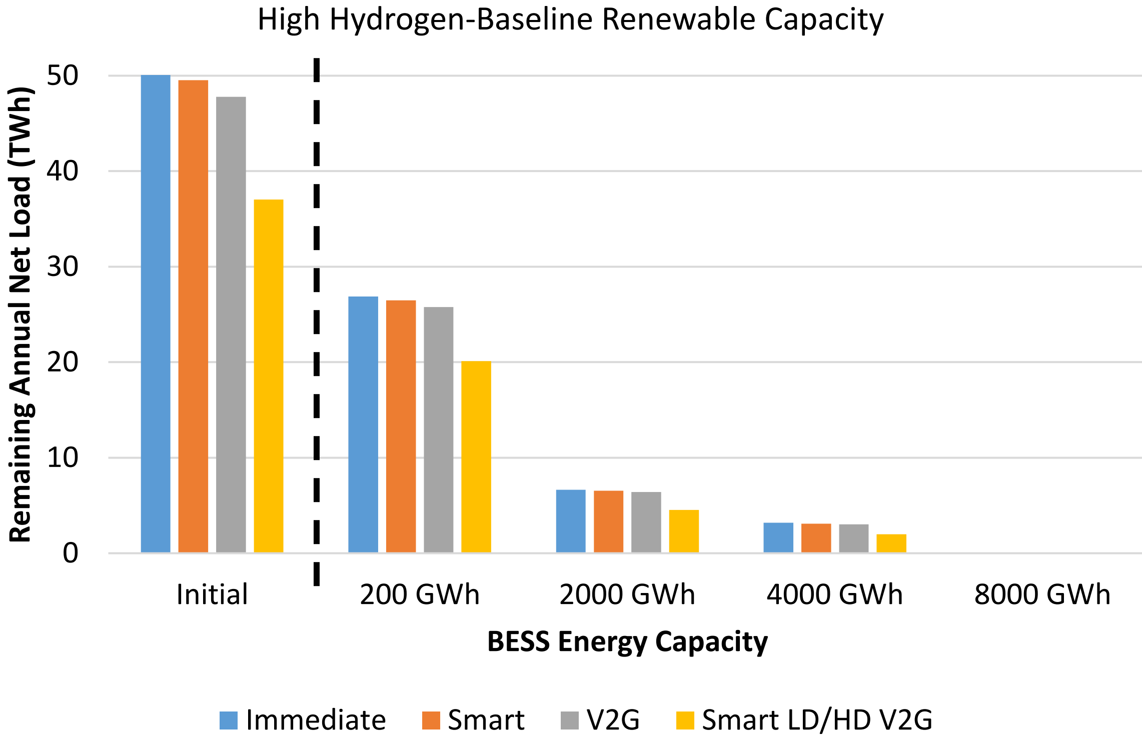


a)

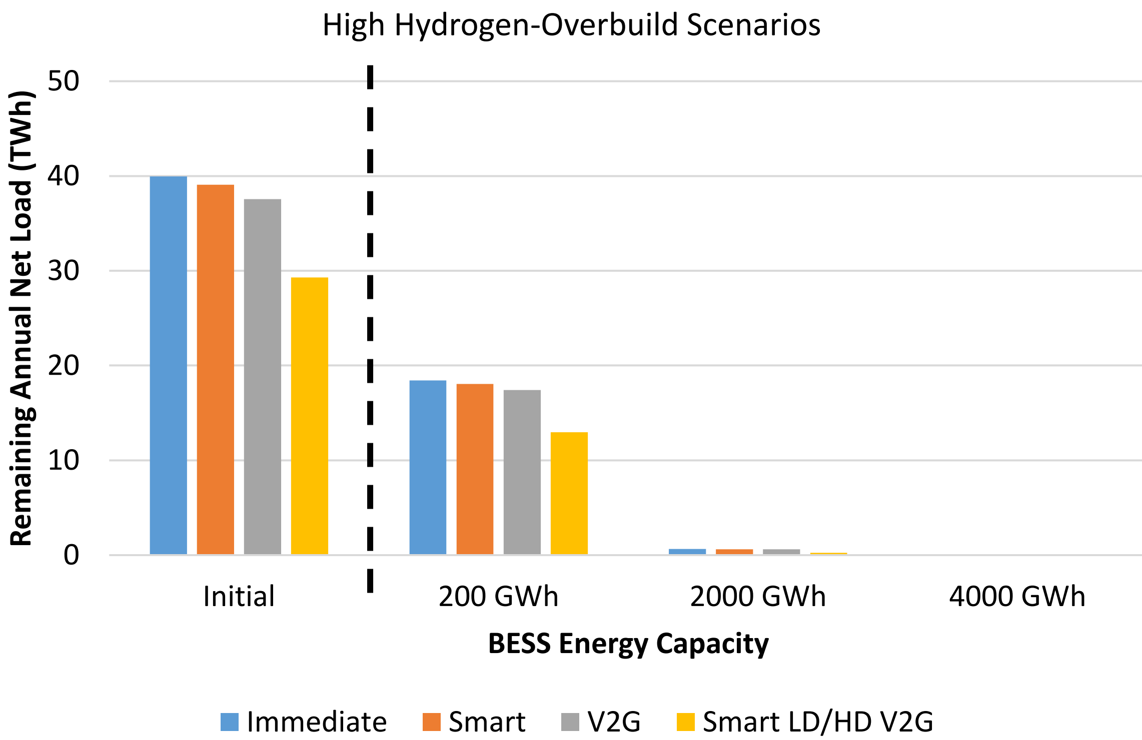


b)

Figure 53. Marginal Decreases in Remaining Annual Demand with Increased BESS Capacity: 40% HD ZEV Scenarios



a)



b)

Figure 54. Marginal Decreases in Remaining Annual Demand with Increased BESS Capacity: High H_2 Scenarios

It is more challenging to reach a 100% clean electric grid for the baseline scenarios due to the lower availability of curtailed renewables. In order to achieve a 100% clean electric grid, curtailed renewable generation must be captured and stored for a large portion of the year. Overbuilding renewable capacity significantly reduces the energy storage capacity required to meet the 100% renewable target for both the 40% HD ZEV and the High H_2 scenarios.

The final BESS energy capacities for each scenario at the 100% clean electric grid target are in Figure 55.

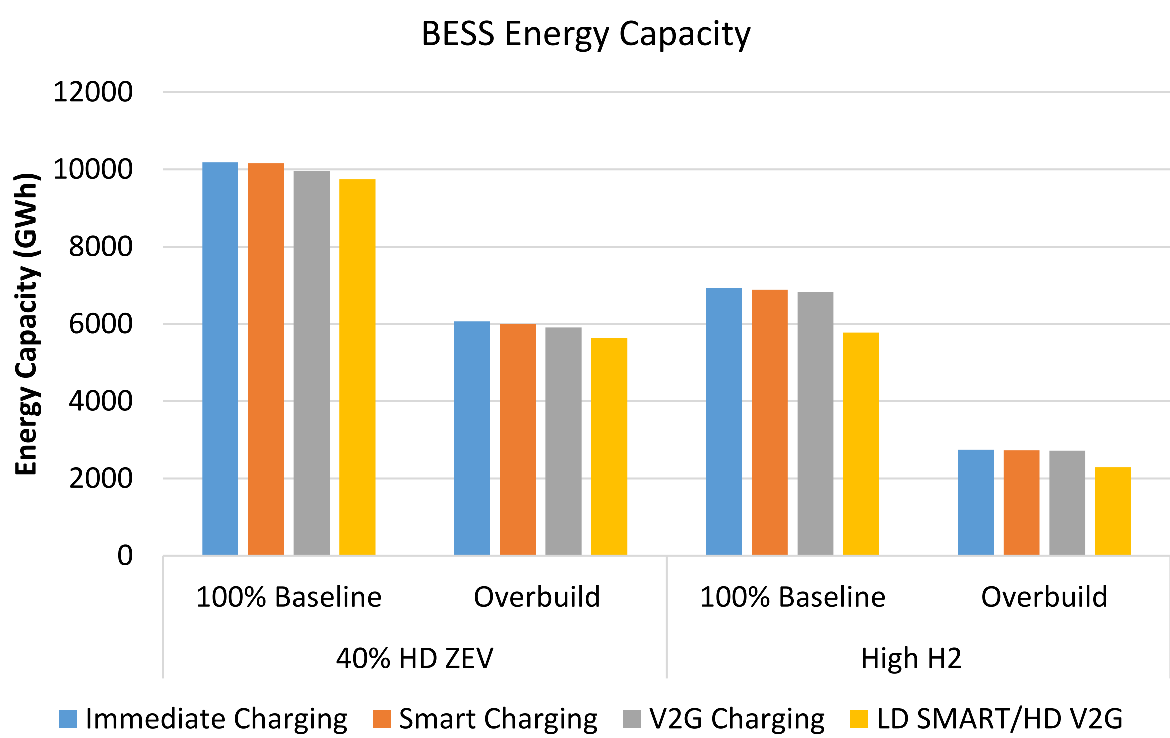


Figure 55. BESS Energy Capacities for 100% Clean Electric Grid Scenarios

Increasing heavy-duty vehicle charging intelligence has relatively small changes in BESS capacity demands. In the 40% HD ZEV and High H2 scenarios, heavy-duty vehicles charge at home base only. Therefore, they are less able to shift demand to increase solar generation utilization, limiting their use to increase renewable penetration. Adding smart charging of light-duty BEVs reduces BESS energy capacity. However, renewable capacity assumptions have a larger impact on energy storage capacity requirements compared to changes in vehicle charging intelligence.

The hydrogen energy capacity required to reach 100% clean electric grid for each scenario is in Figure 56.

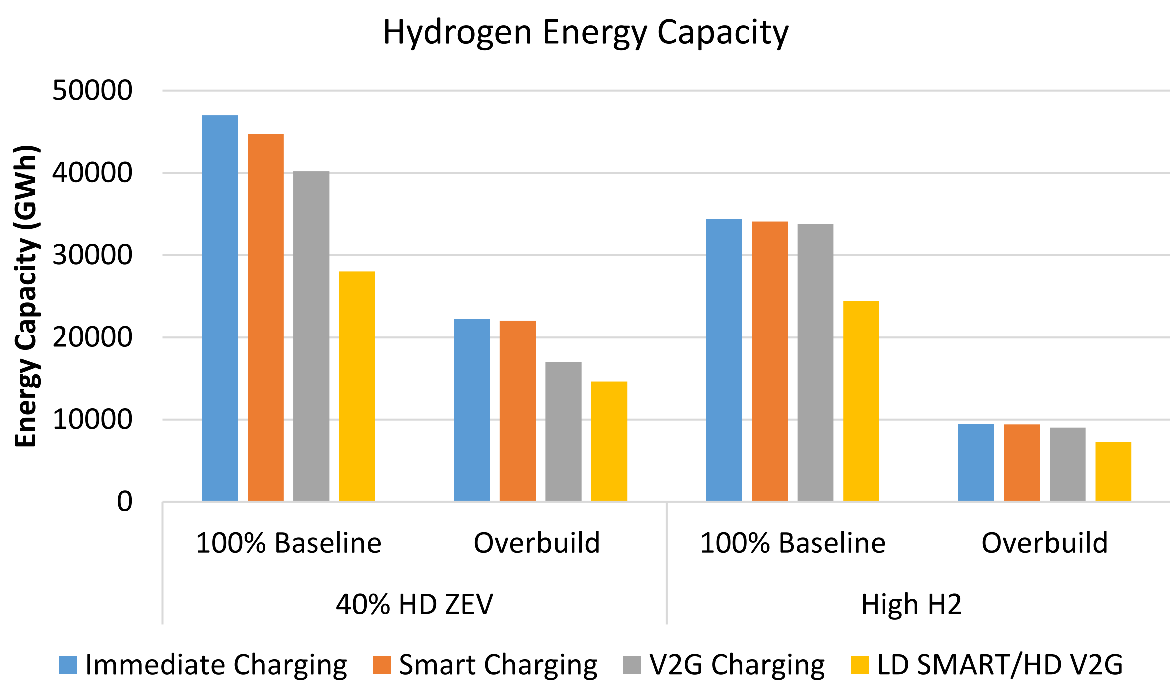


Figure 56. Hydrogen Energy Capacities with 80 GW Power Capacity for 100% Clean Electric Grid Scenarios

The energy capacity required to reach a 100% clean electric grid with hydrogen energy storage is significantly greater than for BESS due to the difference in round-trip efficiencies. However, due to the decoupling of power and energy capacity, the power capacity required to meet a 100% clean grid significantly decreases, see Figure 57, with the minimum required power capacity of the hydrogen energy storage system being equal to the minimum generation required to meet remaining peak demand.

