DOCKETED	
Docket Number:	20-IEPR-02
Project Title:	Transportation
TN #:	234291
Document Title:	EV at Scale - Phase I Analysis - Impacts
Description:	N/A
Filer:	Spencer Kelley
Organization:	California Energy Commission
Submitter Role:	Commission Staff
Submission Date:	8/12/2020 9:42:57 AM
Docketed Date:	8/12/2020

Electric Vehicles at Scale – Phase I Analysis:

High EV Adoption Impacts on the Western U.S. Power Grid

PNNL Report

July 2020

PNNL-29894

PACIFIC NORTHWEST NATIONAL LABORATORY
operated by
BATTELLE
for the
UNITED STATES DEPARTMENT OF ENERGY
under Contract DE-AC05-76RL01830

Printed in the United States of America

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Electric Vehicles at Scale – Phase I Analysis: High EV Adoption Impacts on the Western U.S. Power Grid

PNNL Report

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July 2020

Prepared for
the U.S. Department of Energy
under Contract DE-AC05-76RL01830

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Executive Summary

The use of electric vehicles (EVs) in the United States has grown significantly during the last decade. So much so that the U.S. Department of Energy (DOE) asked Pacific Northwest National Laboratory (PNNL) to perform an authoritative study of the impacts of EVs at scale on the electric grid. "At scale" was defined by high-penetration scenarios performed earlier by the Electric Power Research Institute (EPRI) and the International Energy Agency (IEA). During the discussion of scope with DOE, it became clear that EVs at scale affect the electric infrastructure fundamentally in two different ways: (1) EVs affect the electric infrastructure at the point of common coupling, which for most EV charging stations (also referred to as EV Supply Equipment) is a connection to the distribution system, either at home, at a workplace, or at a public charging station; and (2) EVs at scale affect the bulk power system as an aggregated new load.

This Phase I study focuses on the bulk power electricity impacts; distribution system analysis is left for the follow-on Phase II study. Because of a sense of urgency related to performing the analysis and publishing the results, PNNL recommended that the study focus on the Western grid (i.e., the Western Electricity Coordinating Council [WECC]). The WECC already has a commonly agreed-upon data set for a future grid scenario—the WECC 2028. By using the WECC 2028 scenario, PNNL used the best available future grid scenario definition that included load growth assumptions, generation retirements and additions, as well as transmission expansions. The analysis was based on a production cost modeling approach using the ASEA Brown Boveri Gridview tool.

This EV-at-scale Phase I analysis addressed the following two key questions of interest to DOE related to the impacts of EV at the bulk power level at the time when EVs are deployed at scale:

1. Are there sufficient resources in the U.S. bulk power grid to provide the electricity for charging a growing EV fleet? This question addresses the system adequacy.
2. What are the likely operational changes necessary to accommodate a growing EV fleet? This question addresses changes in
   - generation mix
   - production cost
   - challenges and benefits of accommodating the new EV loads.

The study is unique because it represented for the first time not only the projection for light-duty but also for medium-duty and heavy-duty electric vehicles (LDVs, MDVs, and HDVs). It should be noted that this study did not include a capacity expansion analysis that searches for cost-optimal investments of new grid infrastructure given the new EV loads. Instead this study focused on the resource adequacy question of high EV adoption as the WECC grid planners defined the evolution of the bulk power system to the year 2028.

Key Outcomes of the Study

Assumptions About the Penetration of EVs

This analysis applied for the following penetration assumptions for 2028 expressed as a national figure: LDVs: 24 million, MDVs: 200,000, HDVs: 150,000. The national figures were applied to the WECC footprint by a 0.4 scaling factor.

Modeling of Load Profiles of LDVs, MDVs, HDVs for the 2028 Scenario

The following load profiles were established. LDV load profiles were generated by National Renewable Energy Laboratory using the EVI-Pro tool. MDV and HDV load profiles were modeled by PNNL. Load profiles are shown in the figures below.

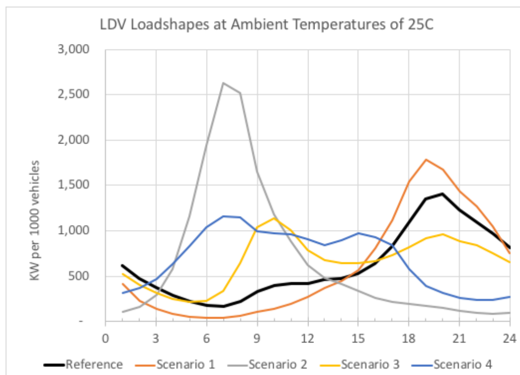

Figure S.1. LDV: Aggregate EV charging profiles for LDVs at the base temperature (25°C).

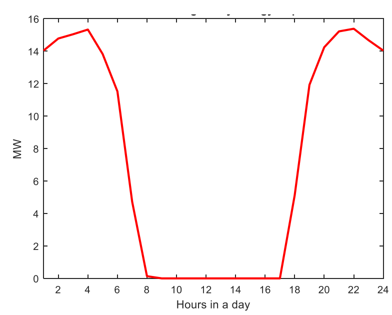

Figure S.2. **MDV:** Average daily load shape to charge 1000 MDVs with night charging, such that vehicles will be charged by the departure time the next morning. Identical to the LDV maximum delay charging strategy.

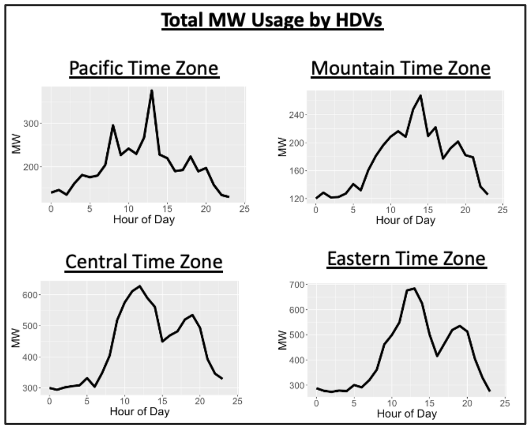

Figure S.3. **HDV:** Charging profiles of simulated HDVs from stations across each time zone. The vertical axis represents the total megawatts used when accounting for all speeds of charging ports.

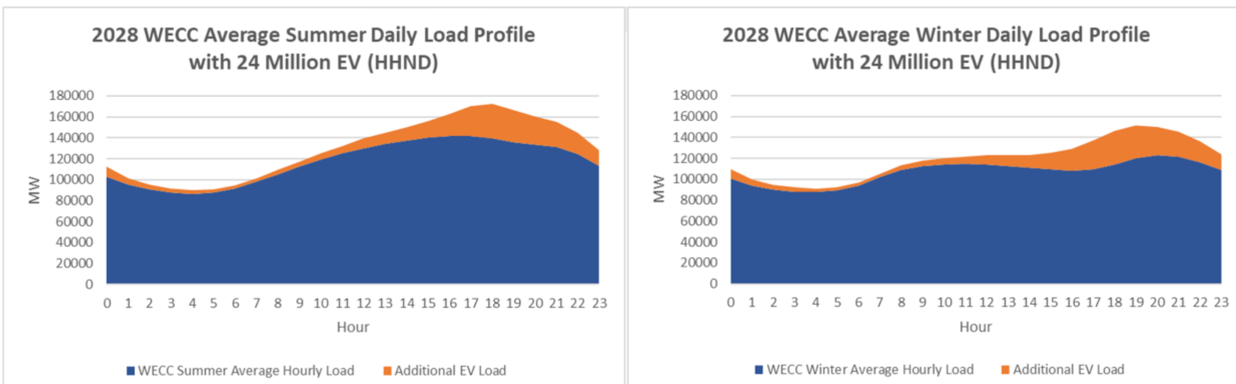

Figure S.4. Illustration of WECC base load and added EV load for "Home High power No Delay charging." EV load consists of 9 million LDVs, 70,000 MDVs, and 94 HDV charging stations. (The left frame represents summer load, the right frame winter load.)

Major Findings

2028 resource adequacy is likely to be sufficient for high EV penetration assumption.

- Under a high-penetration scenario with national electric fleets of ~24 million LDVs, 200,000 MDVs, 150,000 HDVs for a 2028 time frame, we are not expecting resource adequacy issues in the WECC under normal operating conditions (normal system, weather, and water conditions). The corresponding electric fleet sizes for the WECC footprint are 9 million LDVs, 70,000 MDVs and 94 HDV charging stations.

EV resource adequacy can be doubled with managed charging strategies.

The EV resource adequacy for the entire WECC interconnection was estimated for a likely unmanaged charging scenario under which most LDVs were charging at home starting in the evening (Home High power No Delay: HHND). Unmanaged charging is predicated on arrival time at home in the evening, when we assumed that the charging process begins. The maximum number of LDVs when projected to the national fleet was about 30 million (national value) or 9 million for the WECC footprint. Alternatively, if managed charging was applied by hypothesizing a price-minimization scheme, the EV resource adequacy could be expanded to 65 million (national fleet number) or 19.6 million for the WECC. This suggests a significant opportunity to substitute additional generation and transmission requirements with smart charging strategies and much better utilization of the existing grid. Figure S.5 shows the limited resource adequacy for unmanaged and managed charging. Note, the resource adequacy limit is set when the unserved energy becomes greater than zero.

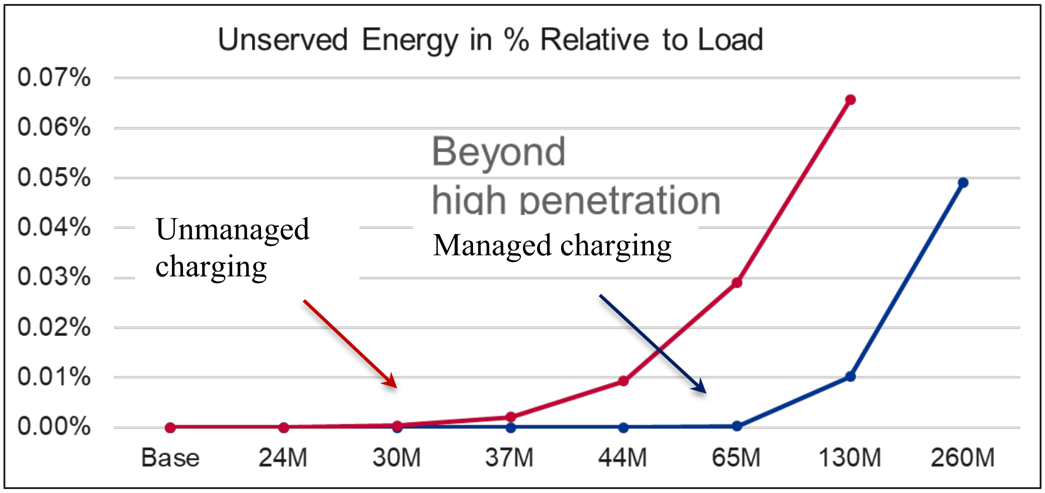

Figure S.5. Limits of resource adequacy for unmanaged charging (red) and managed charging (blue) based on unserved energy under increasing LDV penetration scenarios. Note that the LDV penetration numbers on the x-axis are the national penetration numbers. Penetration numbers for MDVs and HDVs were kept constant at 200,000 and 150,000, respectively. The WECC numbers must be scaled back by a factor of 0.3 because the WECC is projected to operate 30% of the national LDV EV fleet.

- At the maximum number of LDVs, the authors found transmission congestion to be the limiting factor, which means that there are some available power plants in the WECC but the electric power could not be delivered to the load centers because of transmission limitations. The largest transmission congestions were in California (Paths 15, 26).

Operational changes can be made to accommodate EVs.

- The additional generation for charging EVs is likely to be provided by natural gas combined cycle plants and combustion turbine s predominantly throughout the WECC (85%–89% of all new generation). See hourly marginal generation for WECC by technology for two different charging scenarios in Figures S.6 and S.7.
- Storage is used in California to meet the peaks set by EVs. Hydropower generation in Washington State is redispatched to resemble a commonly observed charging/discharge cycle of an energy storage technology. No new hydropower generation is expected because hydropower generation is energy limited—no more water is expected in the Columbia River system.

- All EV charging load is likely to reduce renewable curtailments between 25% and 75% based on when EVs are charged. Managed charging could reduce the curtailment the most by an additional 16%.

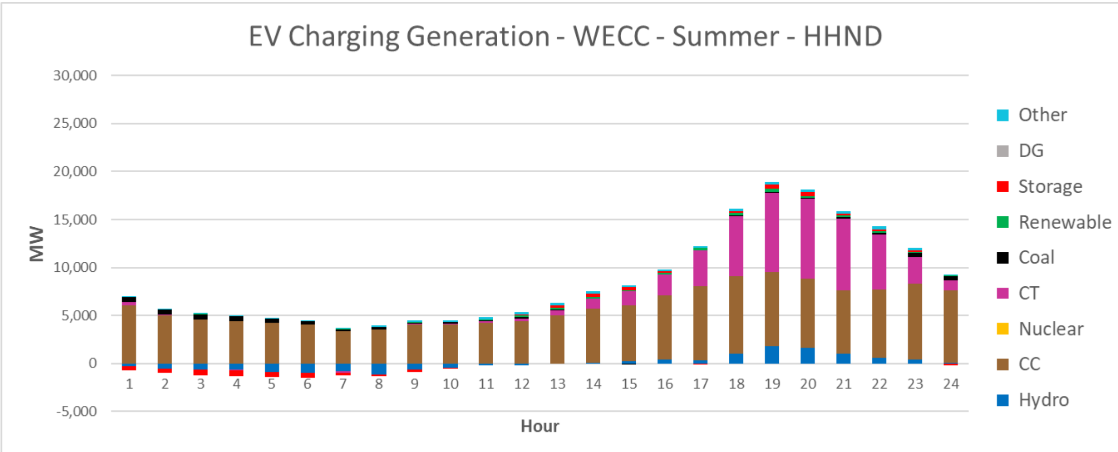

Figure S.6. Generation dispatch delta (with and without EVs) for an average summer day under the HHND (High power Home charging No Delay) charging scenario.

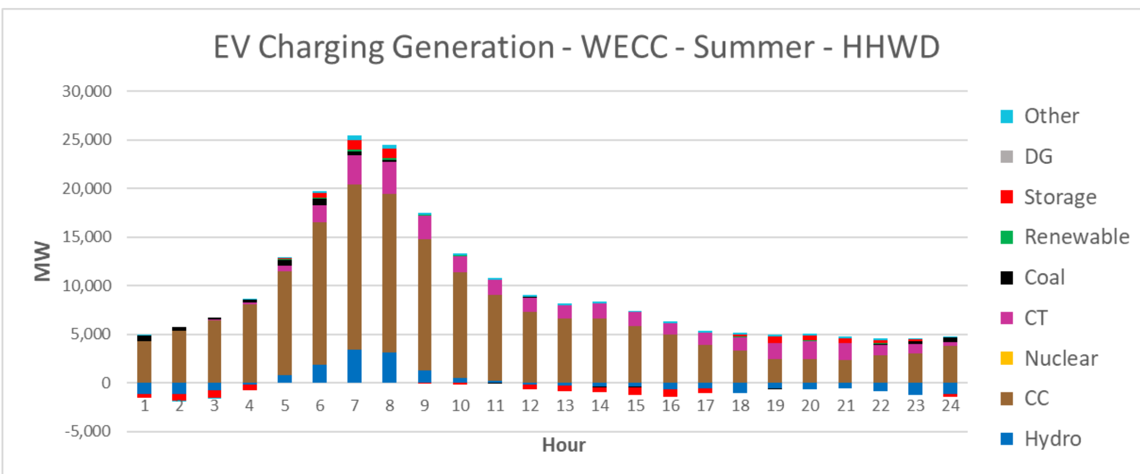

Figure S.7. Generation dispatch delta (with and without EVs) for an average summer day under the HHWD (High power Home charging With Delay) charging scenario.

- The production cost implications due to the additional load varied from 3% in Arizona, where there is some available coal generation, to 23% in California, where combustion turbines are required to meet the peak load set by EVs. It should be noted that all cost estimates were done keeping the generation capacity constant. It is likely that capacity expansion in anticipation of additional load may mitigate the cost increase, particularly, if the additional generation is renewable generation resources.

- Managed charging has significant operational benefits in solar-rich areas such as California. It reduced the duck curve in two ways: (1) it reduced the coincident peak (duck height) and (2) it reduced the ramp requirements in the evening when the sun sets (steepness of the duck's neck).

In addition, the authors analyzed EV-at-scale impacts for Washington State using the WECC results. The results of this higher resolution analysis are as follows:

- Unmanaged EV resource adequacy for Washington State is approximately 1 million LDVs and 4,600 MDVs under normal system, weather, and water conditions. With managed (smart) charging, the resource adequacy can be increased to 2.7 million LDVs.
- Washington State hydropower resources may need to be redispatched to accommodate unmanaged EV load.
- The average production cost implications of high LDV penetration are minor and vary between 4% and 9% based on the generation mix of the utility organization.
- The authors recognize congestion in the transmission system that already exists during high loading in the winter. Congestion is likely to be exacerbated with new EV loading with unmanaged charging, because of transfers from Canada to Washington, Washington to Oregon, and eastern Washington to western Washington under normal system, weather, and water conditions.

The bulk power analysis had inherent limitations.

The employed production cost modeling approach using a grid data set that represents a 2028 future grid realization comes with some inherent limitations.

The production cost model solves the generator unit commitment and economic dispatch problem given the available generators, the transmission system, and hourly loads in the WECC. It can identify system inadequacy by revealing sufficient generation and/or transmission capability to serve loads. It also provides insights into production costs and locational marginal prices on an hourly bases. However, this approach does not consider the evolution of the grid infrastructure as new investments are made. As a consequence, the production cost tend to increase with load additions as more expensive generators are being dispatched. In this analysis, the authors added new EV load beyond what the WECC members estimated in the 2028 data set to test the system adequacy question. Thus, the production cost implications are expected to be higher than if grid evolutions had been considered.

The illustrative distribution system analysis offered insightful results for Phase II analysis.