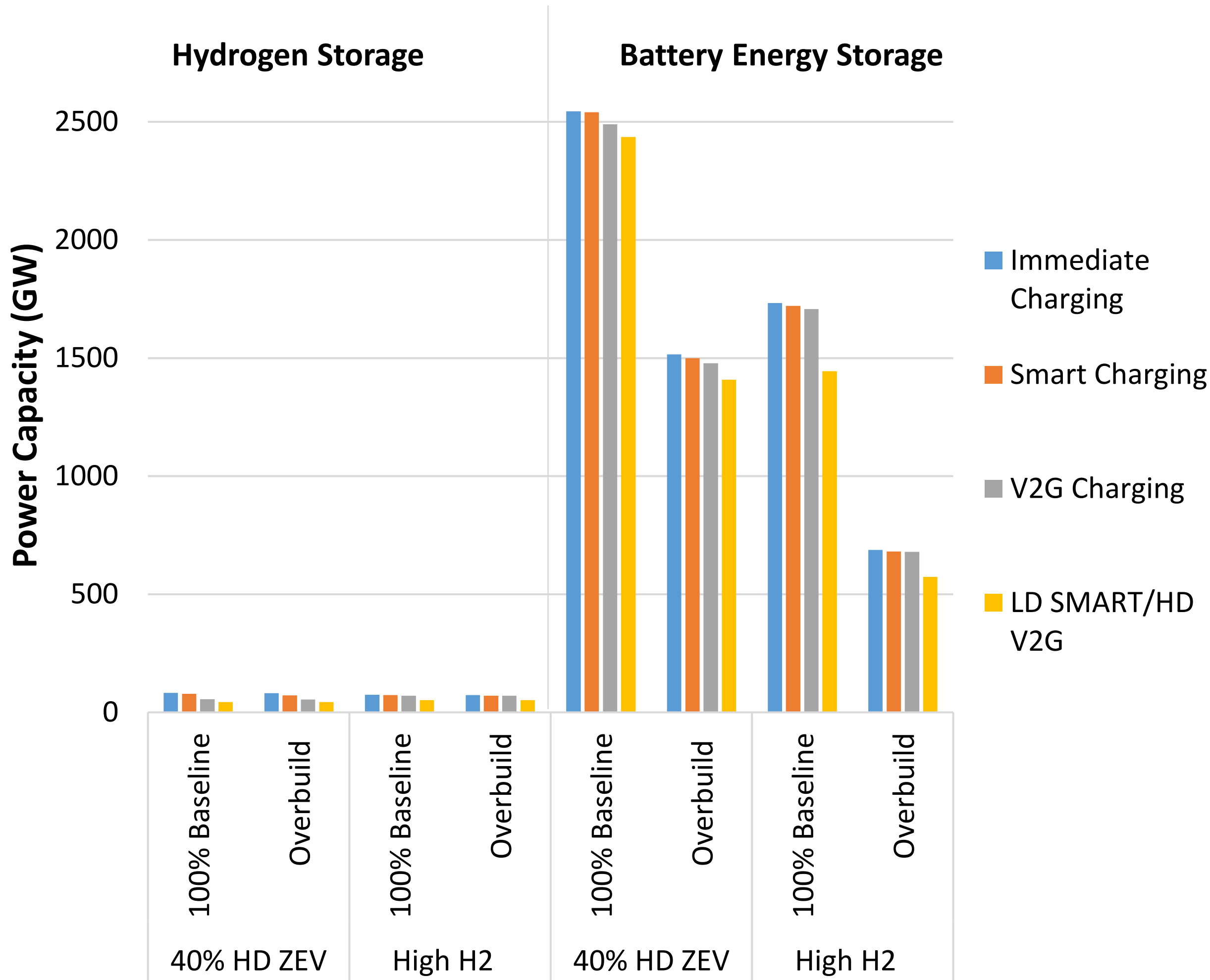


Figure 57. Minimum Energy Storage Power Capacities Required to Reach a 100% Clean Electric Grid Target

The fixed power to energy ratio of 1:4 for the BESS drives the higher power capacity of the energy storage fleet compared to the hydrogen storage cases. Conversely, the lower power capacity of the hydrogen storage is paired with a greater energy capacity that is achieved through longer-term underground storage of the hydrogen.

6.2 GHG Emissions

The integration of renewable electricity is primarily driven by the goal of reducing GHG emissions. Therefore, assessing the impact of deploying heavy-duty zero-emission vehicles on overall GHG emissions is critical. In order to determine the net impact of ZEV deployment, the changes in GHG emissions from both the grid and the transportation sector are assessed. The grid and transportation GHG emissions are calculated in tons of CO_2e using the following equation:

$$CO_2e = 1CO_2 + 25CH_4 + 298\ N_2O \tag{9}$$

where, tons of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) are weighted by their 100-year global warming potential values relative to CO_2. Carbon dioxide is the predominant GHG produced by electricity production and transportation, with a weighted contribution of around 95% of the total tons of CO_2e.

Increases in the ZEV populations will decrease emissions from the transportation sector, but integrating them onto the electric grid, either directly through BEVs or indirectly through hydrogen production, may have positive or negative impacts on the electric grid's GHG emissions, depending on how they are integrated. The change in grid GHG emissions for each scenario is in Figure 58. The CPR base case with immediate charging represents the approximate grid emissions reductions needed to support an economy-wide 80% in GHG reductions compared to 1990 levels. Emissions from the electric grid come from two sources: load-following natural gas combined cycle power plants and natural gas peaker power plants. The change in grid GHG emissions between the scenarios is a fraction of the remaining 20% of emissions still being emitted. In the highest GHG emission case-High H_2 with immediate charging, this translates to 74% reduction in GHG emissions below 1990 levels. The greatest reduction is High BEV with V2G charging: 85% reduction in GHG emissions below 1990 levels.

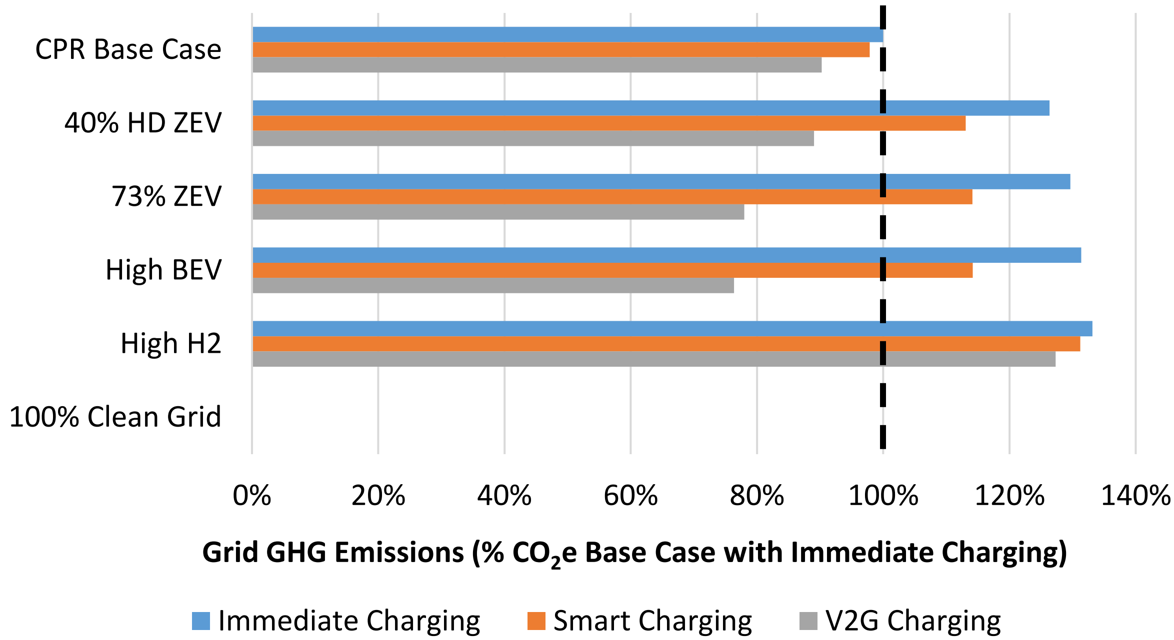


Figure 58. Change in Grid GHG Emissions for All 80% GHG Reduction Scenarios

All immediate and smart charging scenarios result in GHG emissions increases compared to the CPR base case. Increasing heavy-duty vehicle charging intelligence from immediate to smart charging results in reduced emissions. Switching to smart charging is more effective in reducing grid GHG emissions for scenarios with higher heavy-duty BEV deployments (40% HD ZEV, 73% HD ZEV, and High BEV). Increasing charging intelligence is least effective for the High Hydrogen scenarios. Increasing charging intelligence to V2G charging further reduces emissions from the respective immediate charging scenarios, and emissions drop below the CPR base case for the 73% HD ZEV and High BEV scenarios for V2G charging. The 40% HD ZEV scenario with V2G charging results in GHG emissions only slightly higher than the CPR base case.

In the 100% clean electric grid scenarios, the inclusion of additional renewable capacity alone reduces grid GHG emissions compared to the 80% GHG reduction scenarios, see Figure 59. Increasing the renewable capacity by 20% for the baseline 100% clean electric grid scenarios reduces emissions by 17-29% compared to the corresponding 80% GHG reduction scenarios. Further increasing the renewable capacity by 25% for the 40% HD ZEV scenarios reduces emissions by another 11-17% compared to the corresponding 80% GHG reduction scenarios. This reduction highlights the dependency of grid GHG emissions on the renewable capacity installed. It also demonstrates diminishing returns in overbuilding renewable capacity. As shown in Section 6.1.2, as renewable capacity increases, more of the added generation is curtailed and a decreasing margin of the new generation resource offsets natural gas generation.

The trends between charging strategies remain consistent compared to the previous scenarios, with increasing charging intelligence reducing grid GHG emissions. Adding light-duty BEV smart charging to the V2G charging heavy-duty vehicle scenarios further decreases grid GHG emissions. As analyzed in Section 6.1.2, smart charging of the light-duty BEV population further reduces reliance on both peaker and load-following power plants by smoothing the net load and increasing renewable utilization. For the completed scenarios, zero-emission energy storage replaces all natural gas power plants thereby zeroing the GHG emissions coming from electricity generation.

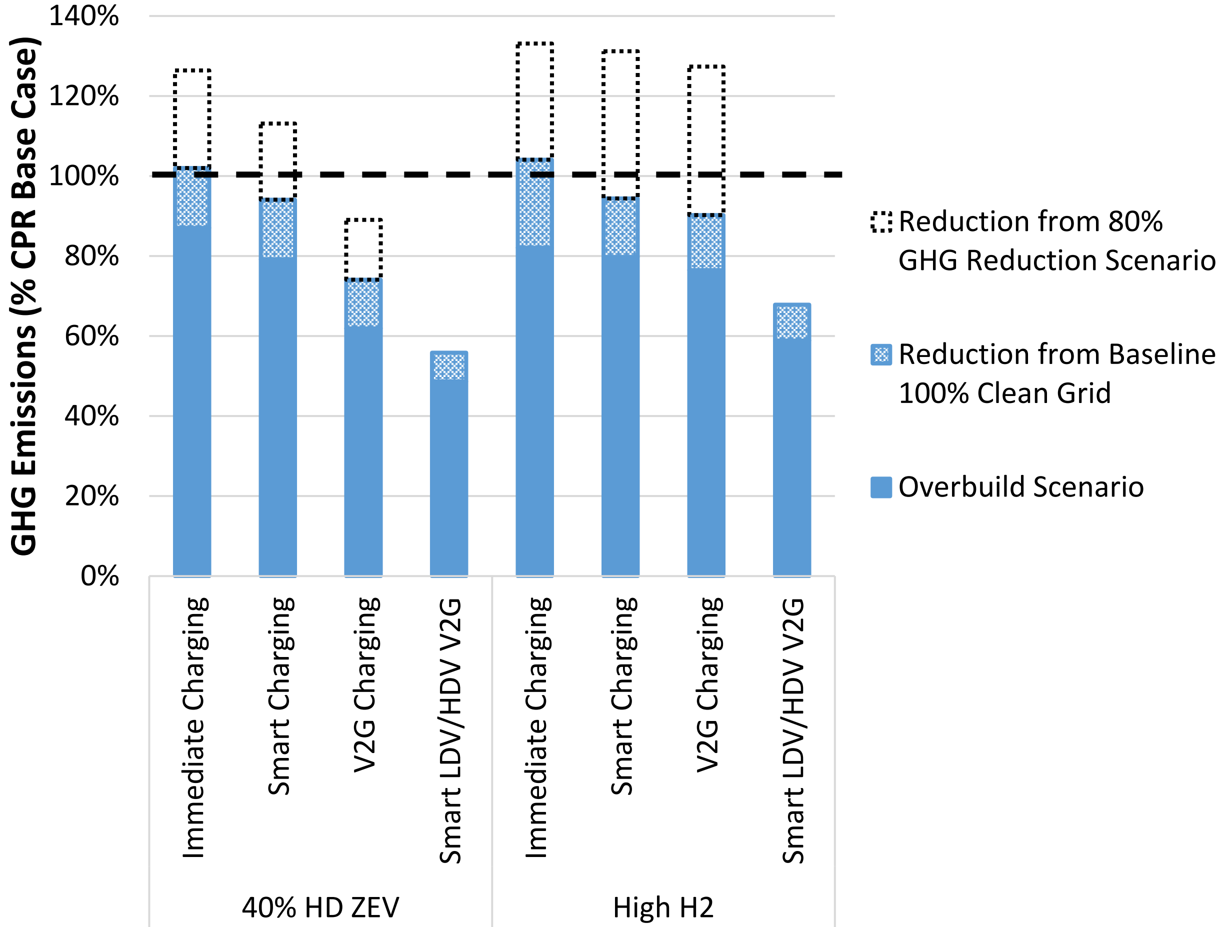


Figure 59. Change in Grid GHG Emissions with Increased Solar and Wind Capacity for 100% Clean Electric Grid Scenarios

Emissions reductions from the transportation sector are driven by the number of vehicle miles that can be met with ZEVs. Switching between immediate, smart, and V2G charging strategies for the same ZEV deployment portfolio does not change the emissions reductions from the transportation sector. The GHG emissions reductions compared to the CPR base case are presented in Figure 60. Emissions for the EMFAC 2050 Baseline are taken from [1] and emissions factors are calculated from [1,150,308]. The EMFAC 2050 Baseline does not incorporate any policies mandating the adoption of ZEVs, the CPR base case incorporates current policies, and the four expanded ZEV scenarios include 80% GHG reduction targets for light-duty and bus categories (kept constant between the four scenarios).

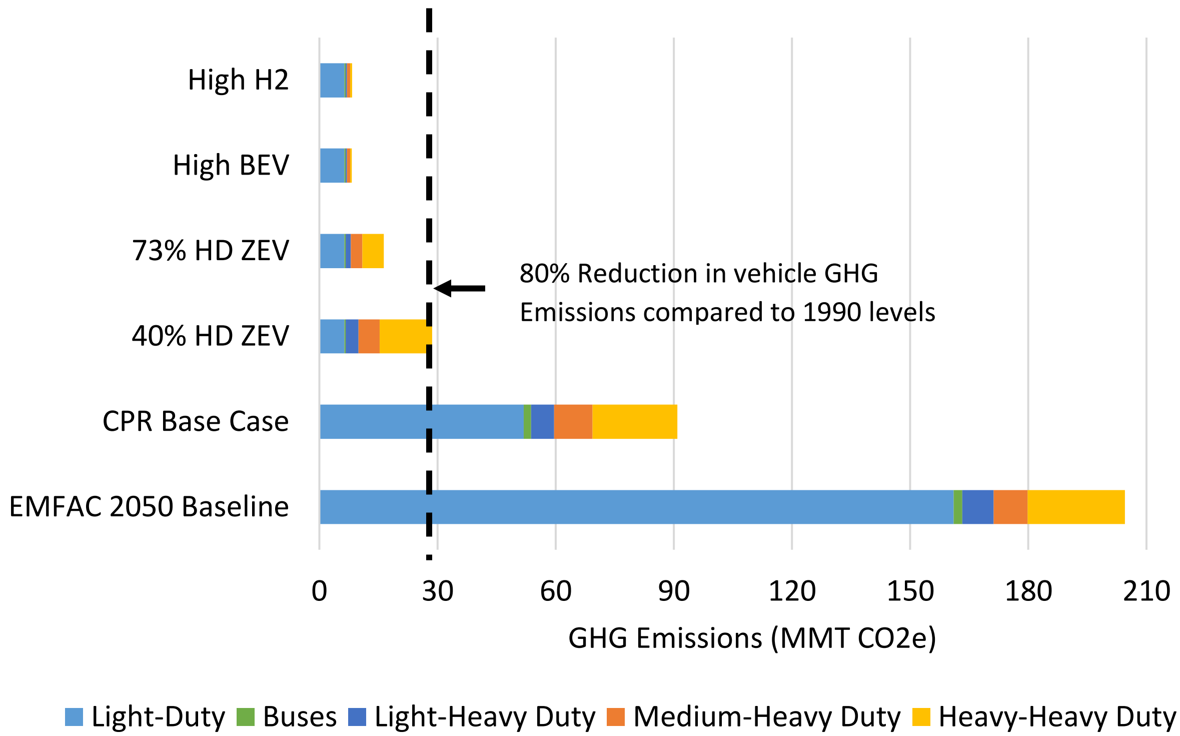


Figure 60. Change in Transportation GHG Emissions for All Scenarios

The 40% HD ZEV scenario results in the target 80% reduction in GHG emissions compared to 1990 levels. The remaining three scenarios (73% HD ZEVs, High BEV, and High H_2) represent a greater than 80% reduction in emissions. Decreasing transportation vehicle emissions below an 80% reduction may offset increased emissions from the grid. Also, the higher reduction in emissions may have increased benefits in terms of air quality.

6.3 Air Quality Analysis

The air quality analysis for the heavy duty ZEV scenarios focuses on changes in ozone and $PM_{2.5}$ concentrations during peak seasonal events. The State and National Ambient Air Quality Standards for tropospheric ozone and $PM_{2.5}$ are listed in Table 25, data from [309].

Much of the state is in nonattainment for ozone and the San Diego, Southern California, and San Joaquin air basins being in non-attainment for $PM_{2.5}$ [11].

Table 25. Ambient Air Quality Standards

Pollutant	Averaging Time	California Standard	U.S. Standard (primary)
Ozone (O_3)	1 hour	90 ppb	(none)
	8 hour	70 ppb	(Same as CA)
Particulate Matter ($PM_{2.5}$)	24 hour	(none)	35 μg/m^3
	Annual average	12 μg/m^3	12 μg/m^3

Two-week periods in January and July are selected as "peak episodes," representing the periods when conditions are prime for peak criteria pollutant concentrations. Peak events for ozone occur during the summer, driven in part by seasonal photochemical conditions [310]. Peak events for $PM_{2.5}$ occur during both winter and summer [311]. The first three days of the simulation are excluded from the results as model spin up, where the initial condition assumptions are dominating pollutant emission concentrations results. The remaining 11 days are used to calculate the average change in pollutant concentrations and the peak change in concentrations.

6.3.1 Air Quality Impacts of Zero Emission Vehicle Deployment

Changes in air quality presented are the result in changes from vehicle and grid emissions compared to the CPR base case. The change in the 8-hour average for ozone concentration and the 24-hour average for $PM_{2.5}$ concentration for select scenarios are in Table 26. It also includes the change in the absolute peak for both criteria pollutants for the same periods. The changes in ozone and PM2.5 concentrations are mostly due to changes in NOx emissions. The change in PM2.5 concentrations includes reductions in NH_3NO_3 particles due to reduced emissions of NOx and NH_3 [312].

Table 26. Change in Criteria Pollutants Compared to CPR Base Case

	Summer Ozone Peak	**Summer Ozone Average**	**Summer PM2.5 Peak**	**Summer PM2.5 Average**	**Winter PM2.5 Peak**	**Winter PM2.5 Average**
40% HD ZEV-Immediate	-5.70 ppb/ -8.5%	-2.31 ppb/ -2.9%	-1.03 ug/m^3	-0.47 ug/m^3	-2.86 ug/m^3	-1.58 ug/m^3
73% HD ZEV-Immediate	-10.36 ppb/ -16.0%	-4.18 ppb/ -6.7%	-2.20 ug/m^3	-1.03 ug/m^3	-6.31 ug/m^3	-3.48 ug/m^3
High BEV-Immediate	-12.59 ppb/ -19.4%	-5.08 ppb/ -8.5%	-2.77 ug/m^3	-1.30 ug/m^3	-7.90 ug/m^3	-4.36 ug/m^3
High BEV-V2G	-12.90 ppb/ -20.1%	-5.44 ppb/ -9.3%	-2.86 ug/m^3	-1.37 ug/m^3	-8.68 ug/m^3	-4.62 ug/m^3
High H_2 - Immediate	-12.58 ppb/ -19.4%	-5.07 ppb/ -8.5%	2.77 ug/m^3	-1.30 ug/m^3	-7.88 ug/m^3	-4.35 ug/m^3

The first three scenarios selected represent increased heavy-duty ZEV deployment for the state. For these scenarios, grid emissions increase 26-31% compared to the CPR base case. At the same time, transportation emissions decrease by 69-91%. The net impact is a reduction in peak and average $PM_{2.5}$ and tropospheric ozone concentrations. Greater reductions in peak and average ozone and $PM_{2.5}$ concentrations are observed as the level of ZEVs increase. The High BEV scenario with immediate charging and the High Hydrogen scenario with immediate charging result in nearly identical impacts on air quality. Grid emissions for both scenarios are within 2% of each other, and they have the same vehicle emissions assumptions. The greatest reduction for the 80% GHG reduction scenarios is achieved for the High BEV scenario with V2G. This scenario combines the highest ZEV deployment and the lowest grid emissions.

In addition to statewide changes in emissions, it is important to consider spatial patterns. The location of pollutant reductions is critical in evaluating the potential health benefits and assessing whether the reduction is occurring in locations currently in noncompliance. Also, while there is an average reduction across the state, it is important to observe whether any regions are negatively impacted. The maximum change in the average 8-hour ozone concentrations compared to the CPR base case are plotted in Figure 61 for the 40% HD ZEV Scenario with Immediate Charging and in Figure 62 for High BEV Scenario – Immediate Charging. High BEV Scenario –V2G is in Figure 63.

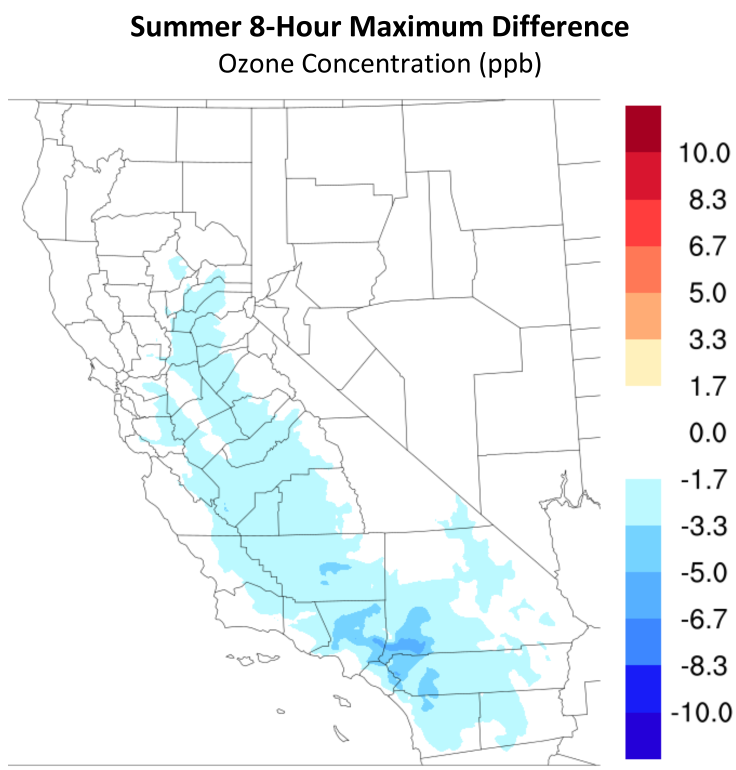


Figure 61. Change in Peak Summer 8-hour Average O_3 Concentration: 40% HD ZEV Scenario – Immediate Charging

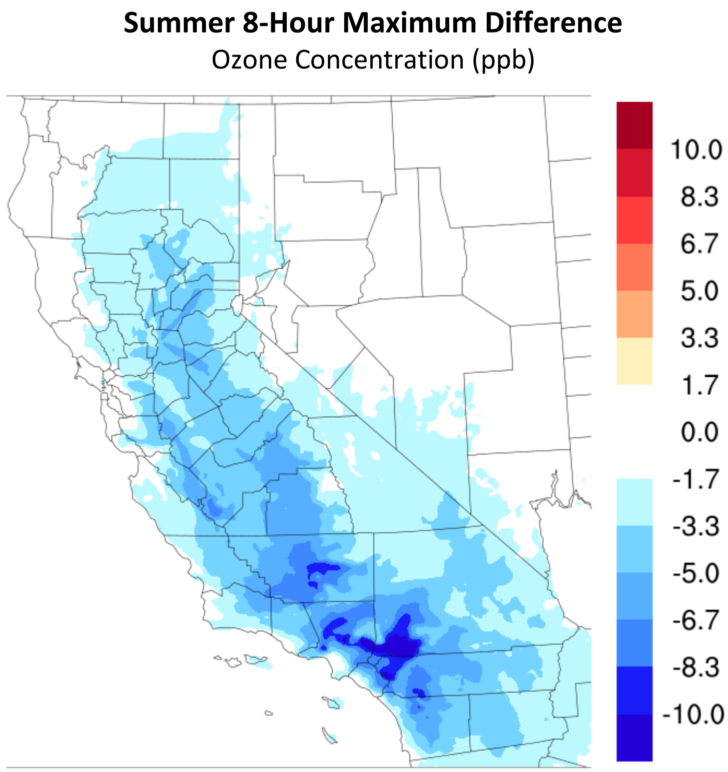


Figure 62. Change in Peak Summer 8-hour Average O_3 Concentration: High BEV Scenario – Immediate Charging

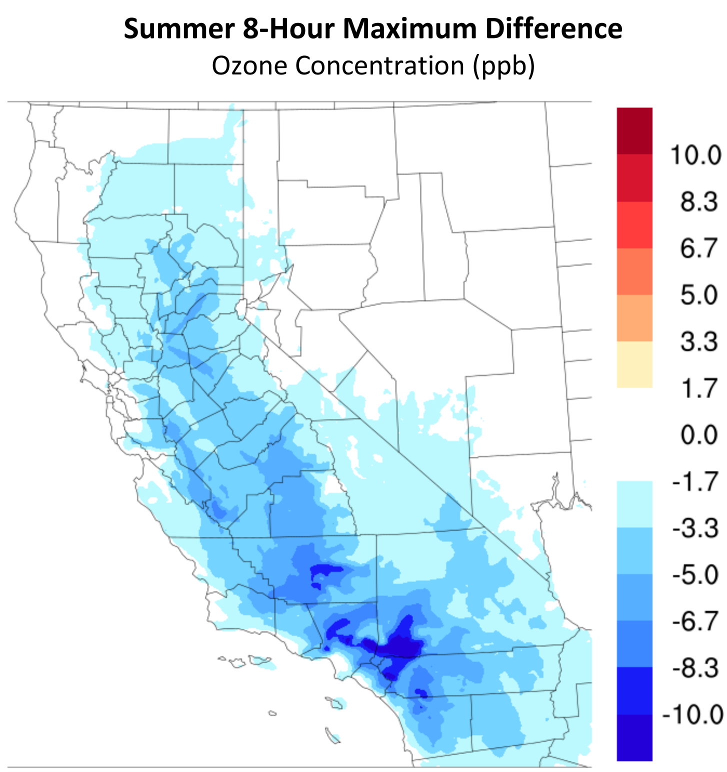


Figure 63. Change in Peak Summer 8-hour Average O_3 Concentration: High BEV Scenario–V2G

Increasing ZEV deployment compared to the CPR base case significantly reduces peak and average ozone concentrations. The difference between the CPR base case and the presented scenarios includes an increase in light-duty, bus, and heavy-duty zero emission vehicles. The greatest reductions are observed in the south coast air basin and Kern County. Reductions extend north, south, with reductions observed for most of the San Joaquin Valley as well as portions of the Sacramento valley and east of Sacramento. Further increasing the heavy-duty ZEV deployment (Figure 62) results in additional reductions, with most of the state seeing reductions in 8-hour ozone concentrations of at least 1.7 ppb during a peak event. Again the highest reductions are observed in the south coast air basin and Kern County, peaking around -11 ppb below the CPR base case. The average reduction across the state is more than twice the reduction observed for the 40% HD ZEV scenario. The difference between these scenarios is a more than doubling of VMT met by heavy-duty ZEVs and a less than 5% change in GHG emissions from the electric grid.