An illustrative distribution system analysis was presented that demonstrated the mechanism of how to perform a distribution system analysis and what the expected results and outcomes are. This illustrative example indicated the following:

- Factors most likely to limit the additional growth of EVs are thermal overloading or reaching the rated capacity of grid assets in the distribution system under fast charging conditions.
- Voltage violations may occur under fast charging conditions that feature high ramping loads during fast charging events.

Acknowledgments

The study authors express their appreciation and gratitude to the U.S. Department of Energy (DOE) for providing the funding for this study. In particular, the team appreciates the guidance by DOE staff and the members of various the U.S. Drive subcommittees to home in on the final research questions and scope of the project. Particular thanks to the DOE project managers Mr. Jake Ward and Lee Slezak for their leadership in directing the project.

The team also thanks fellow national laboratory staff Mr. Eric Wood and Dr. Matteo Muratori from the National Renewable Energy Laboratory (NREL), who provided the load profiles for the light-duty vehicles, and Mr. Marcus Alexander from the Electric Power Research Institute (EPRI), who provided the penetration scenarios for light-duty vehicles by counties for the entire continental United States. In addition, we thank Dr. Jin Zhu from ASEA Brown Boveri (ABB), who developed "smart charging" strategies for the new electric vehicle fleet in the ABB grid-modeling tool GridView, which was used in this analysis. His support was essential in representing the impacts of "smart charging" strategies on the electric vehicle resource adequacy in the Western Electricity Coordinating Council grid.

Acronyms and Abbreviations

ABB	ASEA Brown Boveri
ADS	Anchor Data Set
ANSI	American National Standards Institute
AVA	Avista Corporation
BA	balancing authority (grid zone, in which the frequency is maintained by balancing generation with load)
BEV	battery electric vehicle
BPA	Bonneville Power Administration
BTS	Bureau of Transportation Statistics
CAISO	California Independent System Operator
CC	combined cycle
CEC	California Energy Commission
CT	combustion turbine
DC	direct current
DCFC	direct-current fast charger
DOE	U.S. Department of Energy
DOT	U.S. Department of Transportation
EIA	Energy Information Administration
EPRI	Electric Power Research Institute
ERCOT	Electric Reliability Council of Texas
EV	electric vehicle
EV30@30	30% market share for EVs by 2030
FERC	Federal Energy Regulatory Commission
FMCSA	Federal Motor Carrier Safety Administration
GCPD	PUD No. 2 of Grant County
GHG	greenhouse gas
GWh	gigawatt hours
HDV	heavy-duty vehicle
HHND	Home High power No Delay
HHWD	Home High power With Delay
HLND	Home Low power No Delay
HLWD	Home Low power with Delay
IEA	International Energy Agency
kWh	kilowatt hour(s)
L&R	Load and Resource
LDV	light-duty vehicle

LMP	locational marginal pricing
MDV	medium-duty vehicle
MWh	megawatt hour(s)
NHA	National Highway Administration
NREL	National Renewable Energy Laboratory
OEM	original equipment manufacturer
PCM	production cost model
PHEV	plug-in hybrid electric vehicle
PNNL	Pacific Northwest National Laboratory
PSE	Puget Sound Energy
SCL	Seattle City Light
SoC	state of charge
TEPPC	Transmission Expansion Planning and Policy Committee (A committee within WECC)
TPWR	Tacoma Public Utilities
TWh	terawatt hour(s)
WECC	Western Electricity Coordinating Council
WLND	Work Low power No Delay
WLWD	Work Low power With Delay

Contents

Figures

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1.0 Introduction

The use of electric vehicles (EVs) in the United States has grown significantly during the last decade. So much so that the U.S. Department of Energy (DOE) asked Pacific Northwest National Laboratory (PNNL) to perform an authoritative study of the impacts of EVs at scale on the electric grid. "At scale" was defined for each vehicle segment differently. For light-duty vehicles (LDVs), the high EV penetration scenario by the Electric Power Research Institute (EPRI) was chosen; for medium-duty vehicles (MDVs), the International Energy Agency (IEA) recent forecast was chosen; and for heavy-duty vehicles (HDVs), a brief survey was chosen. Several conversations ensued between DOE staff, various engineers representing the automotive manufacturers and electric utility companies through a membership in the U.S. Drive Partnership,[1] and PNNL to define the scope of the study. It became clear that EVs at scale affect the electric infrastructure fundamentally in two different ways: (1) EVs affect the electric infrastructure at the point of common coupling, which for most EV charging stations (also referred to as EV Supply Equipment) is a connection to the distribution system, either at home, at a workplace, or at a public charging station; and (2) EVs at scale affect the bulk power system as an aggregated new load.

The bulk power system consists of electric generators and the high-voltage transmission network that delivers the electricity to distribution systems. DOE decided to focus first on the bulk power electricity impacts before transitioning to analysis of the distribution systems. Thus, the Phase I analysis documented in this report focused on bulk power, while the Phase II analysis will focus on the impacts of target future distribution systems.

Because of a sense of urgency related to performing the analysis and publishing the results, PNNL recommended that the study focus on the Western grid (i.e., the Western Electricity Coordinating Council [WECC]). The WECC already has a commonly agreed-upon data set for a future grid scenario—the WECC 2028. The same is not true for the Eastern Interconnection, and assembling such a data set for the Eastern Interconnection would have been too time-consuming given the expected timeline for the project. The Electric Reliability Council of Texas (ERCOT) does have data sets for a future grid build-out; however, given the short period of performance for the Phase I analysis, this PNNL study only focused on the WECC because of its currently available data set.

For this WECC bulk power EV-at-scale impact study, DOE was interested in addressing two main questions:

1. Are there sufficient resources in the U.S. bulk power grid to provide the electricity for charging a growing EV fleet? This question addresses system adequacy.
2. What are the likely operational changes necessary to accommodate a growing EV fleet? This question addresses changes in

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[1] U.S. DRIVE stands for *Driving Research and Innovation for Vehicle efficiency and Energy sustainability*. It is a non-binding and voluntary government-industry partnership focused on advanced automotive and related energy infrastructure technology research and development (R&D). More information is available at https://www.energy.gov/eere/vehicles/us-drive

- generation mix
- production cost
- challenges and benefits of accommodating the new EV loads.

The analysis attracted the attention of Washington State agencies, particularly that of the Departments of Transportation and Commerce. Both departments are interested in better understanding some of the potentially limiting electricity supply challenges that will be faced as Washington develops new electrification of transportation strategies for the state. Washington State requested that the study interpret the implications of the EV-at-scale impact analysis for the state. Because no new simulation work needed to be done (Washington State is part of the WECC), this request was incorporated into the study scope and the associated implications are discussed in this report.

This EV-at-scale Phase I study is unique in that for the first time a grid impact study was performed using projected EV load scenarios that included all three categories of on-road transportation: LDVs, MDVs, and HDVs. Many studies conducted, reaching back 10 years, have focused on LDVs by hypothesizing EV infrastructure and associated load profiles. This study is the first that posits MDV and HDV charging profiles in addition to LDV load assumptions. With recent announcements made by Amazon.com Inc. about purchasing 100,000 EV delivery trucks from Rivian for expected delivery by 2024,[1] it was considered prudent to include this new vehicle category in the analysis. Furthermore, because major manufacturers of Class 6–8 trucks are currently demonstrating HDV applications, we included heavy-duty long-haul applications as well.

This report summarizes the EV-at-scale Phase I study, starting with all major input assumptions and scenario definitions, followed by a comprehensive discussion of the results for the WECC. A separate section is devoted to the discussion of the results for Washington State. The WECC bulk power analysis is then summarized and conclusions are provided from the perspectives of the grid planning community and the EV charging infrastructure sector. The report closes with insights about challenges related to addressing the impacts of EVs and/or the grid on distribution systems, which will be the subject of the Phase II study.

Appendices contain supplementary information about the selected MDVs and their characterization (Appendix A); the HDV model and algorithm (Appendix B); county-to-balancing authority mapping for the WECC (Appendix C); 2028 WECC load profiles (Appendix D); the regional distribution of unserved energy over various LDV penetration scenarios (Appendix E); graphs of the seasonal flows under increasing LDV penetration for the WECC paths (Appendix F), and Washington State flowgate impacts (Appendix G).

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[1] https://www.theverge.com/2019/9/19/20873947/amazon-electric-delivery-van-rivian-jeff-bezos-order

2.0 Methodology

The workflow for the bulk power analysis is shown below in Figure 2.1. It followed a very linear process starting with the identification of the EV penetration scenarios. We considered not only LDVs, but also MDVs and HDVs, because they are expected to penetrate the market very soon. Once the penetration scenarios are defined, which includes hypothesizing the numbers of electric LDVs, MDVs, and HDVs on the landscape, the charging profiles need to be estimated. For LDVs and MDVs, we assumed that most vehicles would be charged at their home locations. For the HDV segment, we posited a long-haul business case, in which an EV truck departs from one location and drives across the county, charging at different locations. This required some new transportation modeling approaches, which were developed as part of this project. Finally, the aggregated future EV loads represented by LDVs, MDVs, and HDVs were added to the projected non-vehicular load forecast.

This completed the data development and preparation for the grid modeling, designated in

as a "perform production cost modeling." The analysis used a production cost model of the WECC representing the transmission as a nodal network with generation nodes, where electricity is generated and transmitted through the transmission network to the load nodes. Given a certain hourly load for each load node for an entire year, the model solves for the least cost generator dispatch to meet all loads. The outputs from such a model are generally very large, specifying the operational profile of each generator for each hour in the entire system. Resource adequacy issues, which are represented as unserved energy at a certain location in the network at a certain time, are extracted from the model. The average and marginal costs for generation by regions and by months can be generated to gain insights into the operational changes between cases with and without EV loads.

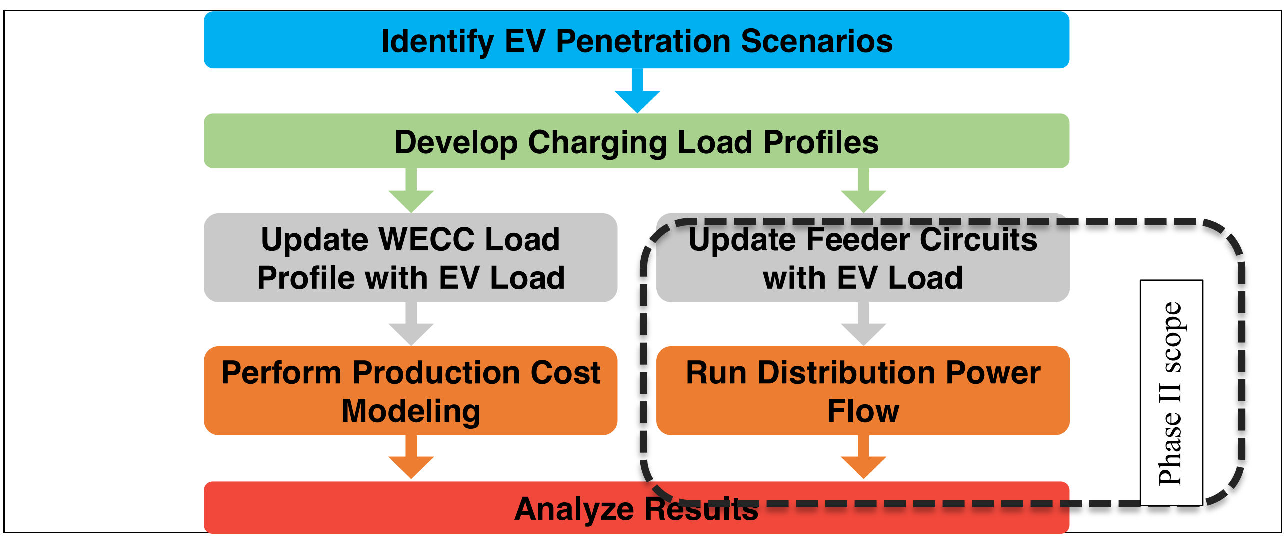


Figure 2.1. Workflow of the bulk power analysis. (Note: The distribution system analysis, framed as Phase II activity, is shown here to indicate how consistency between bulk power and distribution system analysis can be achieved.)

Figure 2.1 also points to the fact that in order to maintain consistent load assumptions between the bulk power and the distribution system analyses, the charging load profiles need to be mapped appropriately to their respective level of aggregation. The bulk power analysis specifies the loads by balancing authority. The distribution analysis requires load data by substation nodes.

3.0 Definition of EV Penetration Scenarios

Assumptions were critical for the outcome of this analysis. This section discusses assumptions related to LDVs, MDVs, and HDVs, and identifies their sources. In each case, national adoption and mapping of the EV fleets to balancing authorities are addressed. Where no appropriate data exist, we used proxy data and provide some rationale explaining the reasoning for their use.

3.1 Light-Duty Vehicles

3.1.1 National Adoption

For this study, we assumed adoption trajectories based on Alexander's EPRI study (Alexander 2017). The EPRI study reviewed key EV projections performed by institutions such as DOE, the National Renewable Energy Laboratory (NREL), U.S. Energy Information Administration (EIA), Natural Resources Defense Council, Navigant Research, and Google.org to establish proxies for high, medium, and low EV penetrations. The sources for the literature review can be found in the Technical Update by Alexander (2017). Figure 3.1 shows the projection scenarios as total national values. [i]

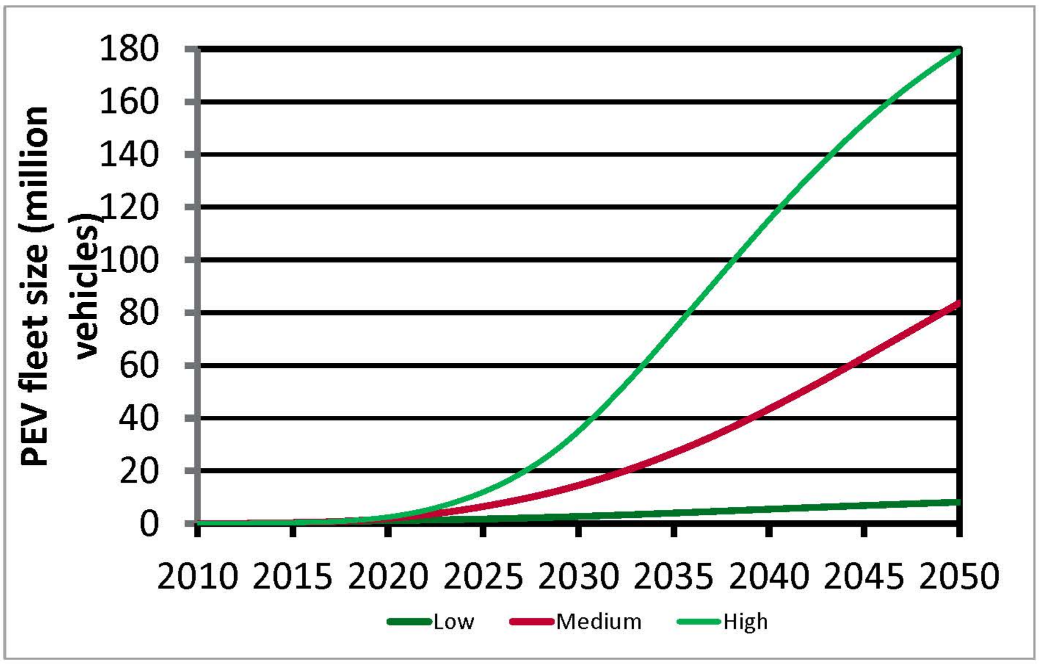


Figure 3.1. EV sales projections (Source: Alexander 2017).

While the EPRI study projected EV penetration out to 2050, for the purpose of this EV-at-scale study, we used the 2028 values only. The year 2028 was chosen as the study year because it is the furthest year out into the future for which data exist that describe a commonly acceptable realization of a bulk power grid in the Western United States.

The EV fleet sizes (EVs on the road) for 2028 for the three scenarios (low, medium, high) are listed in Table 3.1.

Table 3.1. Fleet size of EV projections by scenarios.

Scenario	Fleet Size in No. of EVs in millions
Low	2.3
Medium	10.8
High	**23.6**

The EPRI study provided a regional EV allocation methodology that was based on several factors. First, it factored in the influence of the regulatory requirements enforced in the "Section 177" states (CA, OR, CN, ME, MD, MA, NJ, NY, RI, VT); that is, states that have adopted the California Zero Emission Vehicle program (Clean Air Act 1990). These regulations have established a constraint on the manufacturers for minimum sales of EVs. The numbers for regional EV sales projections in addition to the recent sales history for EVs and non-EVs were used to generate county-specific EV penetration numbers. These county-level projections were in turn aggregated to form state-level and—for grid-modeling purposes—balancing authority-specific projections.

It should be noted that this analysis only used the high-penetration scenario with a nationwide penetration of 23.6 million LDVs in 2028. The low-penetration number appeared to be too pessimistic. We omitted the medium penetration scenario because we considered it not to be an interesting scenario after we learned the results from the high-penetration case.

For practical purposes, we refer to the high-penetration LDV number as 24 million, but the true number for all calculations remained 23.6 million.

3.1.2 Mapping LDV EV Fleet to Balancing Authorities

The end goal of this study is to superimpose the additional load from the charging of EVs on the electrical power systems model to assess potential impacts of EVs at scale on the electric grid. As explained in further detail later in this report, the electrical model aggregates loads, both EV and regular, by county and then into balancing authorities (BAs). BAs are collections of generation, load, and transmission assets that are dispersed geographically. The assets within each BA are managed by a single entity, the balancing authority, which is responsible for maintaining generation-load balance within the area. The electrical model used for this study—the WECC model—includes representation of power grid assets from the western states of the United States. There are a total of 34 BAs in the WECC that vary significantly in terms of the geographic area they serve, and the quantity of load and generation they balance (see Figure 3.2). For example, Seattle City Light covers an area around the city of Seattle, whereas, the California Independent System Operator services a large area covering the majority of the state of California. For this study, the goal is to superimpose the additional EV load on existing BA-specific load available in the electrical model. Toward this end, it was essential to map EV fleet projections to the geographic areas covered by the 34 BAs in the WECC (see Figure 3.3).