Increasing ZEV deployment compared to the CPR base case also reduces $PM_{2.5}$ concentrations, see Figure 64, Figure 65, and Figure 66 for summer results. The 40% HD ZEV scenario with immediate charging results in reductions in the south coast air basin, San Joaquin Valley, and Sacramento region compared to the CPR base case. Increasing heavy-duty ZEV deployment further reduces the average and peak $PM_{2.5}$ concentrations, expanding the impacts across the state. Maximum reductions were still observed in the same regions.

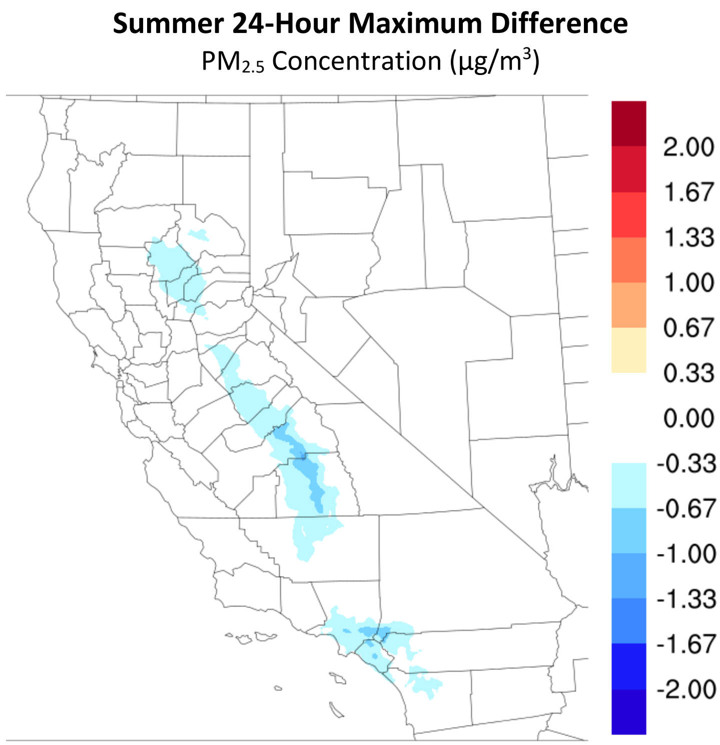


Figure 64. Change in Peak Summer 24-hour Average $PM_{2.5}$ Concentration: 40% HD ZEV Scenario – Immediate Charging

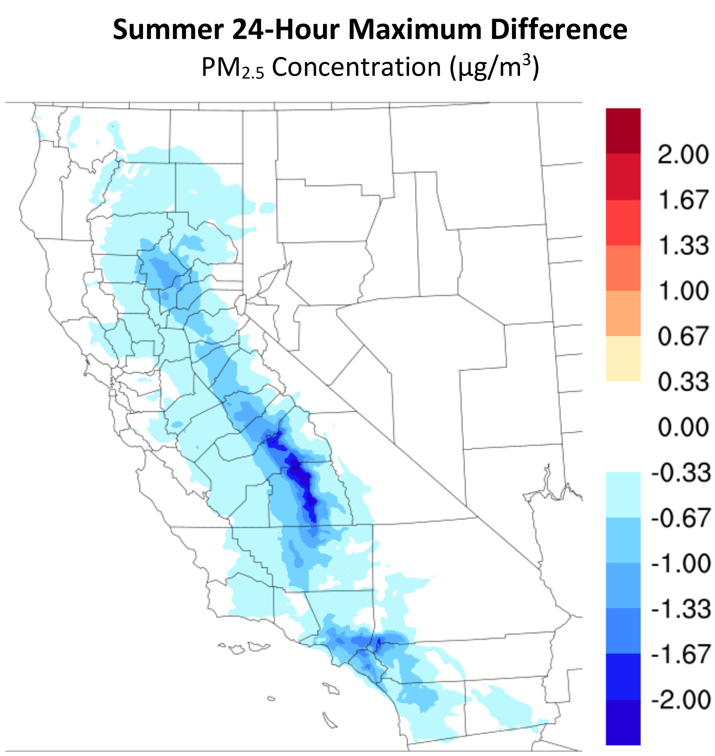


Figure 65. Change in Peak Summer 24-hour Average $PM_{2.5}$ Concentration: High BEV Scenario – Immediate Charging

Summer 24-Hour Maximum Difference

PM$_{2.5}$ Concentration (µg/m^3)

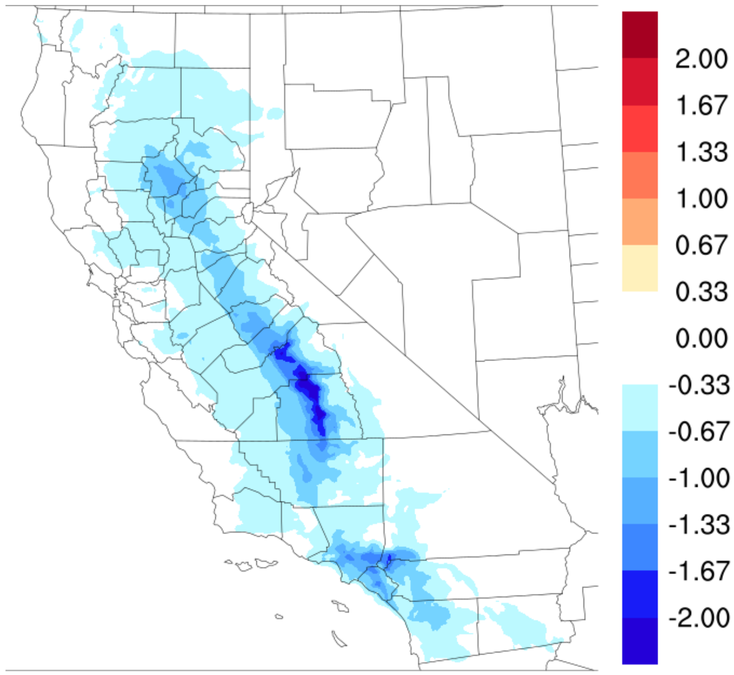


Figure 66. Change in Peak Summer 24-hour Average PM$_{2.5}$ Concentration: High BEV Scenario – V2G

Comparing seasonal impacts, reductions shift west in winter compared to the summer season, see Figure 67, Figure 68, and Figure 69. Also, PM$_{2.5}$ reductions are more concentrated in the Central Valley and, to a smaller degree, the south coast. Observed reductions in PM$_{2.5}$ concentration are also not as widespread across the state in winter compared to summer. The spatial change in winter concentrations is driven primarily by meteorology [312]. Summer tends to be dominated by westerly winds, but in winter, wind direct shifts and speeds slow resulting in more stagnate conditions [313]. For winter, the differences in PM$_{2.5}$ concentration reductions between the High BEV scenarios with immediate charging and with V2G charging are also minimal compared to the changes observed with increased ZEV deployment.

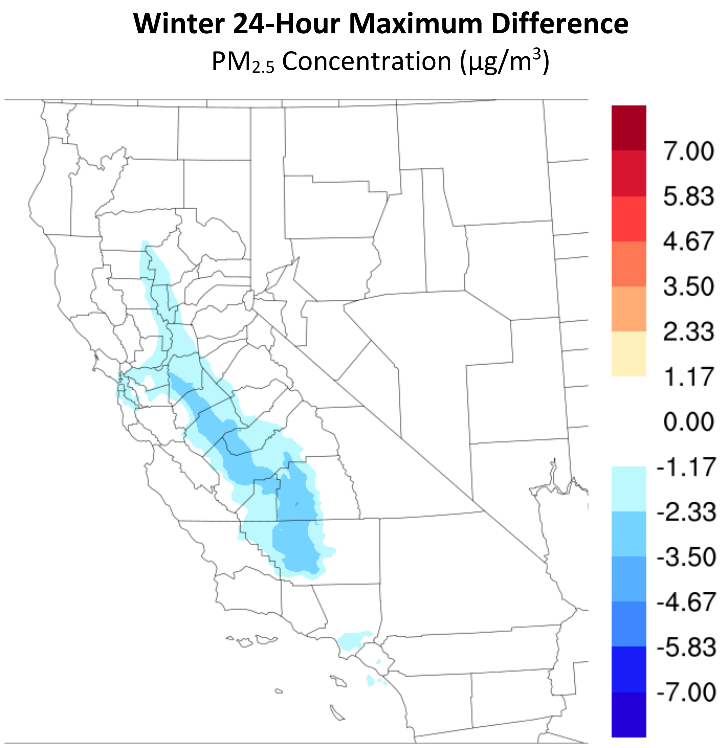


Figure 67. Change in Peak Winter 24-hour Average $PM_{2.5}$ Concentration: 40% HD ZEV Scenario – Immediate Charging

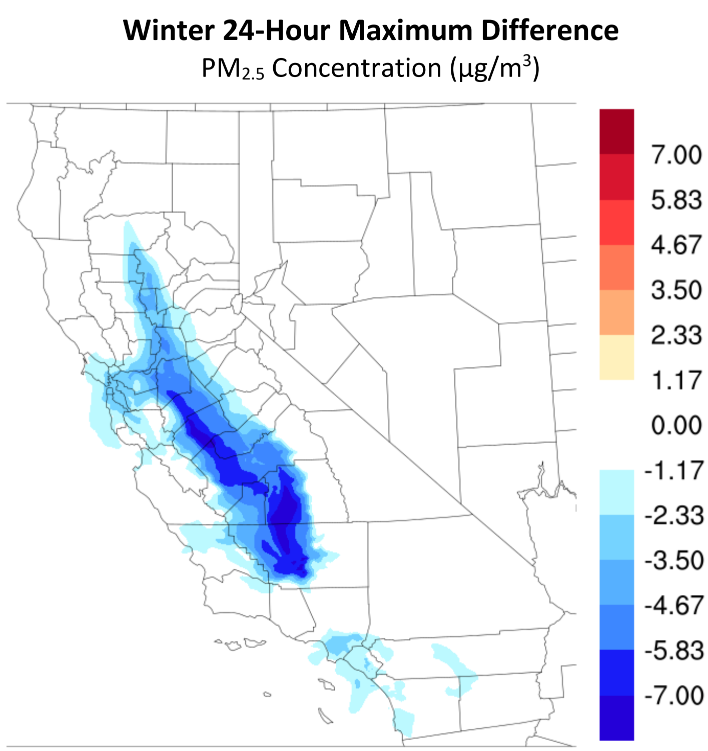


Figure 68. Change in Peak Winter 24-hour Average $PM_{2.5}$ Concentration: High BEV Scenario – Immediate Charging

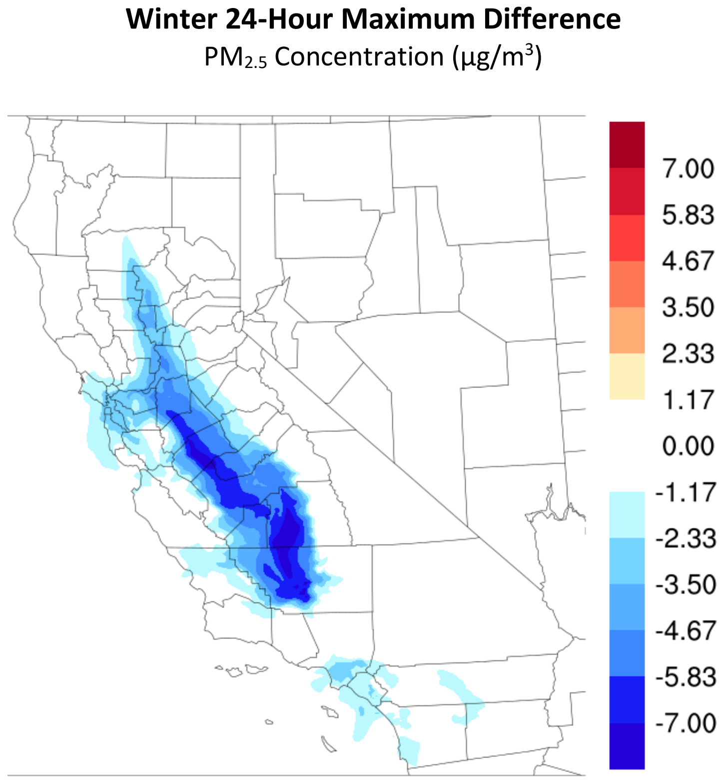


Figure 69. Change in Peak Winter 24-hour Average $PM_{2.5}$ Concentration: High BEV Scenario – V2G

There are much smaller magnitude differences between the High BEV scenario with immediate charging and the High BEV scenario with V2G for both ozone and $PM_{2.5}$ changes, which may not be discernable in the previous figures. The maximum difference between these two scenarios is around 1 ppb or less for ozone concentrations and around 2 ug/m^3 for $PM_{2.5}$ concentrations. The difference in ozone concentration and $PM_{2.5}$ concentration reductions between the two scenarios is plotted in Figure 70.