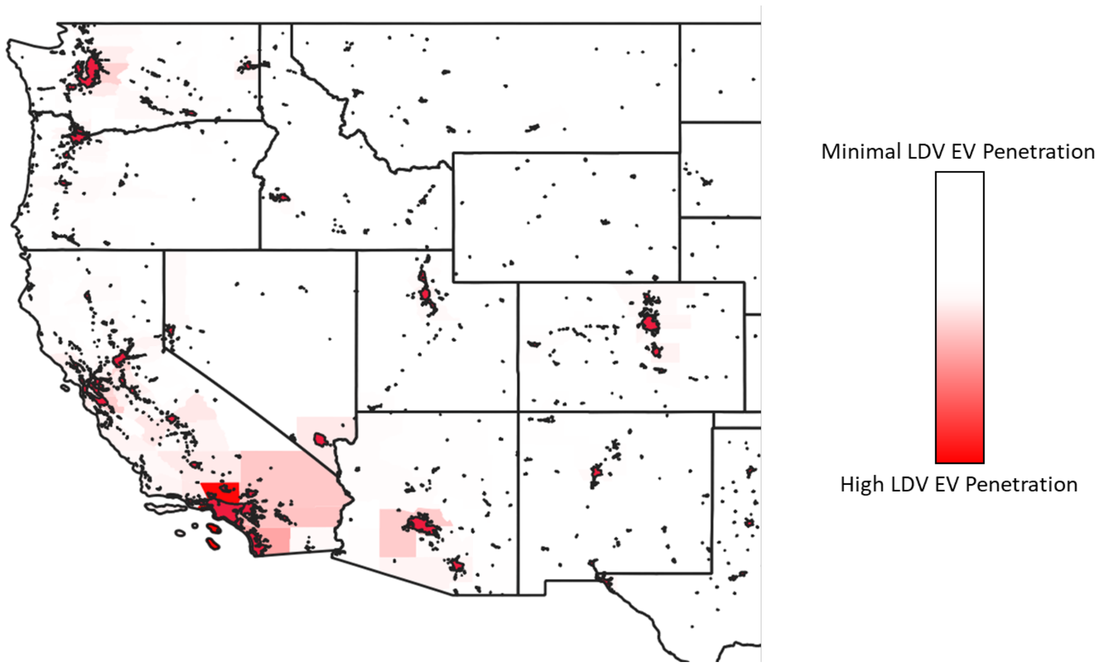
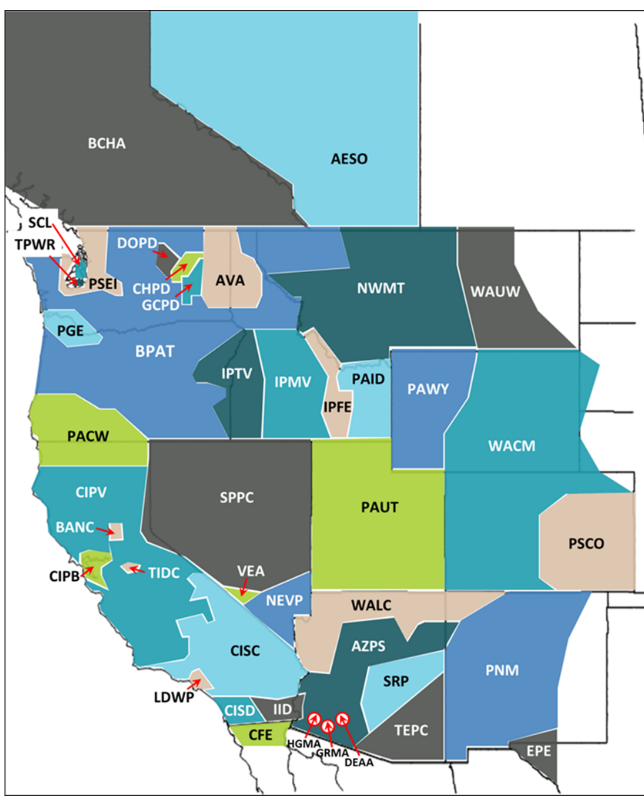


Figure 3.2. Heat map of electric LDV penetration assumptions in the WECC region.



TEPPC Area	Area Description
AESO	Alberta Electric System Operator
AVA	Avista
AZPS	Arizona Public Service
BANC	Sacramento Municipal District
BCHA	British Columbia Hydro
BPAT	Bonneville Power Administration
CFE	Comision Federal de Electricidad
CHPD	Chelan Co PUD
CIPB	Pacific Gas & Electric Bay Area
CIPV	Pacific Gas & Electric Valley Area
CISC	Southern California Edison
CISD	San Diego Gas & Electric
DOPD	Douglas Co PUD
EPE	El Paso Electric
GCPD	Grant Co PUD
IID	Imperial Irrigation District
IPFE	Far East (Idaho Power)
IPMV	Magic Valley (Idaho Power)
IPTV	Treasure Valley (Idaho Power)
LDWP	Los Angeles Dept of Water & Power
NEVP	Nevada Power
NWMT	Northwestern Montana
PACW	PacifiCorp West
PAID	PacifiCorp East – Idaho
PAUT	PacifiCorp East – Utah
PAWY	PacifiCorp East - Wyoming
PGE	Portland Gen Electric
PNM	Public Service New Mexico
PSCO	Public Service Colorado (Xcel)
PSEI	Puget Sound Energy
SCL	Seattle City Light
SPPC	Sierra Pacific Power
SRP	Salt River Project
TEPC	Tucson Electric Power
TIDC	Turlock Irrigation District
TPWR	Tacoma Power
VEA	Valley Electric Association
WACM	Western Area Power Admin Colorado/Missouri
WALC	Western Area Power Admin Lower Colorado
WAUW	Western Area Power Admin Upper Missouri
N/A	DECA, LLC - Arlington Valley (DEAA)
N/A	Gila River Maricopa Arizona (GRMA)
N/A	Harquahala L.L.C. (HGMA)

Figure 3.3. Balancing authorities in the WECC region.

The EV fleet projection data generated by EPRI currently provide the data at the state level. The data in this form are not useful because multiple BAs sometimes operate in a single state. For example, the state of Arizona has eight BAs operating within its territory. To effectively map the

EV fleet charging load to BA load, the fleet data had to be broken into more granular chunks. Toward this end, the state-level EV fleet projection data were divided into county-specific data within the state. The county-specific LDV registration data for 2019 were used as a reference point to identify what percentage of the total number of vehicles in a state was registered in every county. This proportion was then extended to the state-specific EV fleet projection numbers generated by EPRI for 2028. One shortcoming of this approach is that it assumes all counties have the same proportion of EVs and gasoline-powered LDVs across the state. Table 3.2 shows a sample of county-specific data for the state of Arizona, where the EV fleet size for 2028 was projected to be 499,538 vehicles.

Table 3.2. Distribution of the EV fleet projection across Arizona counties for 2028.

Counties in Arizona	Number of EVs in 2028
COCONINO	10,214
MARICOPA	294,495
NAVAJO	8,650
YAVAPAI	19,667
YUMA	16,839
GREENLEE	817
GILA	4,373
PINAL	25,961
COCHISE	11,032
PIMA	64,644
SANTA CRUZ	6,547
APACHE	5,314
GRAHAM	2,772
LA PAZ	1,957
MOHAVE	17,930

The next step in the process involves the aggregation of the data for the above-listed counties into the geographic regions represented by BAs. This was performed by visually comparing the map of BA service territories with the state county maps. In cases where the BA boundary did not align exactly with county boundaries, the county was awarded to the BA that contained most of its area. In addition, in cases where the geographic size of the BA was significantly smaller than the size of the county, the county was awarded to the larger BA in the vicinity. As mentioned earlier, the state of Arizona has eight BAs operating within its territory. Using this approach, the EV fleet projection data for Arizona in Table 3.2 were aggregated into the five BAs listed in Table 3.3.

A similar approach was followed for all the states and BAs in the WECC to arrive at the BA-specific EV fleet projection for 2028 presented in Table 3.4. Note that of the 34 BAs, only 29 BAs are represented because those remaining were too small to assign to counties. County-to-BA mapping for all of WECC can be found in Appendix C. The total number of LDVs in the WECC for the 24 million LDV estimation is 9 million, which is about 40% of the national number.

Table 3.3. 2028 EV fleet projection by BA in Arizona.

Counties in Arizona	Balancing Authority	Projected EV Fleet Size for 2028
Coconino Maricopa Navajo Yavapai Yuma	AZPS	349,865
Greenlee	PNM	817
Gila Pinal	SRP	30,334
Cochise Pima Santa Cruz	TEPC	82,224
Apache Graham La Paz Mohave	WALC	27,973

AZPS = Arizona Public Service; PNM = Public Service Company of New Mexico; SRP = Salt River Project; TEPC = Tucson Electric Power Company; WALC = Western Area Power Administration, Lower Colorado Region.

Table 3.4. 2028 projected EV by balancing authority. Note: The total for WECC is 9 million LDV EVs or about 40% of the national projections of 24 million.

Balancing Authority	2028 Projected LDV EV Fleet Size
AVA	93,959
AZPS	349,865
BANC	265,341
BPAT	451,510
CHPD	11,583
CISO	3,637,413
DOPD	12,302
EPE	62,044
GCPD	14,387
IID	383,160
IPCO	45,843
LDWP	1,409,956
NEVP	189,025
NWMT	34,823
PACE	244,537
PACW	45,535
PGE	184,827
PNM	110,118

Balancing Authority	2028 Projected LDV EV Fleet Size
PSCO	413,475
PSEI	382,376
SCL	103,813
SRP	30,334
TEPC	82,224
TIDC	41,548
TPWR	33,224
WACM	191,738
WALC	27,973
WAUW	6,187
WWA	234
TOTAL	8,859,354

3.2 Medium-Duty Vehicles

3.2.1 National Adoption

The literature about MDV EV market penetration projection is very thin. We only found two recent studies that estimated future truck and bus penetration. The IEA, in its Global EV Outlook 2019 (IEA 2019), published EV projections for the United States for 2030. We used the aggressive growth scenario—"EV30@30" or 30% market share for EVs by 2030. The market share definition includes all vehicle classes as the IEA study specifies them: LDV, bus, and truck. The 30% market share is very similar in size to the 30% EV sales assumptions made in the EPRI study (Alexander 2017) for LDVs for the 2030 projection. For the "truck" vehicle segment, the IEA study projects about 2.5 million vehicles worldwide for 2030. There is no further description of attributes of the "truck" segment that would lend itself to mapping it into the vehicle class definition established by the U.S. Department of Transportation.

Furthermore, the study does not break out the number of trucks for the United States. It only specifies the electric energy requirements for the electric truck segment for the United States.

Using the IEA assumption for energy conversion and miles traveled for the truck segment, we can estimate from the energy requirements the number of trucks projected for 2030, by using the following values provided by the IEA:

- energy conversion for trucks: 0.42–0.3 miles/kWh, used mid-point 0.36 miles/kWh
- miles traveled for trucks per year: 13,750 to 56,875 miles, used 50,000 miles
- annual electric energy consumption of 30 TWh.

We can estimate 216,000 trucks for 2030 as the IEA EV30@30 estimate. We proposed to use 200,000 as the total U.S. MDV estimate in this study for the 2028 study year. Below, we describe how to map the U.S. total numbers into states and BAs

3.2.2 Mapping the MDV EV Fleet to Balancing Authorities

The regional sharing of the national total number of trucks is predicated on the assumption of the use-case of an electric truck. We assumed that the near-term application for an MDV truck would be a delivery service similar to that of a United Parcel Service or Federal Express business model. We assumed that delivery services would first be adopted in metropolitan areas that feature a lot of stop-and-go driving rather than in rural areas that feature higher average travel velocities. An electric drive vehicle may be more competitive than an internal combustion engine vehicle under stop-and-go and low-speed travel conditions, particularly in cities and jurisdictions where clean air regulations (non-attainment zones) may drive zero-emission vehicle policies.

Because of the above rationale, we developed a sharing algorithm based on the populations of cities. U.S. cities above 100,000 population were selected; 313 cities met this criterion. The total number of electric MDVs was then applied based on a proportional percentage of the population of the 313 cities. Figure 3.4 shows the number of metro areas by states in the WECC. There are 123 metro areas in the WECC. The total number of electric MDVs for the WECC are 70,000 or about 35% of the assumed national electric MDV fleet of 200,000.

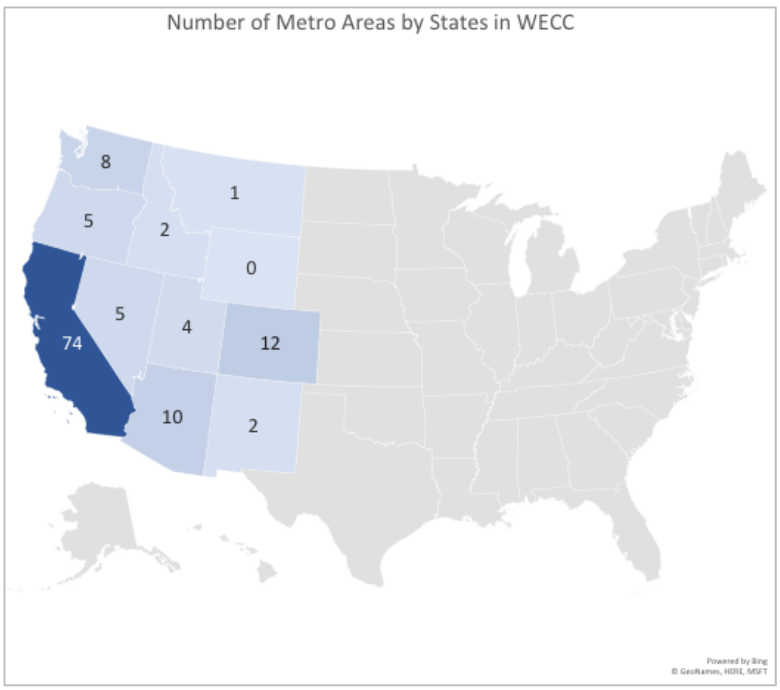


Figure 3.4. Number of metro areas by states in the WECC.

The locations of the metro areas were then mapped into the BAs and the number of electric MDVs were added up by BA.

3.3 Heavy-Duty Vehicles

3.3.1 National Adoption

For the HDV segment, we exclusively limited the EV projections to the long-haul freight application. We applied an abbreviated Delphi method by interviewing truck experts from PACCAR Inc. and Tesla, Inc. to elicit reasonable total EV fleet numbers for Class 8 long-haul trucks. Based on information derived from the conversations, we proposed an optimistic number of 150,000 electric HDVs for the 2028 study year.

3.3.2 Mapping the HDV EV Fleet to Balancing Authorities

The mapping of HDV electric energy consumption was done differently than the mapping of LDV and MDV electric energy consumption. Unlike LDVs and MDVs, HDVs travel cross-country and do not return back to their "home" station every night. Thus, the location of charging changes all the time. We applied a simplified transportation model that models an HDV fleet and records when and where HDV vehicles are charging. More detail about the simplified HDV transportation model is provided in Section 4.3.

We report the charging patterns by charging stations. The charging stations for the simplified transportation model are shown in Figure 3.5 below. Additional details about the charging station locations and their real-world relevance are provided in Appendix B. The energy consumption from each charging station is then directly mapped to the BAs.

There are a total of 271 HDV charging stations nationally and 94 in the WECC.

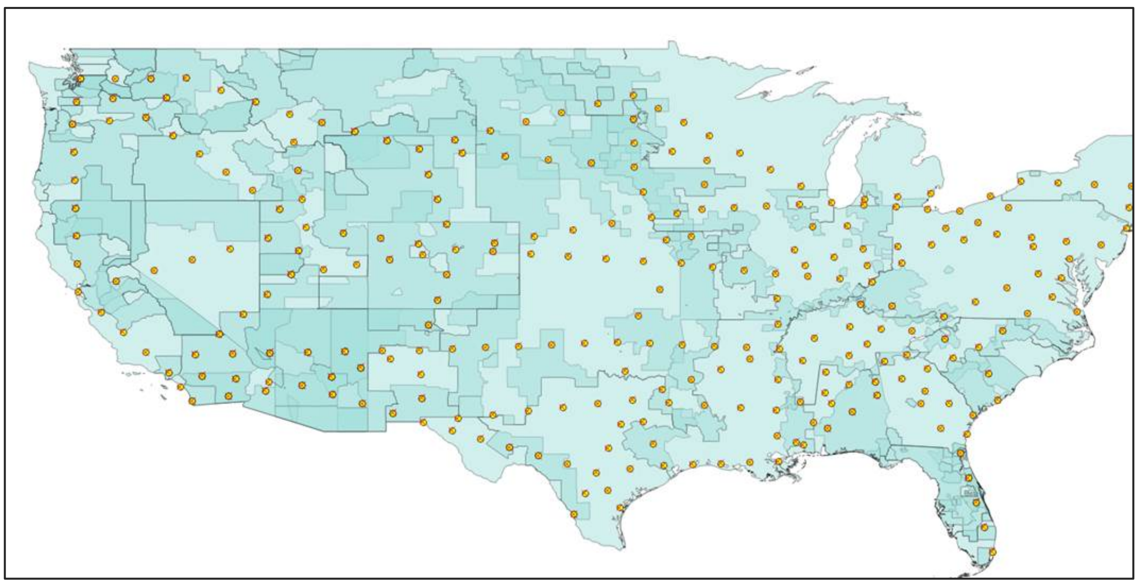


Figure 3.5. Locations of the HDV model charging stations along a simplified interstate network and their corresponding BA boundaries mapped against the U.S. map for better visualization.

4.0 Developing Charging Profiles

4.1 LDV Profile for 2028

The LDV load profile was generated by NREL using the electric vehicle infrastructure projection (EVI-Pro) tool, a bottom-up model developed through a collaboration between NREL and the California Energy Commission (CEC; Wood et al. 2017, 2018; Bedir et al. 2018). EVI-Pro projects EV charging profiles at different locations for LDVs based on household travel data and assuming that future EVs will be driven in a manner consistent with present-day gasoline-powered vehicles. Consumers were assumed to prefer to perform the majority of charging at their homes or workplace locations, depending on the scenario. EVI-Pro then estimates charging requirements at public Level 2 (L2) and corridor/community direct-current fast charger (DCFC) stations as necessary. EVI-Pro uses detailed data about personal vehicle travel patterns, EV attributes, and charging infrastructure characteristics that influence the energy needs and charging profiles. Moreover, EVI-Pro considers energy requirements for heating and cooling the vehicle cabin, leading to different charging needs in different climate zones. It simulates charging profiles for an EV fleet for weekdays and weekends. The analysis included the following inputs:

- EV fleet composition in different scenarios includes different shares of the following:
  - plug-in hybrid electric vehicle 20 (PHEV20) with a nominal electric driving range of 20 miles
  - PHEV50 with a nominal electric driving range of 50 miles
  - battery electric vehicle 50 (BEV250) with a nominal electric driving range of 250 miles.
- Charging infrastructure characteristics:
  - Home Level 1 (L1) charging station with a maximum charge rate of 1.4 kW (120V, 12A)
  - Home L2 charging station with a maximal charge rate of 9.6 kW (240V, 40A)
  - Work L2 charging station with a maximal charge rate of 6.2 kW (208V, 30A)
  - Public L2 charging station with a maximal charge rate of 6.2 kW (208V, 30A)
  - Public DCFC with a maximal charge rate of 150 kW.
- Charging strategy:
  - No delay when arriving at the charging station (i.e., each vehicle starts charging as soon as it is plugged in, and remains plugged in until it is fully charged or taken on another trip).
  - The maximum delay when arriving at the charging station such that each EV is fully charged when unplugged to start the next trip (home and workplace stations only).

The following charging strategies or charging scenarios were considered, including no delay or maximum delay but no smart charging strategy based on electricity supply-side considerations (these scenarios provide bounds for the EV charging flexibility, but not an optimized charging strategy):

1. <u>Reference case</u>: **“home dominant, <u>low</u> power charging, no delay”**
   a. Vehicles are assumed to prioritize home charging.

   b. Home charging rates are relatively low (mix of L1, L2).
   c. Charging begins upon arrival at the destination.
2. <u>Scenario 1</u>: **"home dominant, <u>high</u> power charging, no delay"**
   a. Vehicles are assumed to prioritize home charging.
   b. Home charging rates are relatively high (all L2).
   c. Charging begins upon arrival at the destination.
3. <u>Scenario 2</u>: **"home dominant, <u>high</u> power charging, max delay"**
   a. Vehicles are assumed to prioritize home charging.
   b. Home charging rates are relatively high (all L2).
   c. Charging at home and the workplace is delayed as much as possible.
4. <u>Scenario 3</u>: **"work dominant, <u>low</u> power charging, no delay"**
   a. All vehicles making trips to a workplace are assumed to have access to and prioritize charging at a workplace charger.
   b. Home and the workplace charging rates are relatively low (mix of L1, L2, DC).
   c. Charging begins upon arrival at the destination.
5. <u>Scenario 4</u>: **"work dominant, <u>low</u> power charging, max delay"**
   a. All vehicles making trips to a workplace are assumed to have access to and prioritize charging at a workplace charger.
   b. Home and workplace charging rates are relatively low (mix of L1, L2, DC).
   c. Charging at home and the workplace is delayed as much as possible.

Scenario definitions are provided in Table 4.1.

Table 4.1. Scenario definitions.

Scenarios		HLND	HHND	HHWD	WLND	WLWN
EV Fleet Composition[1]	PHEV20			5.1%		
	PHEV50			25.6%		
	BEV250			69.3%		
	Total			100%		
Home Charging	L1	32%	0%	0%	24%	24%
	L2	43%	91%	91%	31%	31%
Work Charging	L1	1	0%	0%	10%	10%
	L2	3	0%	0%	21	21
	DC1	5%	1%	1%	3%	3%
	Public L2	17%	7%	7%	12%	12%

[1] Fleet composition stems from EPRI (Alexander, 2017)

Scenarios		HLND	HHND	HHWD	WLND	WLWN
Charging strategy	Max delay	0%	0%	100%	0%	100%
HHND = Home High power No Delay; HHWD = Home High power With Delay; HLND = Home Low power No Delay; WLND = Work Low power No Delay; WLWD=Work Low power With Delay.						

The charging profiles are shown in Figure 4.1 for the charging scenarios for an EV fleet of 1000 vehicles. The ambient air condition is 25°C as the base temperature.

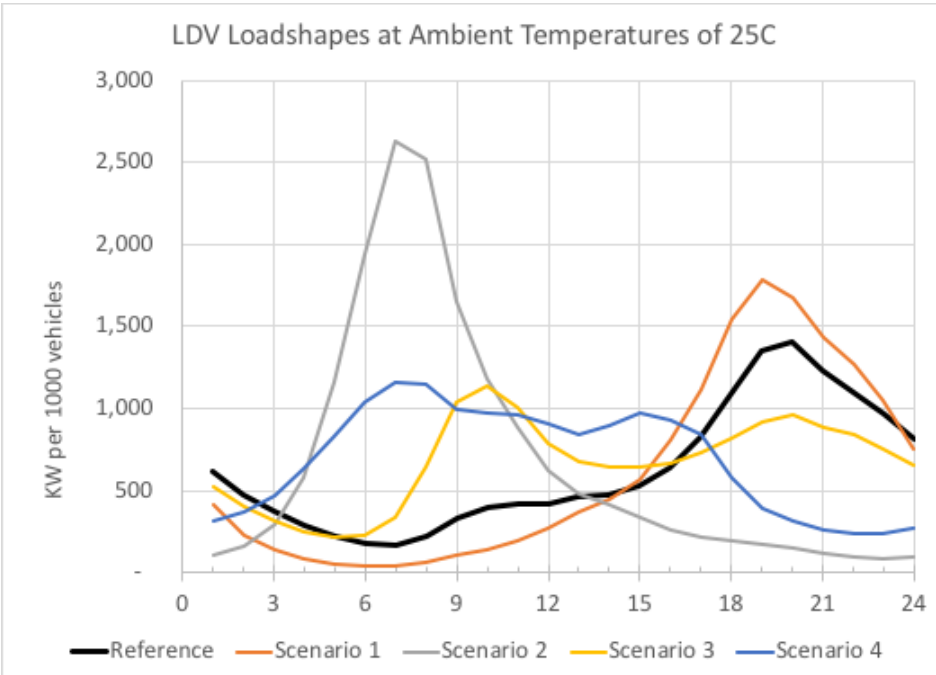


Figure 4.1. Aggregate EV charging profiles for LDVs at the base temperature (25°C).

As modeled in EVI-Pro, the EV charging load changes in different climate zones because of the different ambient temperatures, as shown in Figure 4.2. The differences in EV energy use capture the additional cooling and heating energy requirements at different ambient temperatures. For extreme hot and cold air temperature conditions, the peak demand (kW) can be increased between 30%–40% for the reference scenario with a similar proportional increase in energy increase (kWh), compared to reference temperature of 25°C. It should be noted that particularly under hot conditions, the additional 40% of peak demand increase places a significant burden on the grid because other building loads are likely to peak as well because of intense air-conditioning use.

PNNL decided to use the worst-case temperature scenario, in which all of the zones for the electric system modeling are assumed to be modeled under the hottest conditions (40°C). This assumption leads to over-estimation of the likely energy requirements.

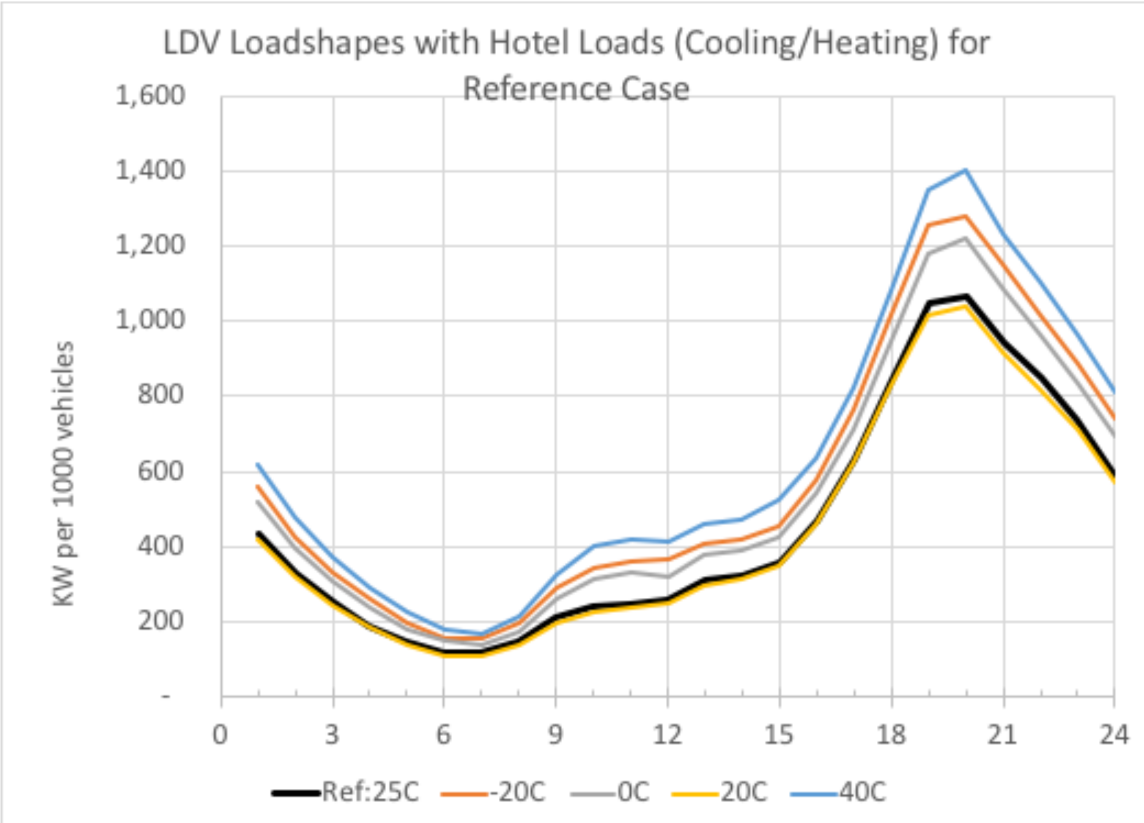


Figure 4.2. Ambient temperature dependency representing the additional cooling and heating energy requirements.

4.2 MDV Modeling for 2028 Charging Profile

MDV modeling tools for estimating the potential charging profile for EVs in this class of vehicles are lacking. Thus, we established a very high-level model that is parameterized to provide some indication of how future charging profiles may look. It is predicated on vehicle Classes 4 and 6 (Figure 4.3) according to the Federal Highway Administration (FHWA 2013). The vehicle class is relevant for the assumed average energy requirements for a vehicle of this class to drive 1 mile (kWh/mile). The use of an MDV modeled in this project resembles a delivery business operating a 1-shift business where drivers would start in the morning from a common truck yard with a fully charged electric truck. The delivery routes are of varying distances. Each driver returns to the truck yard after completing the delivery route. Charging is assumed to occur at the truck yard.

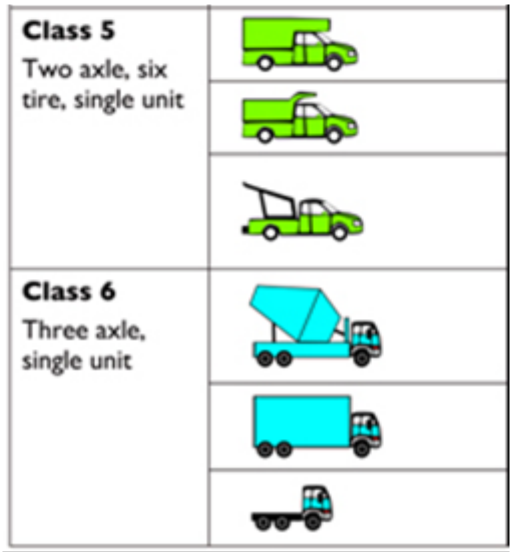


Figure 4.3. MDV classes (FHWA 2013).

4.2.1 Modeling Approach

The delivery route distances were assumed to align with NREL's Fleet DNA Project Data Set (NREL 2019). Furthermore, each vehicle was assumed to start to charge to its full capacity at the end of the day's trip. To obtain an aggregate average daily load profile of the above fleet of electric delivery trucks, the following set of parameterized assumptions was specified:

1. **Trip start time for first trip of the day:** Trip start time is drawn from a normal distribution with a mean of 7:00 AM and a standard deviation of 0.5 hours. The assumption is based on U.S. Census Bureau data (U.S. Census Bureau 2016).
2. **Trip length:** Trip length is modeled according to NREL's Fleet DNA Project Data set (NREL 2019). The trip lengths are represented as a normal distribution with a mean of 110 miles (177 km) and a standard deviation of 15 miles (24.1 km). The trip length is capped at 130 miles (209.2 km) in order to stay within an arbitrarily imposed battery size limit of 200 kWh, which assumed a fuel efficiency of 1.44 kWh/mi (0.89 kWh/km).
3. **Charging rates:** Three charging technologies are assumed to be available at the truck yard with charging rates of 50, 150, and 300 kW. The charging rates are randomly assigned to trucks and trips assuming that all trucks could accept up to 300 kW of charging rates.
4. **Battery size:** Battery sizes are randomly chosen from a range of discrete values of 80, 90, 160, and 200 kWh. The values are aligned with original equipment manufacturer (OEM) announcement of electric trucks by Ford, eCanter – Daimler, Chanje (see Appendix A.1).
5. **Speed:** The speed assumptions are drawn from NREL's Fleet DNA Project Data Set for the delivery vans. The speed-trip length relationship corresponds to the length of trips described above (NREL 2019).
6. **Number of stops:** The average number of stops, adopted from NREL's Fleet DNA Project Data set for delivery vans, is assumed to be 130. The length of average delivery stops is assumed to be 53 seconds and is adapted from NREL's data set (NREL 2019).

7. **Additional trip generation assumptions:**
   a. Each trip starts with 100% state of charge (SoC).
   b. Each trip ends before 20% SoC. It is assumed that the driver never fully depletes the battery to the allowable 20% SoC before arriving at the home truck yard. There will be no opportunity charging somewhere outside the yard.
8. **Charging strategy:** This project assumes that because of the relatively high charging rates and the number of EV trucks that are charged simultaneously, that all of the charging will be performed during off-work hours, which is after drivers return from their delivery trips and not before 6 PM. We modeled strict night charging with the onset of charging not before 6 PM with a delay that assured that the vehicle would be fully charged by the estimated morning start of the next day.

The end-of-the-day SoC of each truck was computed given the assumptions above. Ten thousand trips were generated with different vehicle battery sizes and an assumed fixed efficiency of 1.44 kWh/mile, resulting in aggregated daily charging load profiles for the MDV segment.

4.2.2 MDV Load Shape

The load shape in Figure 4.4 was obtained by first obtaining the normalized load shape from the 10,000 randomly generated trips and scaling it by the daily energy requirement of 1000 MDVs.

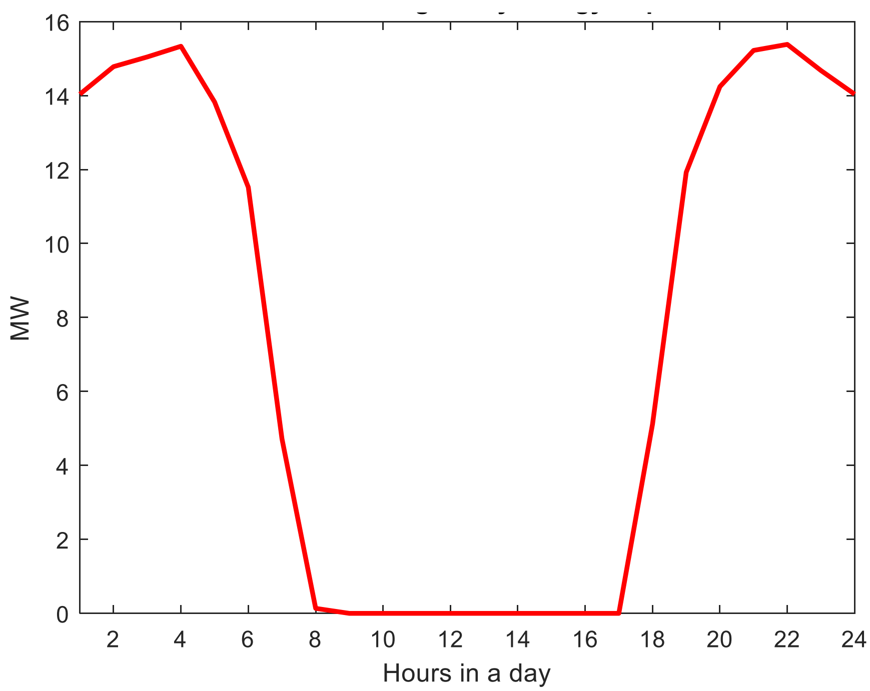


Figure 4.4. Average daily load shape to charge 1000 MDVs with night charging, such that vehicles will be charged by the departure time the next morning. Identical to the LDV maximum delay charging strategy

4.2.3 Exploration of Sensitivities of Assumptions

To explore the sensitivities of some arbitrarily chosen parameters to the overall results, we performed a sensitivity analysis. The following sensitivity cases were defined:

- Reference case with parameters described above
- Case-1: Low charging rate with charging rates of 22–50 kW
- Case-2: High charging rate with charging rates of 300 kW
- Case-3: Narrow spread of start time (mean: 7 AM, standard deviation: 0.1 h)
- Case-4: Wide-spread start time (mean: 7 AM, standard deviation: 1.5 h).