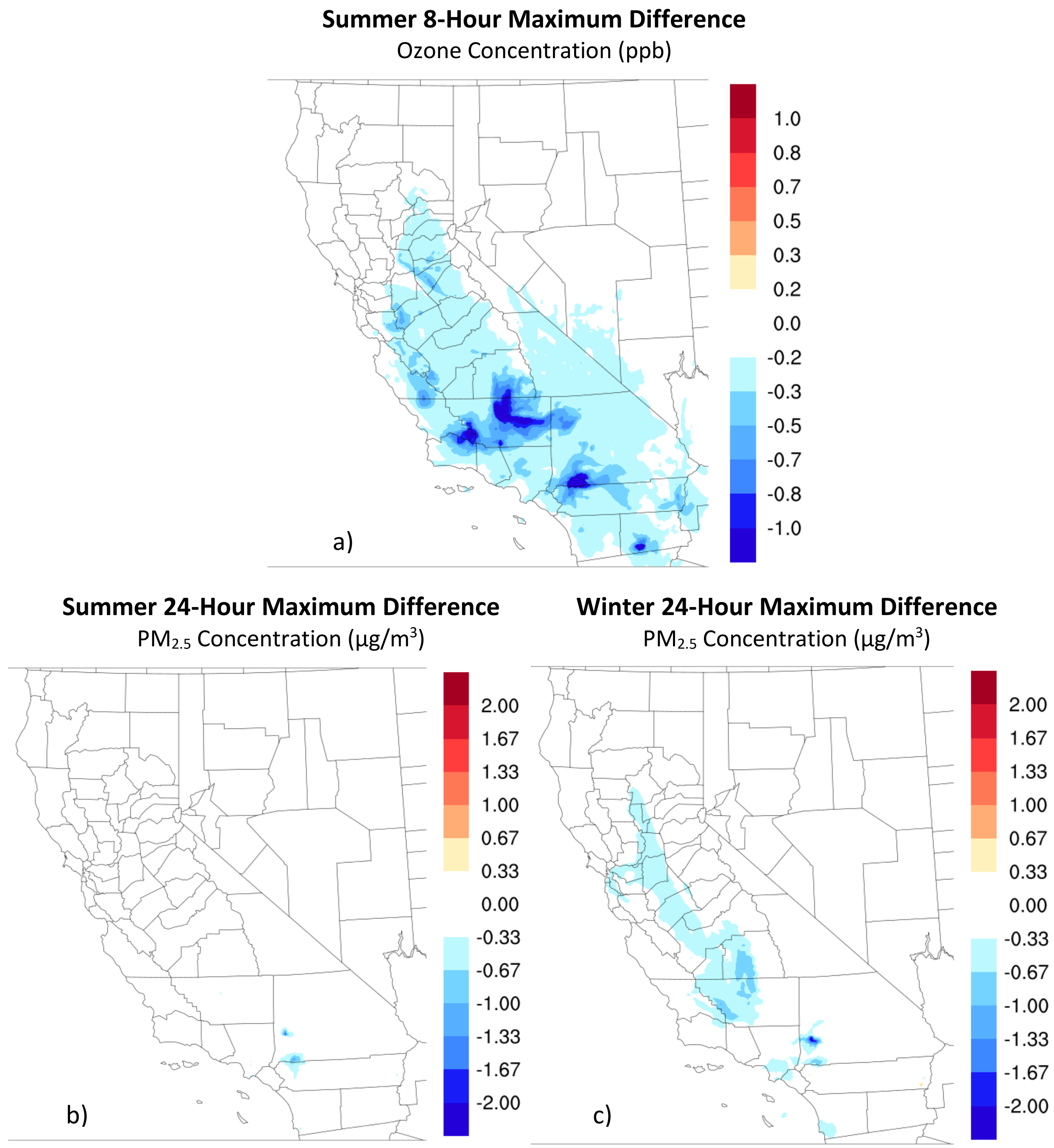


Figure 70. Difference between Immediate and V2G Charging for High BEV Scenario in a) Summer O_3 Concentration Reduction, b) Summer $PM_{2.5}$ Concentration Reduction, and c) Winter $PM_{2.5}$ Concentration Reduction

Switching from immediate charging to V2G charging/discharging does not affect emissions from vehicles, but it results in changes from the electric grid. Immediate and V2G for the High BEV scenario were selected because they represent the greatest difference in emissions from the grid as a result of changing charging intelligence. The High BEV scenario with V2G represents the greatest reduction in grid GHG reductions compared to the CPR base case for the 80% reduction scenarios (-24%), a 42% reduction in grid GHG emissions from the High BEV immediate charging case.

The greatest reductions in ozone and $PM_{2.5}$ concentrations are observed for Southern California, associated with reduced power plant emissions for the High BEV V2G scenario versus immediate charging. Winter reductions in $PM_{2.5}$ concentrations are more widespread than for the summer, including reductions in the San Joaquin Valley. The difference in peak and average ozone concentrations between the two scenarios compared to the CPR base case is -0.31 ppb and -0.36 ppb, respectively. The change in $PM_{2.5}$ concentration for the peak summer period is -0.09 ug/m^3 (peak) and -0.07 ug/m^3 (average). The change in $PM_{2.5}$ concentration for the peak winter period is -0.78 ug/m^3 (peak) and -0.26 ug/m3 (average).

6.3.2 Air Quality Impacts of a 100% Clean Electric Grid

Increasing renewable utilization to achieve a 100% clean electric grid will not only reduce grid GHG emissions to zero, it will also remove criteria pollutant emissions from the electric grid (assuming biopower does not replace natural gas power plants). The removal of power plant emissions will not only affect the surrounding area of each power plant but it will also have more regional impacts due to the natural dispersion of pollutants across the state.

For the 80% GHG grid emissions scenarios, the greatest increase in grid GHG emissions occurred for the High H_2 scenario with immediate charging. This scenario is compared here to the same vehicle scenario but with a 100% clean grid, in order to demonstrate the maximum potential impact of switching to a 100% clean electric grid for the investigated scenarios. The grid emissions from the High H_2 scenario with immediate charging are removed and the resulting criteria pollutant concentrations are compared to the original, 80% GHG reduction High H_2 scenario, see Table 27. The differences in criteria pollutant emissions identified here can be attributed solely to the removal of all electricity generation emissions in the 100% clean electric grid scenario. The vehicle contribution to criteria pollutant emissions is held constant.

Table 27. Change in Criteria Pollutants for High H2 Scenario with 100% Clean Electric Grid

	Summer Ozone Peak	**Summer Ozone Average**	**Summer PM2.5 Peak**	**Summer PM2.5 Average**	**Winter PM2.5 Peak**	**Winter PM2.5 Average**
High H_2 - Immediate	-12.58 ppb/ -19.4%	-5.07 ppb/ -8.5%	2.77 ug/m^3	-1.30 ug/m^3	-7.88 ug/m^3	-4.35 ug/m^3
High H_2 - Immediate & 100% Clean Grid	-16.46 ppb/ -21.2%	-6.65 ppb/ -10.53%	-3.51 ug/m^3	-2.01 ug/m^3	-9.80 ug/m^3	-4.98 ug/m^3

Peak reduction in summer ozone concentration due to achieving a 100% clean electric grid is -3.88 ppb and the average is -1.58 ppb. Peak reduction in summer $PM_{2.5}$ concentration is 0.74 ug/m^3, with an average reduction of 0.71 ug/m^3. Peak reduction in winter $PM_{2.5}$ concentration is 1.92 ug/m^3, with an average reduction of 0.63 ug/m^3. The change in criteria pollutant concentrations across the state are plotted in Figure 71, Figure 72, and Figure 73. Switching to a 100% clean electric grid reduces ozone concentrations across most of southern and central California for the High Hydrogen scenario with immediate charging. The observed changes to $PM_{2.5}$ concentrations vary by seasons. For the peak summer period, reductions in $PM_{2.5}$ concentrations occur in southern California along the coast and smaller areas to the north and east of the south coast air basin. For the winter peak period, reductions in $PM_{2.5}$ concentrations occur in the San Joaquin Valley in addition to the south coast air basin. Again, these seasonal shifts in impacts is due to the different meteorological conditions between summer and winter. In winter, stagnation concentrates primary $PM_{2.5}$ and provides conditions for greater production of secondary $PM_{2.5}$ [314].

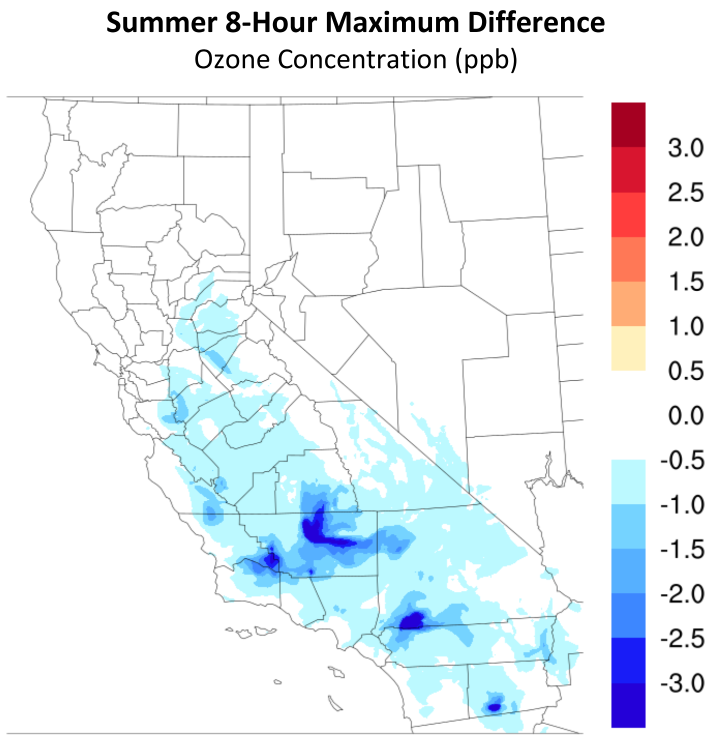


Figure 71. Change in Peak Summer 8-hour Average O_3 Concentration between High H_2 Scenario with Immediate Charging and High H_2 scenario with a 100% Clean Electric Grid

Summer 24-Hour Maximum Difference

$PM_{2.5}$ Concentration (µg/m^3)

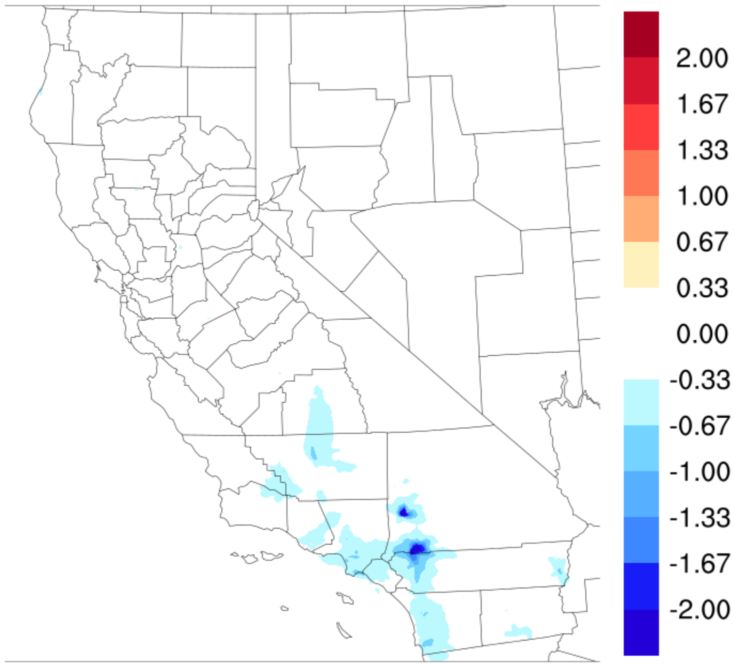


Figure 72. Change in Peak Summer 8-hour Average $PM_{2.5}$ Concentration between High H_2 Scenario with Immediate Charging and High H_2 scenario with a 100% Clean Electric Grid