Figure 4.5 shows the influence of varying key parameters on the daily charging profile. By and large, the charging profile does not vary significantly, because it is very constrained by the few night hours (6 PM to 7 AM the next day).

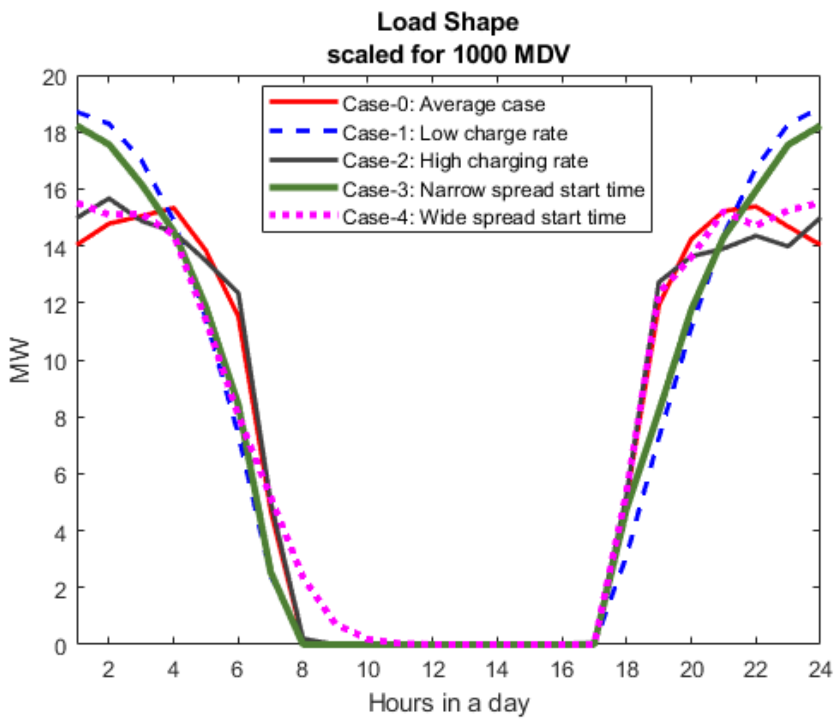


Figure 4.5. Sensitivities to parameters and average load shape to charge 1000 MDVs using evening, random delayed charging.

4.3 HDV Modeling for 2028 Charging Profile

The HDV segment for this study was represented by Class 8 long-haul trucks and their use cases as they transport goods across the nation. A transportation model was developed to gain a better understanding of the potential charging profiles that may emerge as electric HDVs drive long-distance routes throughout the U.S. interstate highway network.

The simulation used the U.S. Department of Transportation's (DOT's) data about HDVs derived from the Bureau of Transportation Statistics (BTS 2017), and driving rules mandated by the

Federal Motor Carrier Safety Administration (FMCSA 2013). Together, these data were used to approximate a simplified U.S. highway network connecting U.S. cities for simulating driving routes with considerations of recharging requirements because of depleted batteries. In addition, the DOT mandatory resting periods were implemented in the simulations.

Figure 4.6 represents a simplified U.S. interstate network connecting 56 cities with charging stations along depicted routes. Cities are represented by squares, and every city includes charging stations. The map includes a total of 271 charging stations, represented by circles, and they were placed along roadways no more than 100 miles away from other charging stations. Each station was assumed to have slow (50 kW), medium (300 kW), and fast (2000 kW) speed charging ports available. The choice of the number of cities was arbitrary, but the locations and connectivity among the cities were modeled after the U.S. interstate system. The charging stations were assumed to have an unlimited supply of charging ports at discrete charging rates of 50, 300, and 2000 kW. We recognize that 2000 kW charging stations do not currently exist, but we assumed that by 2028 extreme fast charging may become available.

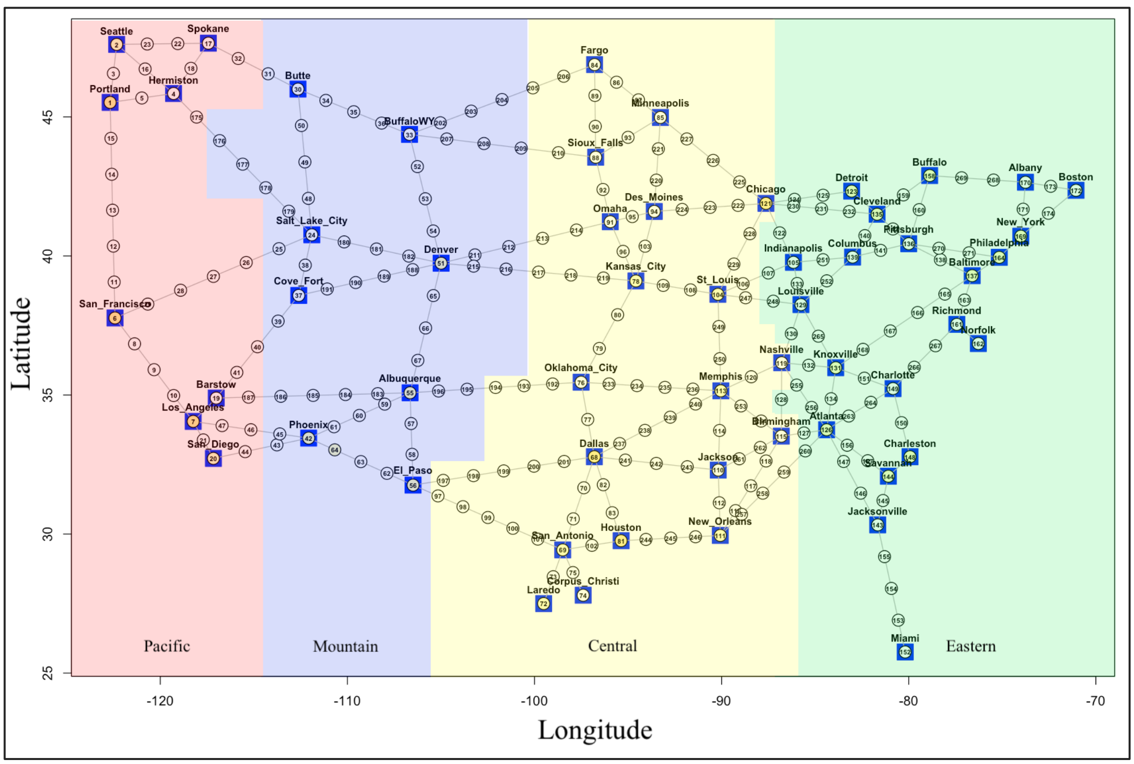


Figure 4.6. Simplified U.S. map and highway network used to simulate HDV truck routes and charging profiles along roadside stations. The 271 charging stations are represented by small circles, and the 56 cities are represented by blue squares.

We performed a simulation that includes an arbitrary number of 35,000 trucks driven over a period of one week with distances that represent that DOT statistics. The simulation randomly chose routes with destinations determined using BTS statistics, and gave preference to those cities through which a high tonnage of freight was being imported and exported and that had a high population level in the city’s metro area. Trucks had a uniform battery size and energy conversion (kWh per mile) that determined driving ranges in the simulation. Charging profiles from different stations were tracked throughout the simulations. Doing so allowed for the approximation of charging needs for electric HDV trucks and their contribution to power requirements that need to be supplied from nearby grid stations. Total charging profiles could be scaled up to represent a larger number of trucks on the road.

Because no publicly available technical specifications exist for Class 8 trucks, we estimated the battery size and vehicle efficiency on the conservative side from the grid perspective, meaning that the energy efficiency assumed would most likely represent a low value. Furthermore, the battery size was assumed to be on the large side, which would lead to fewer charging events with high electric energy transfers from the grid to the battery compared to a smaller battery that would require more frequent charging. The trucks used in this simulation were each assumed to have a 1500 kWh battery capacity. Trucks were assumed to travel at an average speed of 50 mph. The truck performances were uniformly set to 3 kWh/mile.

The simulation results accumulated across each time zone are displayed in Figure 4.7, in which the results for the total megawatts used in each time zone are presented. These plots account for the accumulated profiles from all three charging speeds made available in the HDV simulation. These plots indicate that the total megawatt usage load peaks are shared during the noon hours when most trucks must recharge because of a depleted battery after the morning driving. In addition, it is worth noting that all time zones shared similar load peaks, reflecting the preference for fast charging ports for mid-day charging in the late morning and early afternoon, medium speed charging ports mostly for use in the early evenings, and slow charging ports used for over-night charging. These emergent results are generated from dependencies on route distances from BTS freight transportation data and driver rest requirements mandated by FMCSA regulations. Aside from starting all simulations at 6:00 AM local time, no other day-night cycle patterns were enforced, thus daytime and over-night charging behavior is emergent only from model assumptions.

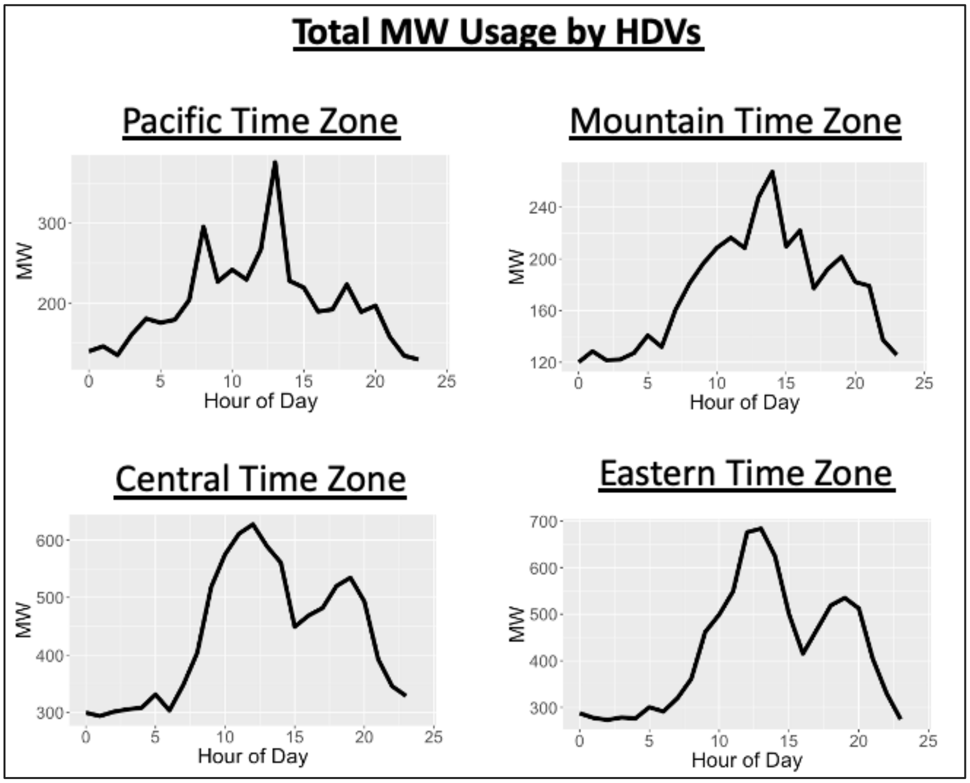


Figure 4.7. Charging profiles of simulated HDVs from stations across each time zone. The vertical axis represents the total megawatts used when accounting for all speeds of charging ports.

In the HDV transportation model presented here, route destinations are partially based on artificial yet reasonable routes dependent on the tonnage of goods moved into and out of gateway cities. Because this does not allow for many of the other major U.S. cities in the model to act as route destinations, the model relied on population levels to mitigate this shortcoming. Additional data about route information and driver timetables would allow for more realistic conditions for how drivers move trucks around the highway network. Doing so would require using a more accurate map, which would also move the model toward an overall more realistic representation of real-world transportation trips.

Major U.S. cities served as starting and destination points for driving routes, and were sampled as such using probabilities dependent on both the tonnage of import and export freight through gateway cities and the population of the city's metro area. Smaller cities did not act as a starting or destination city, rather they were included as nodes in the roadmap network where major interstate highway interchanges are located.

Truck trips were simulated over the entire distances. In several cases, trips took several days to complete. Charging profiles were then estimated over a week-long simulation and averaged for a 24-hour period for each charging station. Finally, charging contributions from each charging station were then mapped into the BAs, as illustrated in Figure 3.5.

4.4 Combining LDV, MDV, and HDV Profiles to Establish EV Loads for the 2028 WECC Grid

For the ensuing grid simulation, the individual EV class-specific charging profiles for each BA needed to be combined to arrive at an aggregated hourly EV load profile for a 2028 penetration scenario that needed to be added to the existing projected electric load from residential, commercial, and industrial customers.

Figure 4.8 through Figure 4.11 indicate the aggregate stacked charging profiles for Scenario 1 "home dominant, high power charging, no delay," which applies only to the electric LDV fleet. This scenario was considered the most likely LDV charging scenario under which the majority of the charging load occurring in the evening hours.

CISO

	LDV	MDV	HDV
No of vehicles (LDV, MDV) and charging events (HDV)	3,637,413	25,571	
% of WECC vehicles	35%	37%	

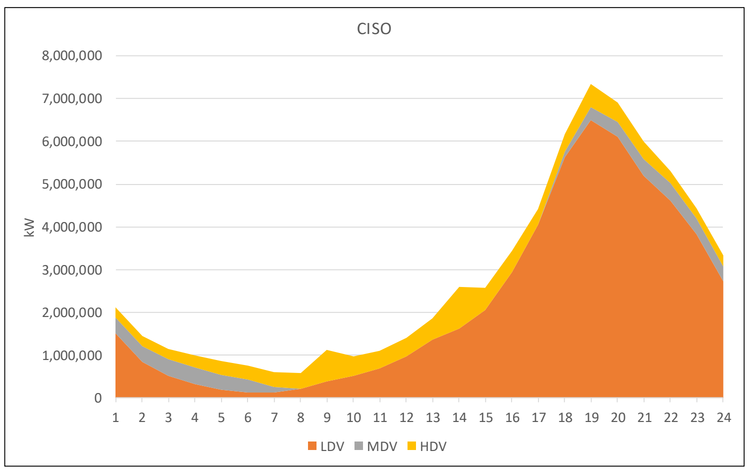


Figure 4.8. Stacked 24-hour charging profile for the California Independent System Operator balancing authority indicating the number of vehicles and charging events by vehicle class.

LDWP

	LDV	MDV	HDV
No of vehicles (LDV, MDV) and charging events (HDV)	1,409,956	14,801	
% of WECC vehicles	14%	21%	

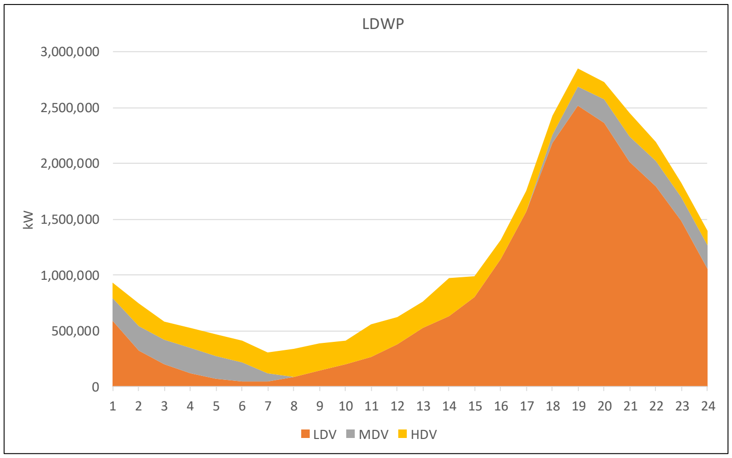


Figure 4.9. Stacked 24-hour charging profile for the Los Angeles Department of Water and Power balancing authority indicating the number of vehicles and charging events by vehicle class.

SCL

	LDV	MDV	HDV
No of vehicles (LDV, MDV) and charging events (HDV)	259,532	1,569	
% of WECC vehicles	3%	2%	

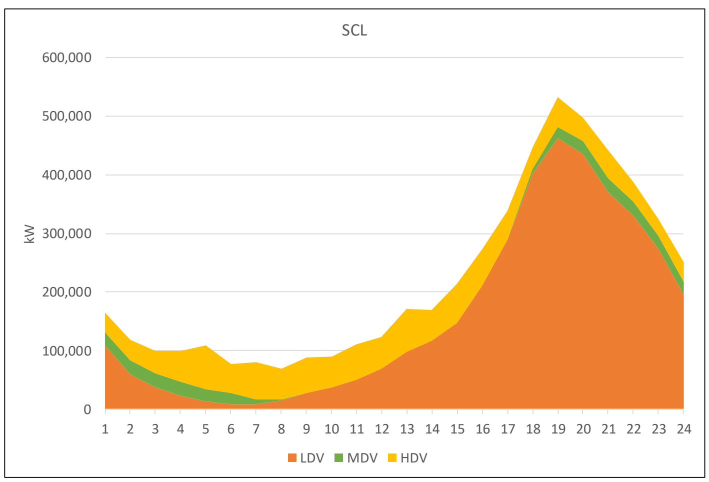


Figure 4.10. Stacked 24-hour charging profile for the Seattle City Light balancing authority indicating the number of vehicles and charging events by vehicle class.