Winter 24-Hour Maximum Difference

$PM_{2.5}$ Concentration (µg/m^3)

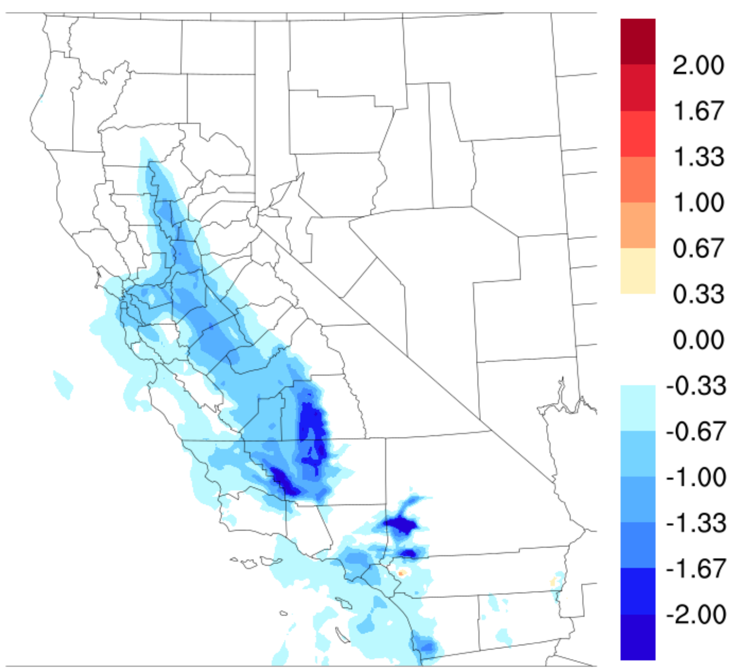


Figure 73. Change in Peak Winter 8-hour Average $PM_{2.5}$ Concentration between High H_2 Scenario with Immediate Charging and High H_2 scenario with a 100% Clean Electric Grid

Changes in criteria pollutant concentrations can be translated into potential human health changes. The Environmental Benefits Mapping and Analysis Program- Community Edition (BenMAP-CE), developed by the U.S. Environmental Protection Agency is an open source tool to calculate the economic impacts of changes in human exposure to criteria pollutants [315]. Economic values are evaluated from treatment costs and "willingness to pay" to avoid negative health impacts [316]. The methodology from Benosa et al. (2018) [317] was applied to two scenarios—High Hydrogen Scenario with Immediate Charging and the same case with a 100% Clean Electric Grid—to evaluate the potential health impacts of decreasing criteria pollutant emissions from heavy-duty ZEV and achieving a 100% clean electric grid. The BenMAP valuation is in Figure 74.

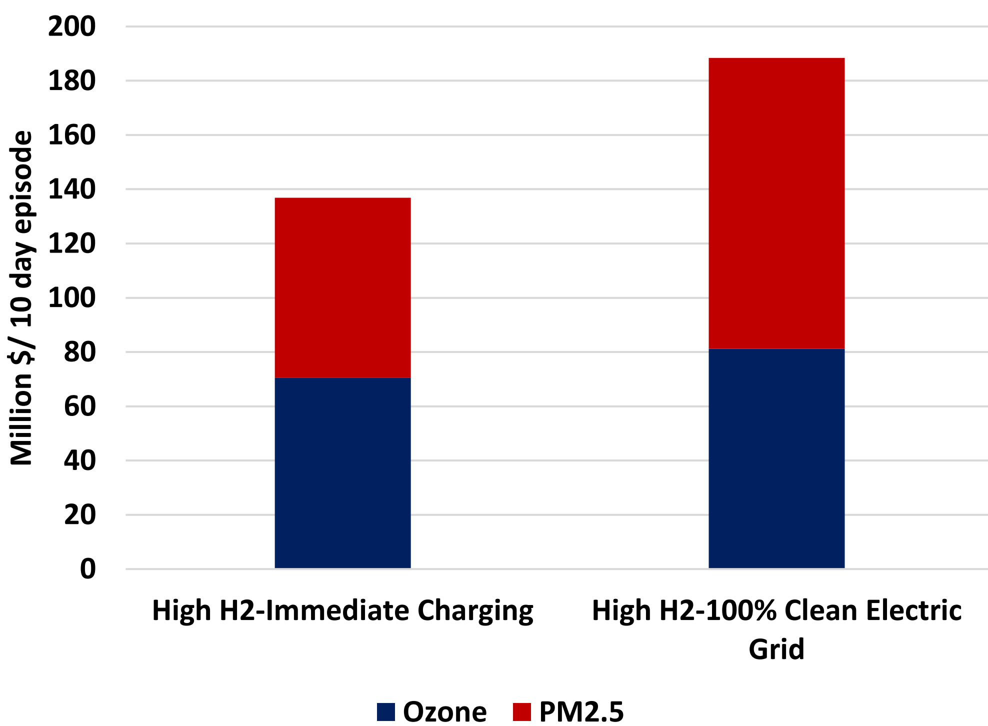


Figure 74. BenMAP Health Impacts Valuation for Peak Summer Episode: High Hydrogen Scenario-Immediate Charging with and without a 100% Clean Electric Grid

The reported health impact valuation is the result of the change in criteria pollutant exposure for the High Hydrogen scenarios compared to the CPR base case. Comparing the High Hydrogen scenario with immediate charging with and without a 100% clean electric grid, the electric grid emissions affect potential health savings/costs, particularly for PM-related illness and death. The degradation in health impacts degradation associated with the electricity sector are $52 million, relative to the $188 million in benefits from electrifying trucks, cars and buses.

6.4 Levelized Cost of Energy

The levelized cost of energy for the electric grid is the cost of energy delivered, levelized over the lifetime of the grid resources. It incorporates costs and resource operating parameters for each deployed technology, such as capital costs, operation and maintenance costs, fuel costs, the lifetime of each resource, and capacity factors [49]. The LCOE values for this analysis are calculated using the existing HiGRID Cost of Generation module, with updated costs for level 3 EVSE as well as transformer costs in order to account for the higher charging rates required for HDVs compared to LDVs. FCEV infrastructure costs, as well as energy storage costs are from Wang et al. (2019) [230].

6.4.1 Levelized Cost of Energy for 80% Reduction in GHG Emissions Scenarios

Transformer upgrades will most likely be required for level 2 charging in residential areas and for level 3 charging in commercial areas [207]. The BEV and FCEV infrastructure costs used in this analysis are in Table 28 and Table 29. The transformer upgrade cost and intelligent charging equipment are included as separate costs in the table but are added to the instant cost in the model. Costs for installing and operating level 3 chargers are based on existing projects, but due to the variability of location-specific costs as well as the relatively small-scale of level 3 EVSE that have been installed, these costs may evolve in the future. Additionally, smart and V2G charging strategies are still in development, so the intelligent charging costs may also evolve as the technologies mature. A sensitivity to the frequency of transformer upgrades will be conducted to evaluate the overall impact of upgrade requirements on LCOE.

Table 28. LCOE Parameters for BEV Infrastructure

	Level 2 (19.2 kW)	**Level 3 (40 kW)**	**Level 3 (120 kW)**	**Level 3 (350 kW)**
Instant Cost ($/kW)*	157.70	1200	650	384.00
Fixed O&M ($/kW-yr)**	131.80	96.00	50.00	50.00
Variable O&M ($/MWh)**	0	0	0	0
Transformer Upgrade ($/kW) +	69.44	65.00	72.22	74.29
Intelligent Charging Equipment ($/kW) ++	221.35	106.25	35.42	12.14

* Values from [202,207], ** Values from [230], +Transformer upgrades costs based on price for 225 kVA and 1000 kVA transformers and the number of chargers that can be supported per transformer [203,204,207,318], ++Smart/V2G Charging hardware/software upgrade assumed to be $4250 per charger [207,208]

*Table 29. LCOE Parameters for FCEV Infrastructure**

	Alkaline Electrolyzer, Onsite for Fueling Station	**Solid Oxide Electrolyzer, Onsite for Fueling Station**	**PEM Electrolyzer, Onsite for Fueling Station**
Instant Cost ($/kW)	289.62	466.60	398.30
Fixed O&M ($/kW-yr)	10.43	15.40	14.32
Variable O&M ($/MWh)	1.24	13.00	0.17

*Values from [230]

The LCOE results for all of the 80% GHG reduction scenarios are in Figure 75. Despite the cost of installing BEV and FCEV infrastructure, the increase in the renewable electricity utilization by ZEVs results in a decrease in LCOE. This trend continues as more ZEVs are integrated. Comparing the High BEV and High H_2 scenarios, where there is an equal level ZEV deployment, the High H_2 scenarios result in a greater utilization of otherwise curtailed renewable electricity and therefore, despite FCEV infrastructure costs, they result in lower levelized cost per megawatt-hour.

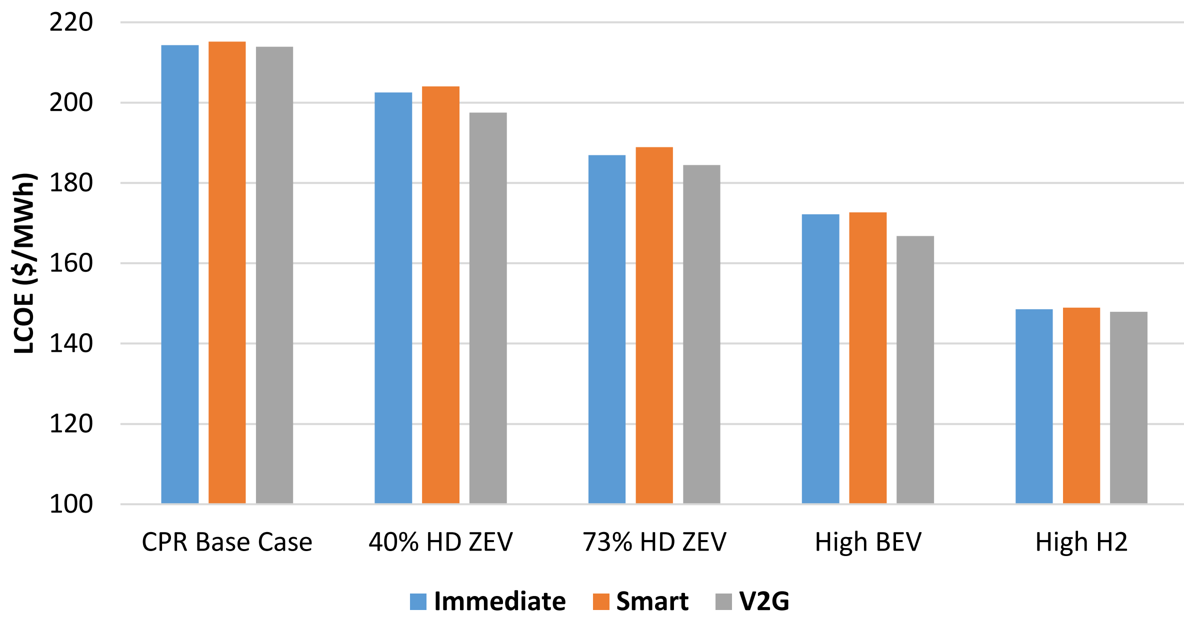


Figure 75. LCOE for All 80% GHG Reduction Scenarios

For each scenario, EVSE capacity was calculated from the peak BEV load demand. For the smart and V2G charging scenarios, the BEV peak demand increased significantly compared to the immediate charging scenarios for the same level of BEV deployment, due to the vehicles' role in providing valley-filling services. Increased peak demand translates to a higher installed capacity for EVSE. Increased EVSE capacity requirements for smart charging result in net increase LCOE compared to immediate charging, but this is not the case for the V2G charging scenarios, where the increase in renewable utilization offsets increased EVSE capacity costs.

The influence of transformer upgrade costs and intelligent charging equipment costs on LCOE values was assessed and was found to have a minimal impact on the portfolio-wide LCOE, see Table 30.

Table 30. Changes in LCOE from Transformer Upgrades and Intelligent Charging Equipment

	CPR Base	40% HD ZEV	73% HD ZEV	High BEV	High H2
Immediate (Without Upgrade Costs Included)	214.31	202.50	186.89	172.18	148.59
Change in LCOE with Transformer Upgrade ($/MWh)	0.02	0.11	0.11	0.12	0.02
Smart (Without Upgrade Costs Included)	215.17	204.04	188.90	172.64	148.93
Change in LCOE with Transformer Upgrade ($/MWh)	0.10	0.30	0.37	0.36	0.05
Change in LCOE with Intelligent Charging Equipment ($/MWh)	0.05	0.15	0.18	0.06	0.15
V2G (Without Upgrade Costs Included)	213.88	197.50	184.43	166.82	147.91
Change in LCOE with Transformer Upgrade ($/MWh)	0.21	0.42	0.80	0.91	0.06
Change in LCOE with Intelligent Charging Equipment ($/MWh)	0.10	0.20	0.39	0.15	0.19

For each scenario, upgrade costs were excluded to determine the "base" cost assuming transformer capacities were not exceeded and intelligent vehicle connectivity did not have an added cost. Then, costs for transformer upgrades and intelligent charging equipment were added back in to isolate the impact of these costs on overall LCOE. The change in LCOE were low, less than $1/MWh, indicating that while these upgrades require a relatively high capital cost, they do not significantly impact the LCOE of the system.

6.4.2 Levelized Cost of Energy for a 100% Clean Electric Grid

For the 100% clean electric grid scenarios, additional stationary ESS capacity is scaled to meet the remaining load demand requirements. The cost parameters for these ESS technologies are presented in Table 31. The range of costs for different hydrogen storage technologies from Wang et al. (2019) is included to demonstrate how different technology assumptions may affect the LCOE [230]. The selected technology combination of alkaline electrolyzers paired with PEM fuel cells represents a mid-range cost compared to the available electrolyzer-fuel cell configurations. These costs also assume underground storage of hydrogen, with costs used in Wang et al. (2019) from [319].

*Table 31. LCOE Parameters for Stationary Energy Storage Technologies**

	Lithium Ion Batteries	Range of Costs for H_2 Storage Technologies	H_2 Storage: Alkaline Electrolyzer with PEM Fuel Cell, Delivered to Grid
Instant Cost ($/kW)	1327.87	1958.53 – 3236.63	2223.50
Fixed O&M ($/kW-yr)	307.78	47.81 – 78.37	53.07
Variable O&M ($/MWh)	2.78	2.99 – 34.44	15.69

*Values from Wang et al. (2019) [230]

The impact of the increased renewable capacity on LCOE are evaluated in Figure 76, excluding stationary energy storage deployment.

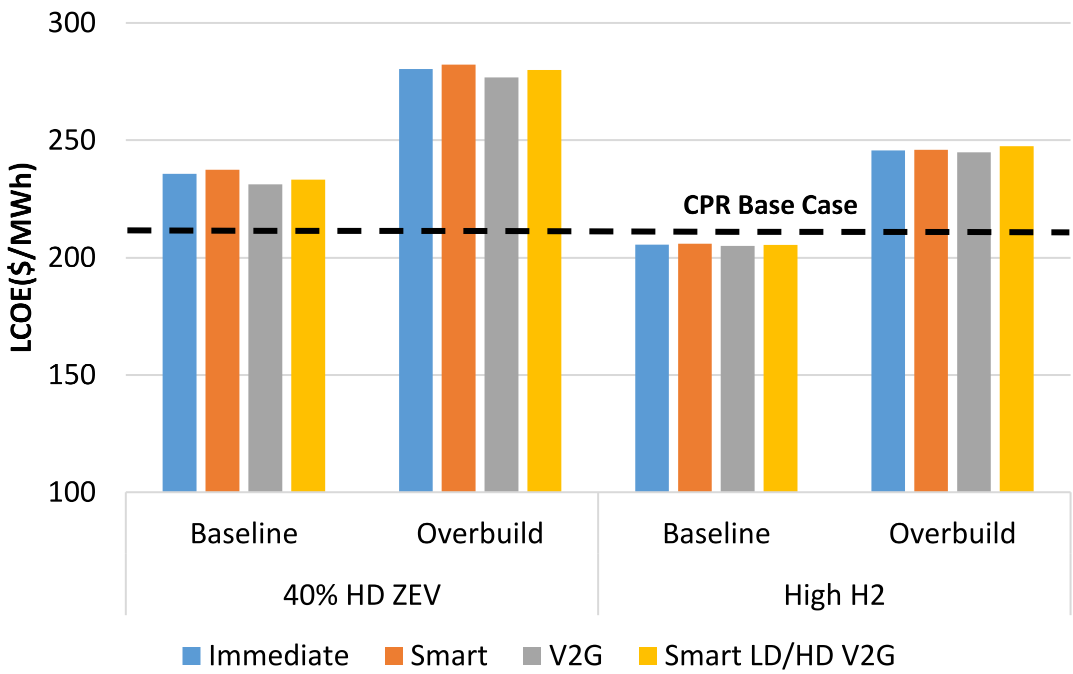


Figure 76. Levelized Cost of Energy for 100% Clean Electric Grid Pre-ESS Deployment

Comparing the baseline and overbuild scenarios, increased renewable capacity increases the LCOE. Although the 40% HD ZEV overbuild scenarios have the same renewable capacity as the

High H2 baseline scenarios, the High H2 baseline scenarios have lower LCOE values, due at least in part to increased renewable utilization (reduced curtailment) compared to the 40% HD ZEV overbuild scenarios. Differences in LCOE between charging strategies is significantly less pronounced compared to LCOE differences between different renewable capacity assumptions. However, the trends between the different strategies are consistent with the 80% GHG reduction scenarios: smart charging results in the highest LCOE and V2G results in the lowest LCOE. Adding smart light-duty vehicle charging results in an increase in LCOE compared to heavy-duty V2G-enabled charging only.

The addition of energy storage (BESS, hydrogen storage) will increase the capacity of resources on the grid, potentially increasing the LCOE. However, at the same time, deploying energy storage will improve renewable utilization, increasing the capacity factors of solar and wind generation, potentially decreasing the LCOE. The resulting LCOE for each scenario with scaled BESS capacity to meet a 100% clean electric grid target is in Figure 77. Adding BESS capacity significantly increases LCOE for all scenarios. For the 40% HD ZEV scenarios, the LCOE increases by over 600% for the baseline renewable capacity case and by over 300% for the overbuild scenarios. For the High H2 scenarios, the LCOE for the baseline renewable capacity scenarios increase by over 300% and by over 100% for the overbuild scenarios.

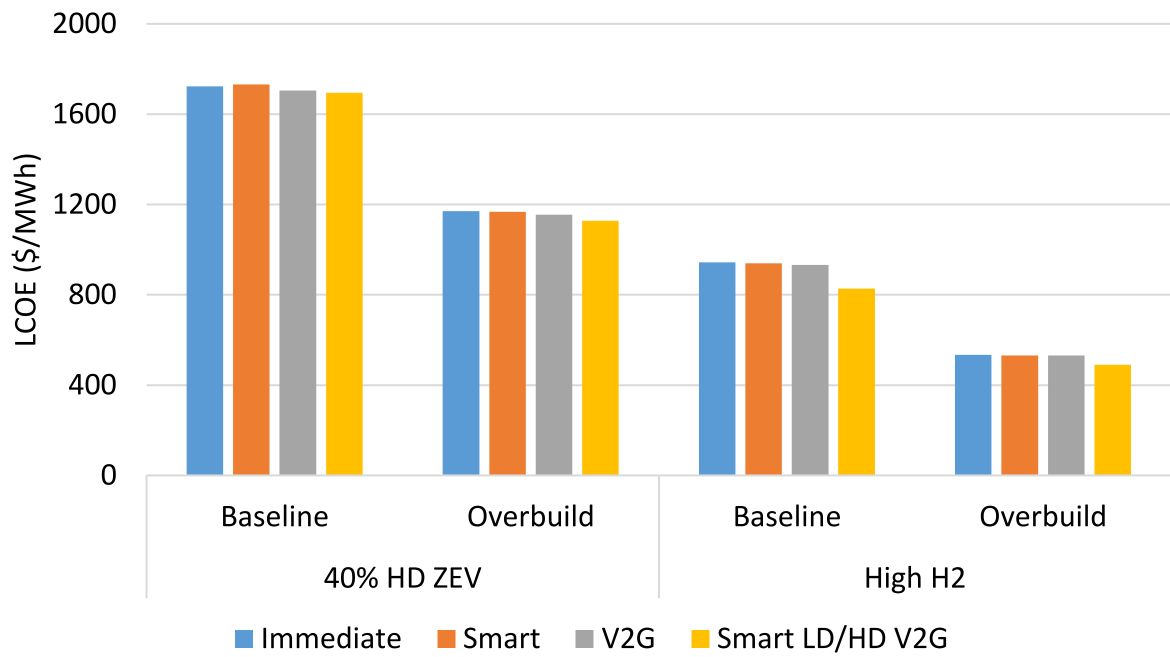


Figure 77. Levelized Cost of Energy for 100% Clean Electric Grid with BESS Deployment

Whereas the overbuild scenarios pre-energy storage deployment resulted in higher LCOE values compared to the baseline scenarios, the overbuilding of renewable capacity increases flexibility for battery charging as well as reducing the remaining load needing to be met with energy storage. This results in a reduction in the stationary energy storage capacity required to meet the 100% clean grid target. The net impact is lower final LCOE values for the overbuild scenarios compared to the respective baselines. Again, the difference in LCOE between the different BEV charging strategies is overshadowed by the impact of renewable capacity. Increased charging intelligence does reduce energy storage capacity required to meet the 100% target, and smart light-duty BEVs with V2G-enabled heavy-duty BEVs result in the lowest LCOE for all the charging strategy cases.

The LCOE values for the 100% clean electric grid scenarios with hydrogen energy storage are presented in Figure 78.

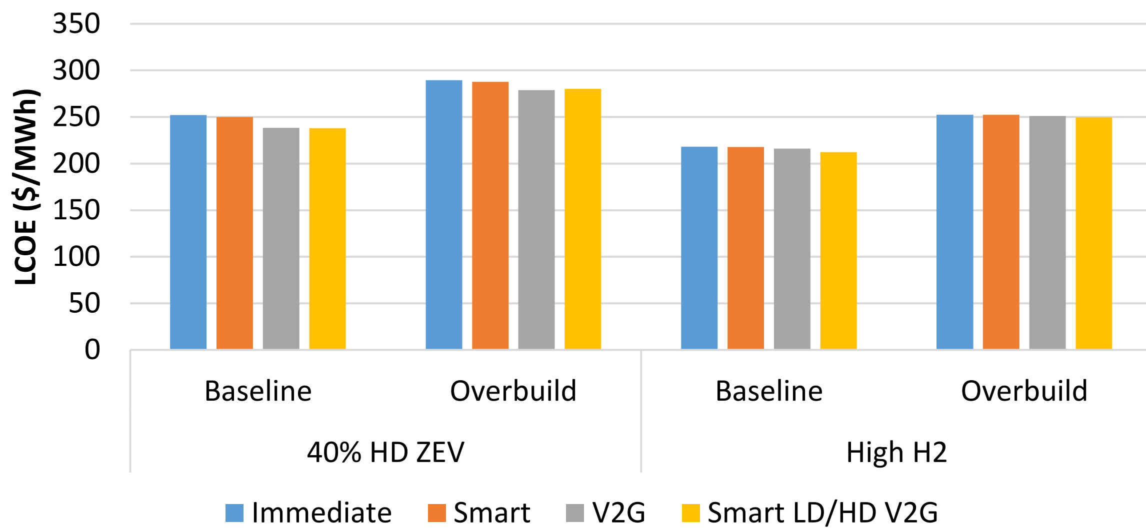


Figure 78. Levelized Cost of Energy for 100% Clean Electric Grid with Hydrogen Energy Storage Deployment

LCOE values for the hydrogen storage scenarios are about 10% greater than the respective scenarios without energy storage deployed. The lower LCOE values of the hydrogen energy storage compared to the BESS scenarios is due in part to the difference in how these two systems are deployed. The power-energy ratio of the BESS system is fixed at 1:4, resulting in a high power short duration configuration. In order to meet the high energy capacity requirements of a 100% clean electric grid, a high power capacity must be deployed, significantly increasing the cost of the energy storage system. Conversely, for the hydrogen energy storage system, the power capacity and energy capacity are scaled independently, resulting in a much lower power capacity compared to the BESS cases. Fuel cell and electrolyzers are scaled to meet peak “charging” and “discharging” demand, and hydrogen storage is scaled to meet energy capacity requirements. The assumption that storage of hydrogen underground is relatively cheap means that a large energy capacity can be maintained without driving up the LCOE.

Due to the long-duration storage potential of hydrogen storage, there is reduced need for the increased renewable generation provided by the overbuild scenario. The reduction in storage capacity requirements with overbuilding does not offset the increased cost of installing greater renewable capacity. The net result is that the overbuild scenarios retain a higher LCOE compared to their respective baseline renewable capacity scenarios.

6.5 Chapter Summary and Conclusions

This chapter analyzed the impacts of integrating zero-emission vehicle load demands onto a highly renewable grid for the year 2050. The impact of heavy-duty ZEV deployment on meeting two different grid GHG emissions goals were evaluated: a) an 80% reduction in GHG emissions from 1990 levels and b) a 100% clean electric grid. The difference in grid balancing requirements, GHG emissions, air quality, and levelized cost of electricity were determined.

Based on the results of this chapter, the following conclusions can be drawn:

1. **Home base charging only does not maximize renewable utilization.** Home base only charging limits renewable utilization by heavy-duty vehicles due to misalignment with peak solar. Either target vehicles that have dwell periods during the day (limited), have publically available chargers for in-route charging, or utilize an interim medium, such as hydrogen which can be produced during renewable periods, stationary energy storage, or battery swapping stations.
2. **Enabling intelligent charging of BEVs is critical for reducing peak electricity demand.** Immediate charging of light-duty and heavy-duty vehicles adds to peak demand periods, increasing the balancing generation capacity required. For a grid with natural gas power

plants, increased peak demand and the associated ramping demand can increase the need for simple-cycle peaker plants and increase grid GHG and criteria pollutant emissions. For a 100% clean electric grid, it can increase the energy storage capacity required to balance the grid and subsequently increase the levelized cost of energy.