NEVP

	LDV	MDV	HDV
No of vehicles (LDV, MDV) and charging events (HDV)	189,025	3,278	
% of WECC vehicles	2%	5%	

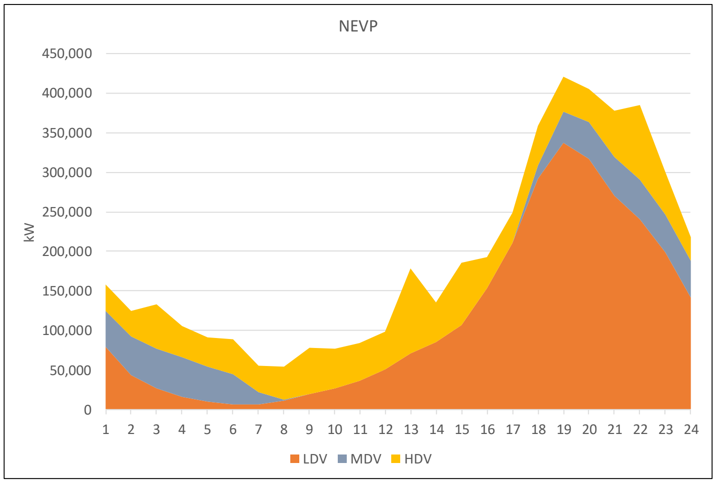
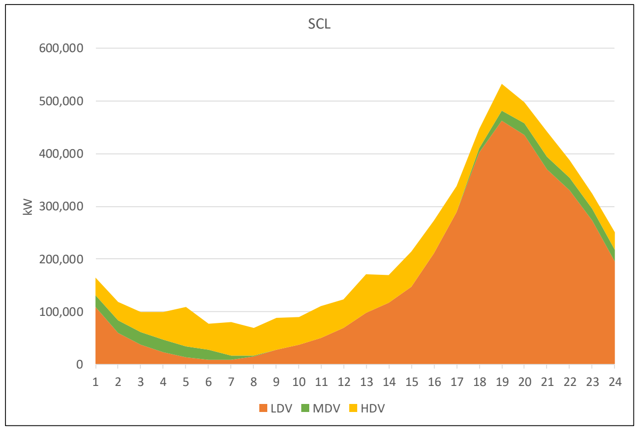


Figure 4.11. Stacked 24-hour charging profile for the Nevada Power balancing authority indicating the number of vehicles and charging events by vehicle class.

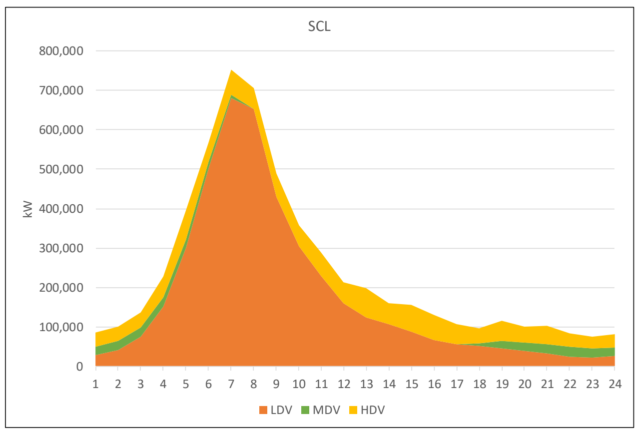
As expected with the selected scenario for these profiles, that is, home-focused charging at high power with no time delay, the overall charging profiles, and specifically, the LDV profiles, have peak energy requirements during evening hours when typical EV owners are home and start charging their vehicles as soon as they get home. Generally speaking, HDV charging occurs throughout the day in all locations, and MDV charging occurs in the mornings and the evenings. See the previous sections for additional details about the assumptions used for each type of profile.

Figure 4.12 below shows the aggregate stacked charging profile for Seattle City Light (SCL) for three different charging scenarios. The SCL profiles are generally representative of other regions. Again, as expected with the different scenarios, the charging profiles vary accordingly by hour. The largest energy requirements stem from LDV charging and thus the impacts in terms of setting a peak are driven by the LDV load shape.

(a)



(b)



(c)

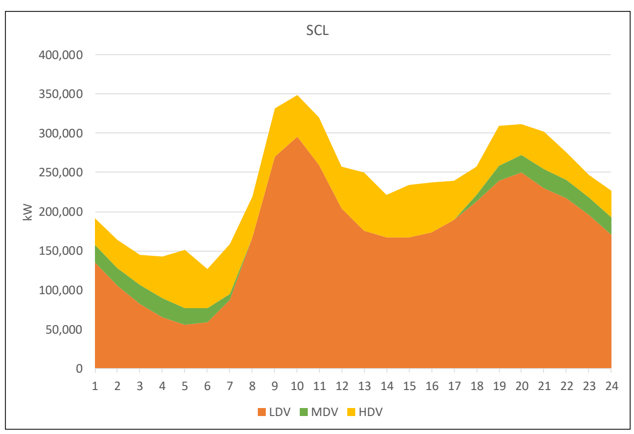


Figure 4.12. Aggregate stacked charging profile for Seattle City Light: (a) Home High power No Delay; (b) Home High power With Delay; (c) Work Low power No Delay.

5.0 Modeling the Western Grid for a 2028 Scenario

The United States is made up of three interconnections: the Western Interconnection (WECC-U.S.), Eastern Interconnection (EI-U.S.), and Electric Reliability Council of Texas (ERCOT) Interconnection. These interconnections and their states of installed capacity and load as of 2019 are show in Figure 5.1.

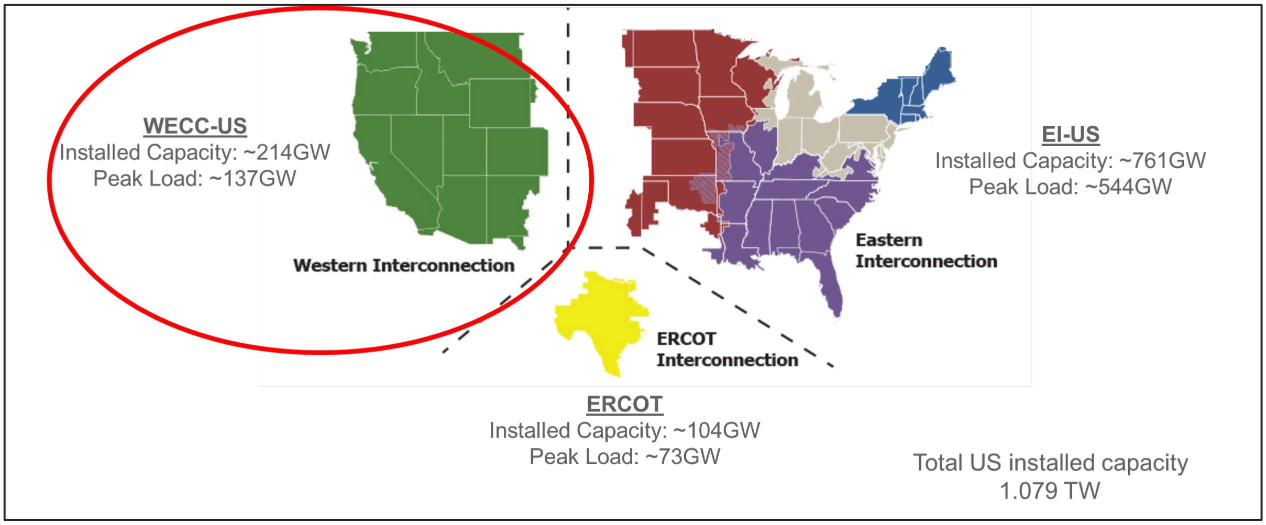


Figure 5.1. Overview of the U.S. interconnections and 2019 installed capacity and load (NERC, AEO 2019).

As mentioned before, this analysis focuses on the Western grid because of the readily available data that represent a future grid scenario for the year 2028. Data for the other U.S. interconnections are more difficult to compile and use. Because of the short time frame allowed for completion of this study, the analysis was limited to the WECC, and some discussion of how the WECC results may apply to the rest of the nation's power grid.

The following section provides an overview of the grid-modeling tool—GridView software—used to perform the detailed EV-at-scale analysis for a 2028 scenario.

5.1 GridView Software

PNNL used ASEA Brown Boveri's (ABB's) GridView software to analyze bulk grid impacts in WECC (GridView). The choice of GridView was predicated on the WECC Transmission Expansion Planning Policy Committee's (TEPPC's) earlier decision to use GridView as an analysis tool. Thus, PNNL could use all of the data sets developed by WECC for a 2028 grid scenario.

GridView integrates engineering and economic analysis of the electric power grid to simulate security-constrained unit commitment and economic dispatch of electric generators in large-scale transmission networks. It is a tool that is widely used to study the utilization of generators and transmission lines, production cost of generation, locational marginal pricing (LMP), transmission congestion, and much more. An overview of GridView components and functions incorporated into the tool is provided in Figure 5.2.

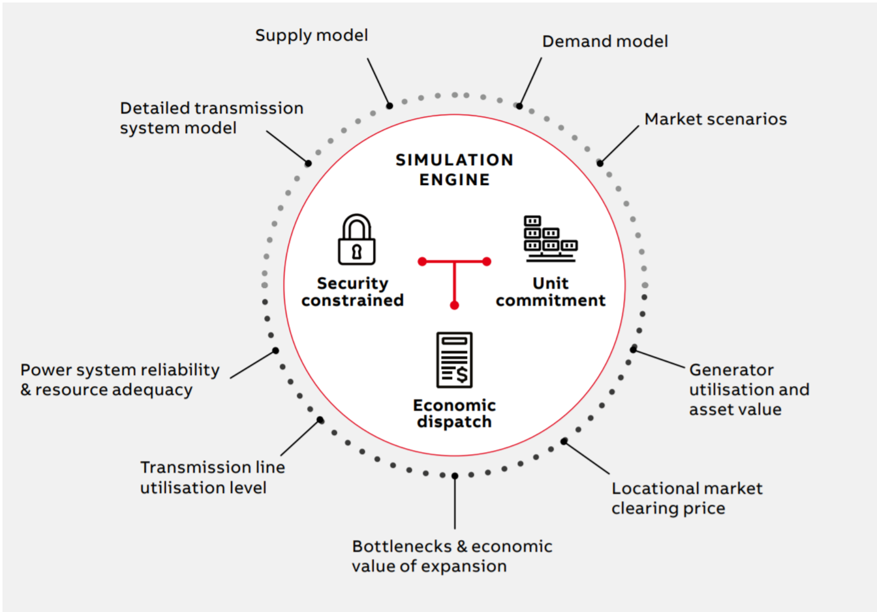


Figure 5.2. Overview of ABB's GridView market simulation software.[1]

Within WECC's GridView model, expected loads, new power plants, and transmission expansions 10 years into the future are compiled by members of WECC using a consensus mechanism for defining a plausible grid scenario that includes the current grid plus all capacity retirements and capacity additions. WECC establishes and maintains an Anchor Data Set (ADS) for system planning that is the best representation of the Western grid's evolution over a 10-year planning horizon that is based on member consensus. The *ADS Data Development and Validation Manual* describes in more detail this data collection process and the production cost modeling practices (WECC 2018).

5.2 The Future Grid for 2028

The GridView model used the 2028 ADS V2.0 production cost model (PCM) base case made available in July 2019. This case was the best available projection of new generation and transmission assets and generation retirements from the grid planning community within WECC at the time. Henceforth, we refer to the GridView model with the 2028 ADS V2.0 PCM base case data set as the WECC 2028 TEPPC model. PNNL largely used this case "as is" and did not make any changes to resources, transmission, or topology contained within the case, except for adding new EV load by BA to the existing load assumptions. EV loads were defined as hourly loads for a period of 1 day. The daily EV load pattern was then repeated day by day.

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[1] ABB GridView is a production cost simulation tool that is available at https://new.abb.com/enterprise-software/energy-portfolio-management/market-analysis/gridview.

It is worth noting that the TEPPC assumed a significant portion of new generation would be brought online in the next 10 years (until 2028). WECC projected additional capacity in California, Arizona, Colorado, Nevada, and Utah. This new capacity is predominantly forecasted to be solar photovoltaic (PV) and wind. Natural gas technologies, including combined cycle (CC) and combustion turbine (CT) facilities, are also expected to add capacity over the next 10 years. Figure 5.3 and Figure 5.4 show installed capacity by type and state currently in the WECC 2028 TEPPC case, along with capacity additions expected to come online by 2028. PNNL did not add any additional generation capacity to the WECC model.

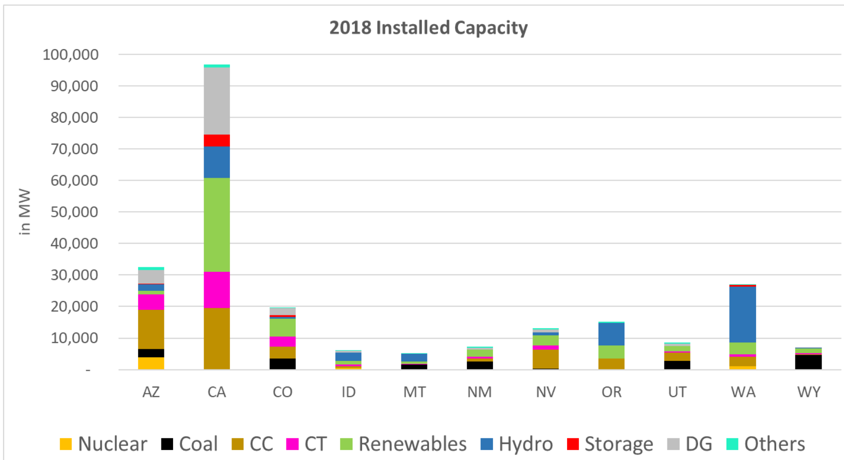

Figure 5.3. Installed capacity at the start of 2018 reflected in the WECC 2028 ADS V2.0 GridView case.

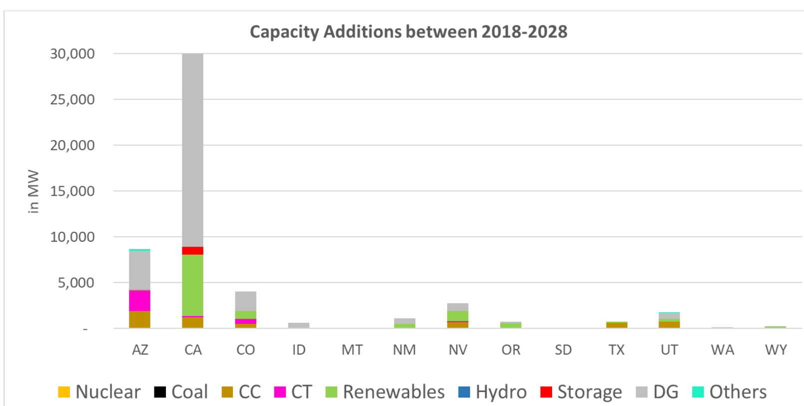

Figure 5.4. Capacity additions between 2018 and 2028 reflected in the WECC 2028 ADS V2.0 GridView case.

Transmission representation in the WECC 2028 TEPPC case provides the best available projections of future topology and transmission capacity. It incorporates the addition of transmission projects in the 10-year planning horizon made publicly available to the grid planning community. Because future grid topology path ratings may not yet be established, the WECC Path Rating Catalog (WECC 2018) is used as a starting point for assigning operating path ratings in the region and the ratings are modified as needed for forecasted transmission expansion. These ratings are already reflected in WECC's 2028 TEPPC data set. Figure 5.5

illustrates the major transmission paths in the WECC region as of a 2006 DOE study (DOE 2006). For the most part, these paths are still relevant and well reflected in the WECC 2028 PCM case. PNNL did not add any additional transmission capacity to the WECC PCM.

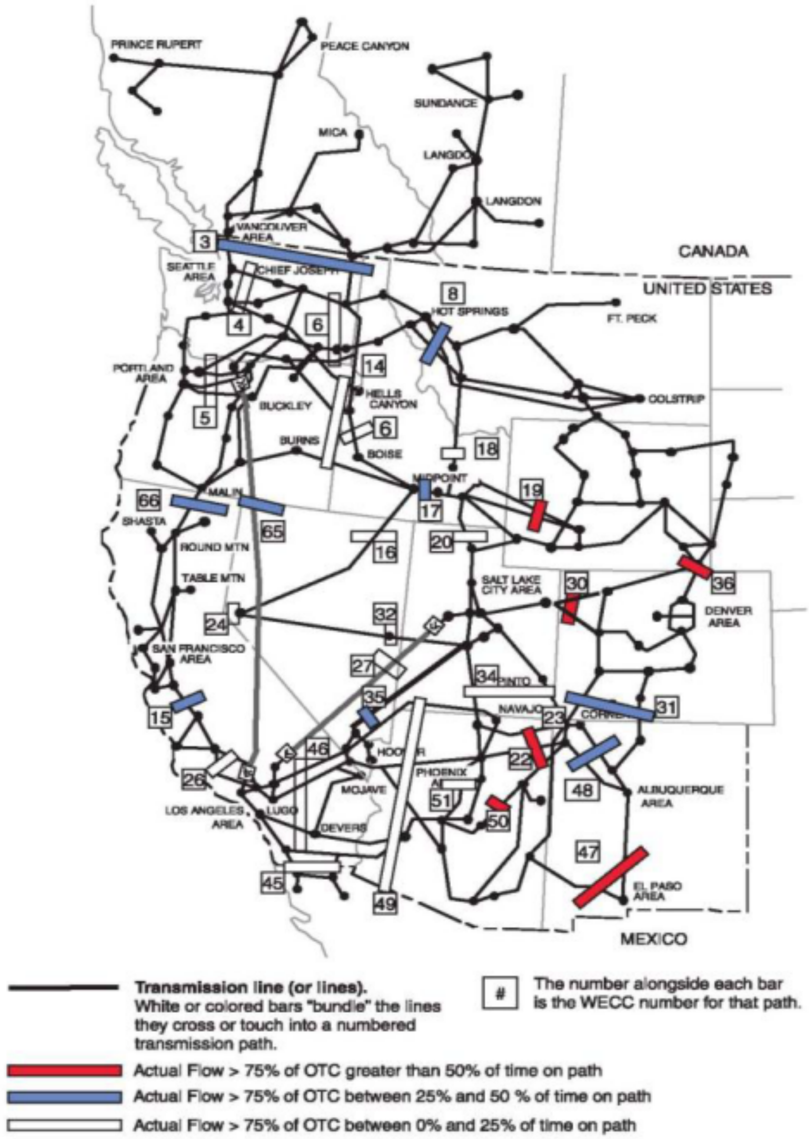

Figure 5.5. WECC transmission paths as of 2006 (DOE 2006).