3. **While a high degree of BEV charging intelligence and/or renewable hydrogen production through electrolysis can significantly reduce ramp rates, intermittent high magnitude ramping events will still need to be addressed with additional support technologies.** Integrating zero-emission vehicles onto the grid is able to provide load smoothing support, but there remain sporadic high ramping events that need to be balanced. The reduction in the frequency of high ramping rates reduces reliance on peaker plants, however, it does not fully remove the need for fast-responding, dynamic power supply.
4. **The conversion of the heavy-duty vehicle fleet to zero-emission vehicles to meet an 80% reduction in transportation GHG emissions may have positive or negative impacts on electric grid emissions depending on charging strategies.** Heavy-duty BEVs relying on uncoordinated charging can increase peak load demand and exacerbate power plant ramping. Intelligent charging of heavy-duty BEVs and renewable hydrogen production are both effective methods for utilizing otherwise curtailed renewable generation and reducing ramping requirements, but may still increase grid GHG emissions if relying on natural gas power plants for grid balancing. Heavy-duty BEVs equipped with V2G capability can effectively reduce peak electricity demand and increase renewable

penetration. At very high levels of heavy-duty BEVs with V2G charging, grid GHG emissions can be halved compared to immediate charging.

5. **Increased GHG emissions from the electric grid for the immediate and smart charging scenarios are more than offset by reductions in GHG emissions from the transportation sector.** While the grid emissions increase significantly under immediate and smart charging of a high penetration of heavy-duty BEVs, the net impact is an overall reduction in system wide GHG emissions. In 2050, the greatest increase in grid GHG emissions is on the scale of 10 MMT CO_2e, whereas the decreases in the transportation sector range from 60 MMT CO_2e or more. The impact of the spatial shift in criteria pollutant emissions can be observed in the air quality results.
6. **Overbuilding renewable capacity can reduce grid GHG emissions regardless of additional zero-emission support technologies, but has diminishing returns and may increase LCOE**. The increase in renewable capacity from the 80% reduction scenarios resulted in additional GHG reductions. However, the marginal GHG reduction potential of overbuilding decreases as renewable capacity increases. Additionally, if the added renewable generation is left under-utilized, LCOE will increase.
7. **Utilizing intelligent charging of heavy-duty BEVs has only marginal impacts in reducing the scale of energy storage required to meet a 100% clean electric grid.** While intelligent charging of heavy-duty vehicles decreased grid emissions and reduced ramping requirements for balance generation for the 80% GHG reduction scenarios, meeting a 100% clean electric grid requires energy shifting across longer timescales than

heavy-duty vehicles can provide, and therefore, significant additional energy storage capacity was required for all scenarios.

8. **Hydrogen energy storage can be more efficiently scaled than battery energy storage to meet the balancing requirements of a 100% clean electric grid.** The buildout of battery energy storage required a BESS power capacity well over 1000 GW for most cases, despite peak net demand 75 GW or less and minimum negative load associated with curtailed renewable generation about 160 GW or less. The high power capacity of the BESS system is required in order meet the energy shifting requirements of a 100% clean electric grid. An energy storage technology, such as hydrogen storage, that has power and energy capacity decoupled such that each can be scaled appropriately may reduce costs of meeting a 100% renewable grid. The net impact on LCOE of a different storage technology will depend on the cost of storing energy (eg. in the natural gas pipeline, underground storage, tanks, etc.).
9. **An 80% reduction in GHG emissions from HDVs through ZEV adoption has significant air quality co-benefits.** Expanding zero-emission vehicle deployment into the heavy-duty sector significantly reducing peak ozone and PM2.5 concentrations in key regions of California that are currently in nonattainment.
10. **Further reducing grid emissions to achieve a 100% clean electric grid has non-trivial impacts on air quality.** While reducing heavy-duty vehicle emissions has a greater impact on air quality across the state, achieving a 100% clean electric grid can reduce criteria pollutant concentrations.

11. **The integration of zero-emission vehicles onto the grid can reduce the LCOE due to the increased utilization of renewable generation.** The expanded heavy-duty vehicle deployment scenarios resulted in a decrease in the LCOE. The High Hydrogen scenarios, which utilized the most otherwise curtailed renewable generation resulted in the greatest reduction in LCOE compared to the CPR base case (about 31% lower).

Chapter 7. Summary, Conclusions, and Future Work

7.1 Summary

The goal of this dissertation was to identify and assess the role of zero-emission heavy-duty vehicles in supporting an ultimate target of a 100% clean electric grid system. To achieve this goal, the literature was reviewed, and several gaps were identified for critical study, including the ZEV feasibility for the California heavy-duty sector, the impact of heavy-duty zero emission vehicles on the electric grid assuming different deployment strategies, and the potential for grid-connected heavy-duty vehicles to provide grid services. This work developed a heavy-duty vehicle charging model to evaluate the charging behavior of future instate heavy-duty BEVs under different deployment assumptions. It also employed an existing hydrogen demand model to simulate FCEV demands on the electric grid.

Scenarios with expanded heavy-duty ZEV deployment were developed for the year 2050 assuming a) an 80% reduction in grid GHG emissions and b) a 100% clean electric grid. These deployment strategies were evaluated based on changes to grid performance and balancing requirements, GHG emissions, air quality, and levelized cost of electricity. For the scenarios, tradeoffs between the different metrics were discussed and air quality improvements were translated into potential health benefits.

7.2 Conclusions

In addition to the Chapter 4 and Chapter 6 conclusions, the following are overarching conclusions from this dissertation:

1. **Significant heavy-duty ZEV deployment is achievable with existing and near-term technologies.** About half of heavy-duty vehicle travel demand can be met with battery and fuel cell electric vehicle models available or in development, given their reported technical specifications. A majority of this travel demand will be for light-heavy and medium-heavy duty vehicles. Increasing the share of heavy-heavy duty vehicle travel demand that can be met with ZEVs will require improving vehicle design and optimizing charging/fueling strategies. The actual adoption rate of heavy-duty ZEVs will depend on cost, willingness to adopt, vehicle turn-over rates, and infrastructure availability to support charging and/or refueling needs.
2. **Heavy-duty ZEV deployment will require significant infrastructure expansion.** Expanding ZEV adoption will require investment in charging stations, grid upgrades, and hydrogen refueling stations to support ZEVs. Heavy-duty ZEVs require three or more times the energy per mile compared to light-duty ZEVs, and therefore, Level 3 charging will be required to support higher volumes of heavy-duty BEVs and high capacity hydrogen refueling stations will be needed to meet the travel demands of FCEVs.
3. **As more sectors are electrified, it will be important to maximize the flexibility of these new loads in order to maintain grid performance.** In this analysis, integrating uncoordinated heavy-duty BEVs resulted in increased peak electricity demand and higher ramping rates. This in turn made it more difficult to achieve the emissions reduction targets of an 80% GHG reduction and a 100% clean electric grid. By increasing vehicle load flexibility, grid performance improved, and with V2G-enabled charging, vehicle integration reduced grid balancing requirements. Other sectors, such industry or

residential, that are planning to reduce their emissions by electrifying equipment and/or processes have the same potential to hinder or support the electric grid's performance.

4. **Utility pricing structures and market participation rules may need to be updated in order to support heavy-duty vehicle participation in grid services.** Increasing the charging intelligence of heavy-duty BEVs resulted in increased charging peaks. The net impact is improved grid performance at the regional scale. However, in order achieve load smoothing, it requires that vehicles are not penalized for increasing local peak demand. As previously discussed, commercial buildings are charged a "Demand Charge" based on their peak electricity use as a way to disincentive them from exceeding local transformer limits, which may result in transformer repair and upgrade costs. However, demand charges would be a disincentive vehicles to provide certain grid services. Utilities must consider, as BEV adoption grows, which is more valuable: to have dynamic load support or to limit transformer upgrades.

5. **Reducing GHG emissions in the electric grid sector and/or transportation sector by more than 80% can provide greater flexibility to sectors that are not well-equipped to reduce their emissions.** In order to meet the 80% reduction in GHG emissions from 1990s levels, increases in grid or transportation emissions would need to be offset by another sector. Conversely, decreases in either grid emissions or transportation emissions beyond the 80% GHG emissions target may provide other sectors some flexibility in how much they reduce their emissions. A 100% clean electricity grid would provide further flexibility to other sectors. However, replacing equivalent reductions in

GHG emissions in another sector may have varying impacts on air quality, due to differences in criteria air pollutant emissions between sectors.

7.3 Future Work

Historical travel patterns were assumed for this analysis. However, there may be opportunities for drivers to shift their behavior in response to fueling and charging constraints of heavy-duty zero-emission vehicles. Future work should investigate the willingness of drivers to change routes to meet charging demand or to better align with renewable generation.

The literature review for this work identified uncertainty surrounding the share of Class 2B/3 vehicles operated for commercial versus personal use. Due to their relatively high fuel efficiency and large share of total heavy-duty VMT, these vehicles are an important potential market for zero-emission vehicles. Further examination of Class 2B/3 travel behavior can provide insight into zero emission vehicle feasibility for and refine our understanding of future grid impacts from electrifying these vehicles.

This dissertation focused on the electrification of in-state vehicles, due to their more-likely candidacy for zero-emission vehicles, but also due to limited data on out-of-state vehicle trip data. Future work should investigate BEV feasibility for out-of-state vehicles and how charging behavior of out-of-state vehicles will differ from in-state vehicles, including charging time, charging EVSE requirements, and the reliance on public versus home base locations for charging. Additionally, surveying out-of-state businesses that send vehicles to California may provide insight into their willingness to adopt zero-emission vehicles.

Further investigating vocation-specific behavior can help identify fleets whose travel behavior are well-suited for zero-emission vehicles and have dwell times that align well with renewable availability. It can also identify fleets where FCEVs may better meet travel demands and where vehicle dwell periods do not align well with renewable generation and may benefit from either FCEV or intelligent BEV deployment to avoid negative impacts on the grid.

Lastly, the air quality analysis identified general regions where air quality improvements would occur with heavy-duty ZEV deployment. However, further work should identify the net impacts on disadvantaged communities. It should also investigate whether nonlinear ozone formation dynamics may result in an increase in ozone concentrations in disadvantaged communities.

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Appendix

Table A.1 Operation Days for EMFAC Vehicle Categories, data from [1,2]

VCC	EMFAC2011	Fuel	Days
32028	All Other Buses	Dsl	292
12100	LDA	Dsl	347
13100	LDA	Elec	347
11100	LDA	Gas	347
21100	LDT1	Gas	347
22100	LDT1	Dsl	347
23100	LDT1	Elec	347
21200	LDT2	Gas	347
22200	LDT2	Dsl	347
21400	LHD1	Gas	327
22400	LHD1	Dsl	327
21500	LHD2	Gas	327
22500	LHD2	Dsl	327
41000	MCY	Gas	347
22300	MDV	Dsl	347
21300	MDV	Gas	347
51000	MH	Gas	327
52000	MH	Dsl	327
32027	Motor Coach	Dsl	292
31028	OBUS	Gas	327
22703	PTO	Dsl	312
32026	SBUS	Dsl	327
31026	SBUS	Gas	327
22601	T6 Ag	Dsl	312
22605	T6 CAIRP Heavy	Dsl	312
22604	T6 CAIRP Small	Dsl	312
22609	T6 Instate Constr. Heavy	Dsl	312
22608	T6 Instate Constr. Small	Dsl	312
22611	T6 Instate Heavy	Dsl	312
22610	T6 Instate Small	Dsl	312
22613	T6 OOS Heavy	Dsl	312
22612	T6 OOS Small	Dsl	312
22602	T6 Public	Dsl	312
22614	T6 Utility	Dsl	312
21600	T6TS	Gas	327
22701	T7 Ag	Dsl	312
22706	T7 CAIRP	Dsl	312
22707	T7 CAIRP Constr.	Dsl	312
22715	T7 NNOOS	Dsl	312
22716	T7 NOOS	Dsl	312
22717	T7 Other Port	Dsl	312
22718	T7 POAK	Dsl	312
22719	T7 POLA	Dsl	312
22702	T7 Public	Dsl	312
22720	T7 Single	Dsl	312
22721	T7 Single Constr.	Dsl	312
22724	T7 SWCV	Dsl	312
24724	T7 SWCV	NG	312
22722	T7 Tractor	Dsl	312
22723	T7 Tractor Constr.	Dsl	312
22714	T7 Utility	Dsl	312
21700	T7IS	Gas	327
32025	UBUS	Dsl	327
34025	UBUS	NG	327
31025	UBUS	Gas	327
23200	LDT2	Elec	347
23300	MDV	Elec	347
24602	T6 Public	NG	312
24605	T6 CAIRP Heavy	NG	312
24608	T6 Instate Constr. Small	NG	312
24609	T6 Instate Constr. Heavy	NG	312
24610	T6 Instate Small	NG	312
24611	T6 Instate Heavy	NG	312
24614	T6 Utility	NG	312
24702	T7 Public	NG	312
24706	T7 CAIRP	NG	312
24707	T7 CAIRP Constr.	NG	312
24718	T7 POAK	NG	312
24719	T7 POLA	NG	312
24720	T7 Single	NG	312
24721	T7 Single Constr.	NG	312
24722	T7 Tractor	NG	312
24723	T7 Tractor Constr.	NG	312
34026	SBUS	NG	327
34028	All Other Buses	NG	292