In the WECC model, all loads are modeled as hourly loads for the entire year by BA. The load data are based on annual Load and Resource (L&R) data submittals that contain monthly energy and peak forecasts for 1 to 10 years into the future. These data are then broken down from monthly to hourly data by applying historical the Federal Energy Regulatory Commission Form 714 (FERC 2007) hourly load shape. The WECC 2028 TEPPC model currently uses a 2008 historical load shape to create the 2028 hourly load profile by applying the monthly peak load and total energy reported in the L&R data. The historical 2008 load shape represents an average load year with average weather conditions WECC-wide. PNNL changed each BA's load to reflect the additional EV loading.

PNNL created additional 2028 load scenarios for various EV charging and penetration scenarios as discussed in Section 4.4. The same EV load profile was applied to every day of the year, with no distinction between weekday and weekend charging behaviors. An illustration comparing the WECC base load with the incremental EV load for one charging and penetration scenario is shown in Figure 5.6. Additional graphs of EV load additions for other charging scenarios can be found in Appendix D.

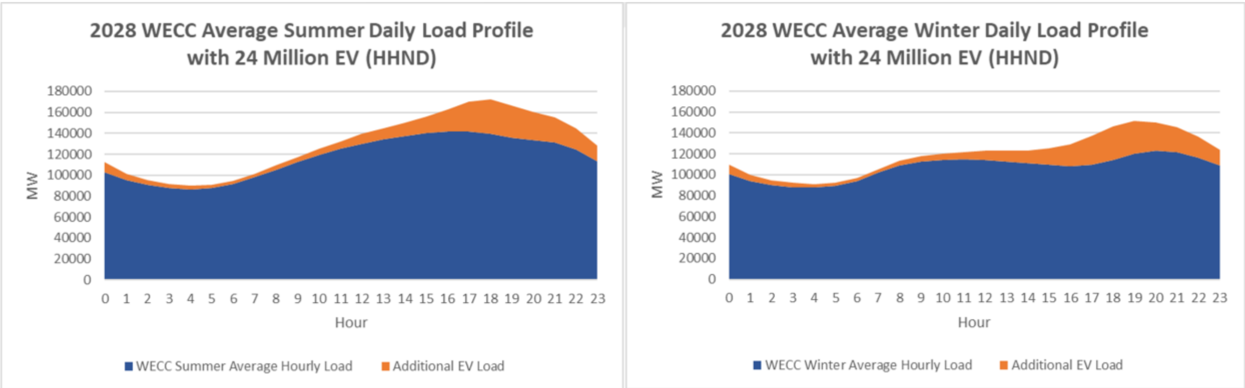

Figure 5.6. Illustration of WECC base load and added EV load for "Home High power No Delay charging." (The left frame represents summer load, the right frame winter load.)

Note that in the original WECC 2028 TEPPC load scenario definition, only California's WECC members added EV loads to their load projections. None of the other members considered any appreciable load contribution to their respective loads in their 2028 projections. To avoid any double counting, PNNL removed the implicit EV load requirements as determined by California WECC members. PNNL consulted with the CEC to understand the specific underlying assumptions about the implicit EV loads.

6.0 Discussion of Results

This section discusses the results of grid simulations conducted for the various EV charging and penetration scenarios described in previous sections. The analysis was performed under normal system conditions, without additional system contingencies, or changes in system topology.

Using WECC's 2028 data set, PNNL performed 1-year-long grid simulations on the following grid scenarios:

- Base Case (no additional EV)
- 24 Million LDV Nationwide with Charging Scenario Home High power No Delay (HHND) (Figure 5.6)
- 24 Million LDV Nationwide with Charging Scenario Home High power With Delay (HHWD)
- 24 Million LDV Nationwide with Charging Scenario Home Low power No Delay (HLND)
- 24 Million LDV Nationwide with Charging Scenario Home Low power With Delay (HLWD)
- 24 Million LDV Nationwide with Charging Scenario Work Low power No Delay (WLND)
- 24 Million LDV Nationwide with Charging Scenario Work Low power With Delay (WLWD)
- 30 Million LDV Nationwide with Charging Scenario HHND
- 37 Million LDV Nationwide with Charging Scenario HHND
- 44 Million LDV Nationwide with Charging Scenario HHND
- 65 Million LDV Nationwide with Charging Scenario HHND.

The following sections describe the findings regarding EV resource adequacy in WECC, impacts of managed charging on the EV resource adequacy, as well as considerations of grid operations under high EV load assumptions.

6.1 EV Resource Adequacy in the WECC

Study results indicate that the generation and transmission resources reflected in the WECC 2028 case meet the needs of electric loads under the 24 million LDV nationwide penetration scenario under normal grid conditions. This means that with the best available information for a 2028 scenario, the grid would have sufficient resources to meet the additional EV loads under the high-penetration scenario for the most challenging electric LDV load assumption of evening charging (HHND). We investigated at what electric LDV penetration one would expect the onset of reliability issues. The results indicated that the first issues would occur between 30 and 37 million EVs, at which point load could not be reliably met. We call this limit the EV resource adequacy of the bulk power system in the WECC. The resource adequacy was associated with the assumption that the EVs are charged at home in the evening using the HHND charging profile. Figure 6.1 indicates the EV resource adequacy by representing a commonly used metric of "unserved energy" as a criterion for the lack of system adequacy that indicates insufficient resources to meet load. As can be seen in the figure, the unserved energy remains at about zero percent for penetration up to about 30 million LDVs. At the 37 million level, the unserved energy becomes non-zero.

Note that these outcomes are predicated on normal grid conditions, absent of any grid contingencies, such as generator or transmission outages, extreme weather scenarios, extreme high loads, or fire conditions that require deactivation of major transmission lines. For the purpose of this study, normal grid conditions are defensible assumptions to explore potential system adequacy issues. Contingency analyses are usually done for interconnection requests of large industrial loads or new generation or transmission assets. They are very time- and resource-intensive.

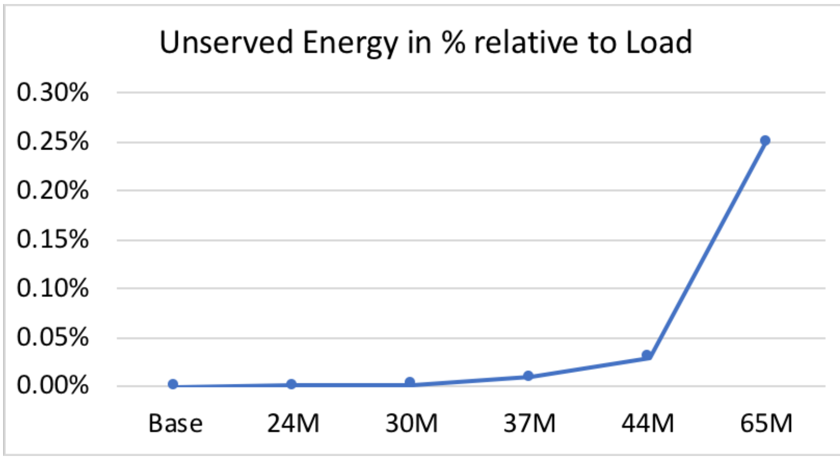

Figure 6.1. Percent of unserved energy relative to load in WECC, showing the onset on resource inadequacy. Note that the LDV penetration numbers on the x-axis are the national penetration numbers. The WECC penetration levels must be scaled back by a factor of 0.4 because the WECC is projected to operate about 40% of the national electric LDV fleet.

6.1.1 Impact of Managed Charging on EV Resource Adequacy

The EV resource adequacy of 30 million EVs in a 2028 WECC grid is contingent upon the unmanaged charging assumptions. The capability was set by the HHND profile that demands additional load in the evening hours, which was the most limiting case. We considered unmanaged charging as an aggregated charging behavior of the entire LDV fleet, in which there are neither price incentives to schedule the charging process nor any incentives to charge at a certain location, for instance at work or at a place of shopping.

It is of interest to explore how much of the EV resource adequacy could be extended if one applied "smart charging" strategies. With support of ABB Consulting, we explored a smart charging strategy that would be the functional equivalent of price-based charging, i.e., a charging at minimal cost to EV owners. Under such a strategy, EV charging would be moved day by day and would be regionally different, as would be the regional locational marginal cost of electricity (Zhu et al. 2020). Under such a premise, the EV resource adequacy could be extended by a factor of 2 or more, because the additional load would now be moved to low load conditions away from the system peak (as seen in Figure 5.6). With managed charging, the EV resource adequacy could be pushed from 30 million electric LDVs to 65 million, as can be seen in Figure 6.2.

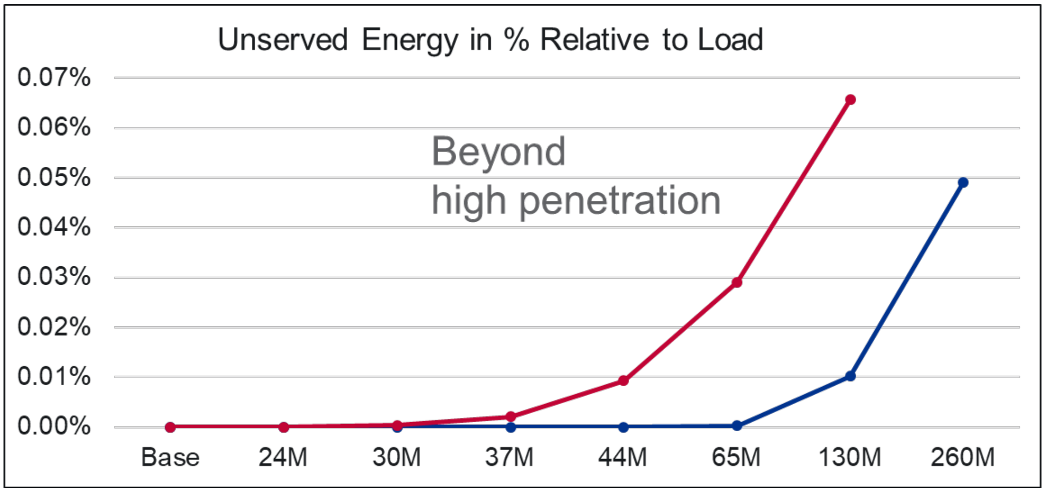

Figure 6.2. Illustration of unmanaged charging (red) and managed charging (blue) when comparing unserved energy under increasing LDV penetration scenarios. Note that the LDV penetration numbers on the x-axis are the national penetration numbers. The WECC numbers must be scaled back by a factor of 0.4 because the WECC is projected to operate 40% of the national LDV EV fleet.

6.1.2 Regional Perspective of EV Resource Adequacy: Where Do Supply Limits Occur First?

The limiting factor that establishes the EV resource adequacy varies across the WECC footprint. A regional evaluation of unserved energy indicates that California is the largest load area in which the resource inadequacy issue would be manifested, followed by Arizona and Washington States. California and Washington States are the load centers that have the largest EV penetrations. Arizona would be affected most likely because of that state's close coupling to the California electricity market and thus also would be affected as supply deficiencies emerge. Figure 6.3 shows the regional distribution of unserved energy during conditions of increasing LDV penetration. A detailed breakdown of unserved energy by BA can be found in **Error! Reference source not found.**.

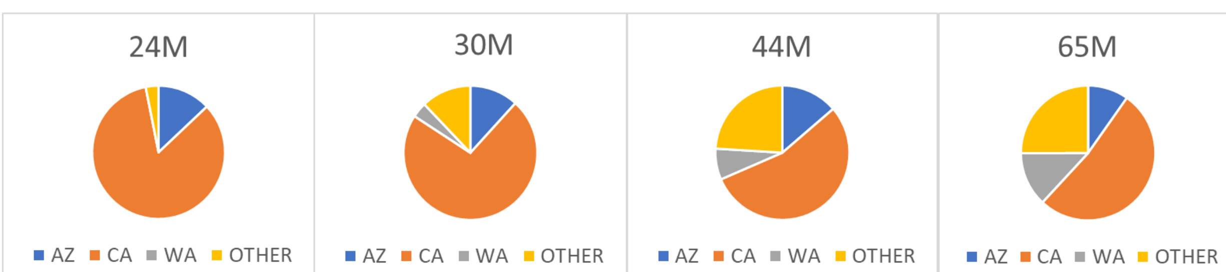

Figure 6.3. Regional distribution of unserved energy during increasing LDV penetration.

6.1.3 What Causes the Limitation of EV Resource Adequacy: Lack of Generation or Transmission?

Unserved energy was the criterion used for lack of system adequacy. System inadequacy means too much load for the generation and transmission capability during a certain hour at a certain location in the network. This would be caused by (1) insufficient generation capability in the WECC to meet the load, or (2) sufficient generation but not at the right location. In this case, the transmission system would be limited in its ability to deliver electricity to a particular load location. We investigated whether (1) or (2) would be the limiting factor.

To answer this question, we used a crucial grid metric—*reserve margin*—to indicate the percent of how much more generation capacity in a BA or in the entire WECC exists above the system load peak. The NERC planning reserve margin is 15% (WECC 2007), which would allow the system to respond to contingencies such as unplanned outages of a generator or a transmission line. Figure 6.4 shows the reserve margins for the entire WECC footprint for the different load profiles.

All charging scenarios indicate that reserve margins are maintained higher than 15% at the high penetration of 24 million LDVs nationwide. Unmanaged charging (HHND and HLND) shows significant decreases in reserve margin compared to the base case (no EV load), caused by coincidence of unmanaged peak EV load with WECC's evening peak. More generation capacity, previously unused, is now being used to serve incremental EV load.

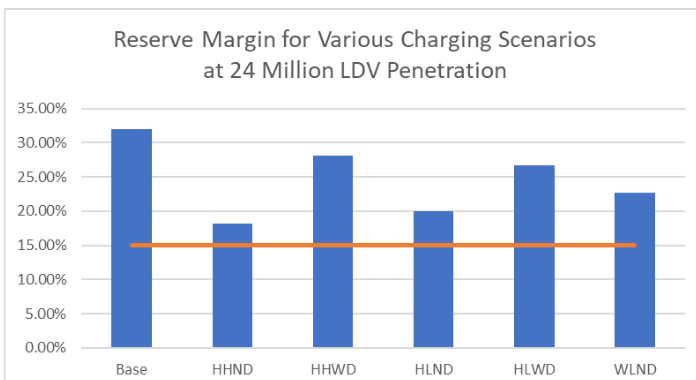

Figure 6.4. WECC-wide reserve margin impact under varying LDV charging scenarios on a peak load day at the peak hour. The red line indicates NERC's 15% reference reserve margin. Note that the WECC reference reserve margin varies by region between 14% and 16%.

Figure 6.5 shows the WECC-wide reserve margin for the HHND charging profile with increasing penetration. Recall from Figure 6.1, that a lack of system adequacy is emerging between 30 and 37 million LDVs. However, from a total WECC-wide perspective, sufficient generation capacity is installed, but not at the right locations to serve all EVs. We see that smart charging pushes the system adequacy threshold to EV penetration of 65 million EVs (Figure 6.2), because there is sufficient generation capacity available, but a different charging strategy is required to use the load valley. This indicates that the limiting factor for unmanaged charging is not the generation capabilities but the transmission system.

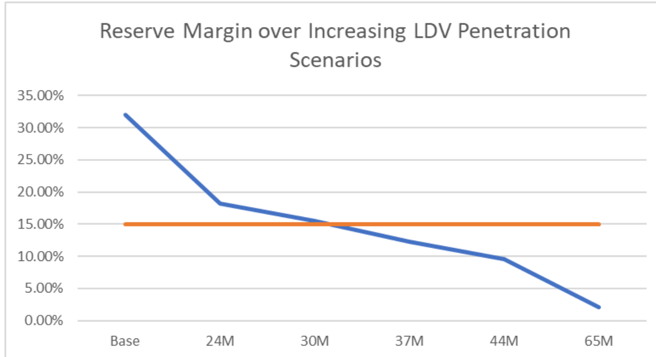

Figure 6.5. WECC-wide reserve margin impact under increasing nationwide LDV penetration with unmanaged EV load using the HHND charging scenario. Note: The reserve margins reflected in Figure 6.4 and Figure 6.5 do not reflect margins maintained under unforeseen increases in demand caused by extreme weather conditions and unexpected outages of existing capacity.

6.1.4 Locational Aspect of Transmission Congestions

To evaluate the locational aspects of the transmission bottlenecks, we explored the seasonal LMPs and WECC path flows as metrics of congestion. We observed increased transmission congestion during evening peak hours (HHND charging scenario).

Transmission Path 15 and Path 26 (see Figure 5.5) flows, providing electric power from northern to southern California, indicate congestion during the evening. This is shown in Figure 6.6. Corresponding spikes in LMP constraining flows on these paths during coincidental peak hours indicate that flows are reaching their path rating limits.

More generally, we observed that transmission limitations along the western U.S. coastline exist at high EV penetrations for unmanaged charging during the evening hours (HHND).

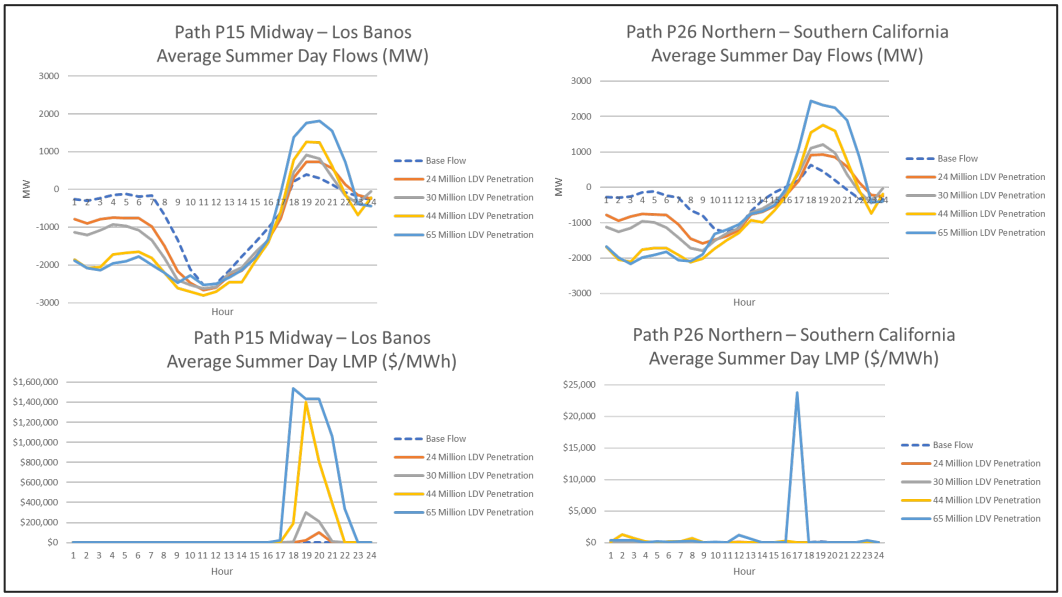

Figure 6.6. WECC Path 15 and Path 25 showing congestion during peak hours under conditions of unmanaged LDV charging and increasing LDV penetration.

6.1.5 Summary of Resource Adequacy Limitations

PNNL's study results indicate that with unmanaged charging the WECC paths listed below would experience transmission congestion during evening peak hours under increasing levels of EV penetration beyond 30 million LDVs nationwide. Paths that experience congestion starting at 24 million LDVs nationwide during summer evening peak hours are marked with an asterisk (*). Detailed plots showing seasonal flows under increasing LDV penetration for the WECC paths listed below can be found in **Error! Reference source not found.**.

- Path 3: Northwest to British Columbia
- Path 8: Montana to Northwest
- *Path 15: Midway – Los Banos
- Path 16: Idaho – Sierra
- Path 18: Montana to Idaho
- Path 22: Southwest of Four Corners
- Path 24: Pacific Gas and Electric – Sierra
- Path 26: Northern – Southern California
- *Path 30: TOT-1A
- Path 32: Pavant Inter-mountain – Gonder
- Path 35: TOT-2C
- *Path 45: San Diego Gas and Electric – Comisión Federal de Electricidad (CFE)
- Path 66: California Oregon Intertie

In summary, PNNL's findings indicate that the main bulk grid bottlenecks for accommodating increasing numbers of EVs assuming unmanaged evening charging in the WECC are related to transmission capacity limitations. This suggests that the generation resources are not at the locations where the additional EV load is projected to occur.

A compelling mitigation strategy is a managed or "smart" charging strategy that uses the load valleys more effectively to extract more generation from the bulk power system to charge increasing numbers of EVs.

6.2 Operational Considerations for Supporting EVs at Scale

Incremental EV loads and their regional placement are likely to alter generation dispatch in the WECC. Figure 6.7 shows generation dispatch WECC-wide during an average summer day prior to adding EV load. With the addition of EV load, the WECC-wide generation dispatch "delta" for the 24 million LDV HHND and HHWD charging scenarios becomes that shown in Figure 6.8 and Figure 6.9. The delta represents the difference in hourly generation mix between the scenario with and without EVs.

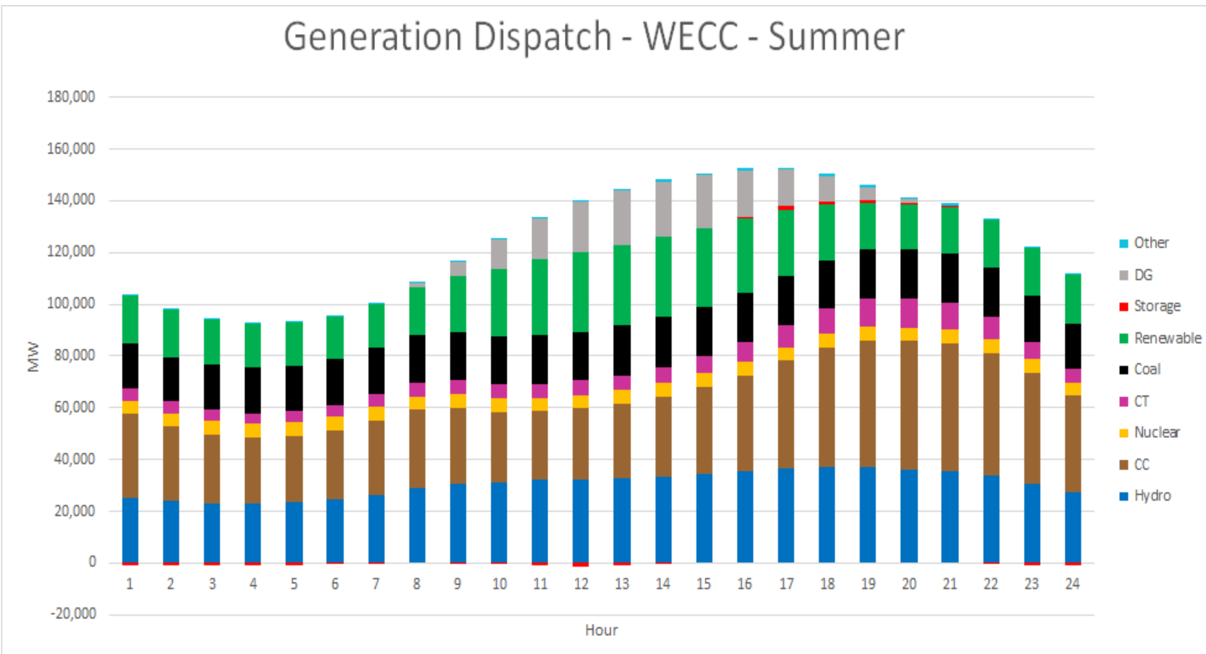

Figure 6.7. Average summer day WECC-wide generation dispatch without EV load.

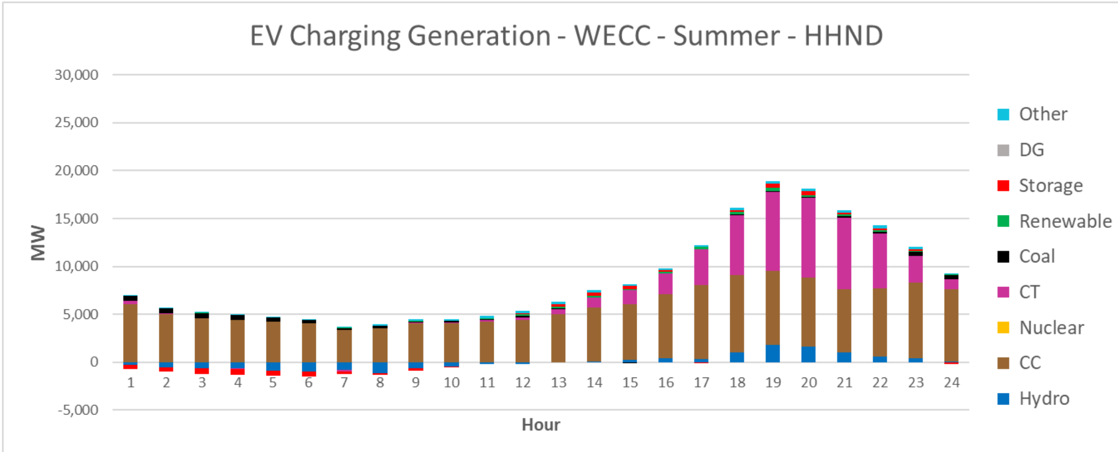

Figure 6.8. Generation dispatch delta for an average summer day for 24 million LDVs nationwide under the HHND charging scenario.

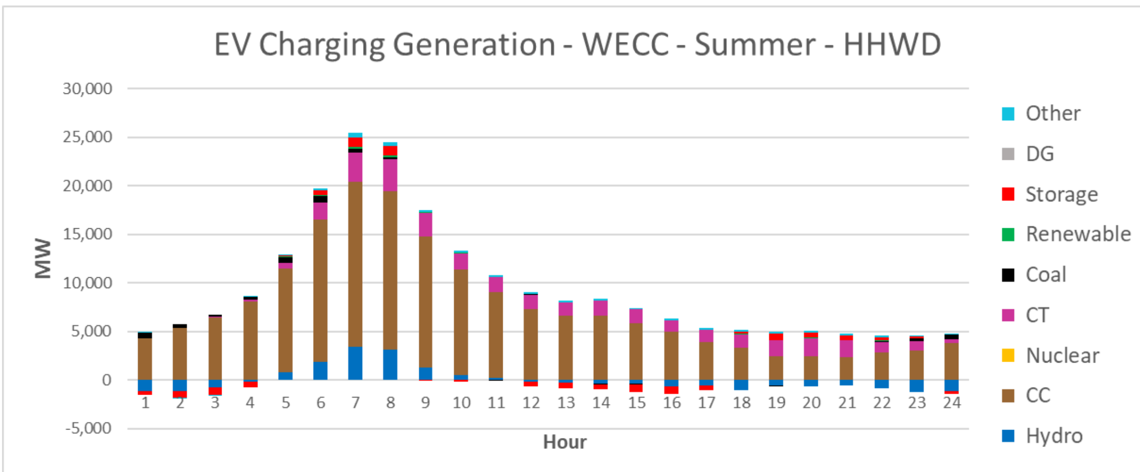

Figure 6.9. Generation dispatch delta for an average summer day for 24 million LDVs nationwide under the HHWD charging scenario.

As can be seen in the preceding figures, the generation delta between the base case and that with 24 million LDVs nationwide is primarily supplied by CC (brown) and CT (purple) resources. We also see a slight increase in energy storage and renewable utilization, which reduces some renewable curtailment.

When comparing the generation dispatch deltas of the two different charging scenarios—HHND and HHWD—some differences can be identified. The major difference is that the HHND case requires more energy from CTs than the HHWD scenario. This is because the HHND case, which reflects unmanaged evening charging, coincides with WECC's peak load when there is no CC generation capability left to provide the energy for EV charging. CTs are next in the dispatch order to serve the evening EV loads.

Table 6.1 lists the breakdown of incremental generation dispatch by charging scenario for the 24 million LDVs nationwide case. Natural gas technology with CC and CT resources makes up the majority of the marginal generation.

Table 6.1. Generation types of EVs by charging profile.

	HHND	HHWD	WLND	WLWD	HLWD
Nuclear	0%	0%	0%	0%	0%
Coal	8%	6%	9%	10%	9%
CC	67%	78%	72%	75%	77%
CT	18%	11%	12%	10%	9%
Renew	3%	2%	4%	4%	3%
Hydro	0%	0%	0%	0%	0%
Storage	1%	1%	0%	0%	0%
DG	0%	0%	0%	0%	0%
Other	3%	2%	2%	2%	2%
	100%	100%	100%	100%	100%

HHND = Home High power No Delay; HHWD = Home High power With Delay; HLND = Home Low power No Delay; WLND = Work Low power No Delay; WLWD=Work Low power With Delay.

Figure 6.10 illustrates the aggregated generation dispatch delta from California BAs.

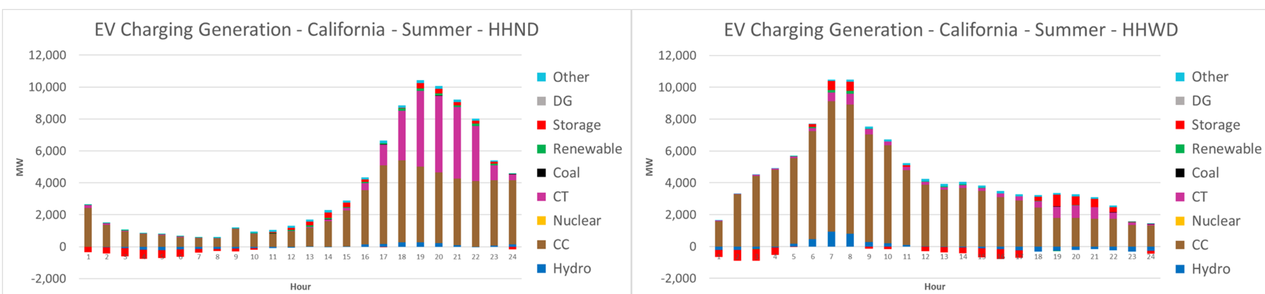

Figure 6.10. California EV generation dispatch delta for an average summer day for 24 million LDVs nationwide under the HHND and HHWD charging scenarios.

California contains more than half of the EV charging load in the WECC. The charging energy required to serve EVs in California would be primarily served by CC and CT resources. With an increase in energy storage capacity in California by 2028, we see the intra-day use with one stationary storage charging/ discharging cycle for morning EV charging (HHWD) and two intra-day cycles for the evening dominant EV charging scenario (HHND). This example illustrates that higher penetrations of energy storage may play an effective role in serving EV charging load in the future.

Figure 6.11 illustrates the aggregated generation dispatch delta from Washington State's BAs. The charging energy required to serve EVs in Washington would be primarily served by hydroelectric, CC, and CT resources in that order. However, hydroelectric power is only redispatched, meaning that it is backed off during times in the day to then be used during later periods. There is no net additional hydropower generation because the hydro system is energy limited and all of the generation has already been allocated in the base case with EV load. The hydropower dispatch indicates that use of hydro technology similar to that of a stationary energy storage system that has a daily charging/discharging cycle. It conserves water behind the dam during the off-peak hours to be used during the peak hours. Whether Washington State's hydropower resources are flexible enough on their own to operate with this altered dispatch was not investigated. These resources are primarily run-of-river but do have some storage capability. Further investigation would be necessary to fully validate the modeled flexibilities.

Resources that fall in the "Other" category are largely made up of biofuel resources, such as biofuel-operated steam resources and combustion engines, and they make up less than 2% of the overall generation portfolio.

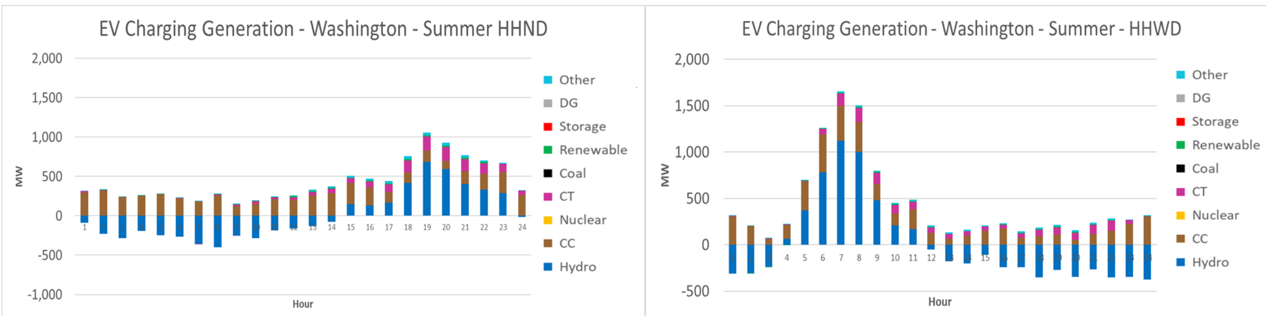

Figure 6.11. Washington State EV generation dispatch delta for an average summer day for 24 million LDVs nationwide under the HHND and HHWD charging scenarios.

The following sections discuss the production cost implications of EV loads under varying charging scenarios, duck-curve impacts in solar-rich regions, and how smart charging can be leveraged to improve system operations and the accommodation of renewables.

6.2.1 Production Cost Implication of EV Loads

WECC-wide the cost impact of serving EV load in 2028 would be an increase of 13% based on the average production cost. Table 6.2 breaks down production cost impacts by charging strategy and selected states. California would see the largest impact on production costs because it has the largest levels of forecasted EV penetration.

Table 6.2. Production cost impacts under the 24 million LDV penetration scenario for varying charging scenarios.

Production Cost ($/MWh)							
	Base	HHND	HHWD	HLND	HLWD	WLND	WLWD
WECC	14.48	16.44	16.44	16.31	16.13	16.24	16.05
AZ	20.77	22.15	21.89	21.91	21.45	21.67	21.30
CA	18.77	22.99	23.12	22.74	22.45	22.58	22.22
WA	5.60	6.09	6.05	6.07	6.08	6.11	6.11

% Increase in Production Cost from Base						
	HHND	HHWD	HLND	HLWD	WLND	WLWD
WECC	14%	14%	13%	11%	12%	11%
AZ	7%	5%	6%	3%	4%	3%
CA	22%	23%	21%	20%	20%	18%
WA	9%	8%	8%	8%	9%	9%

The cost impacts based on LMP are affected the most for unmanaged charging. In the HHND scenario, where EV peak charging load occurs during existing evening peak loads, EV charging causes increased transmission congestion. Other charging scenarios are under the threshold of causing significant congestion when 24 million LDVs nationwide are deployed (see Figure 6.12).

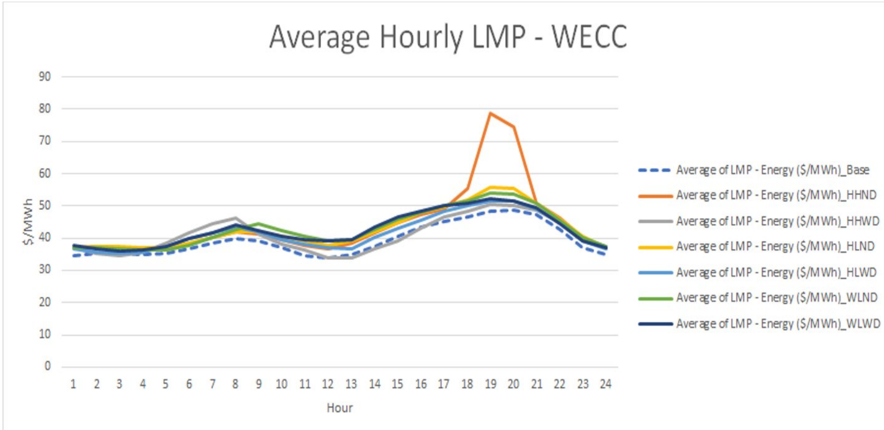

Figure 6.12. Average hourly LMP in the 24 million LDV penetration scenario for varying charging scenarios.

6.2.2 Duck Curve for Solar-Rich Regions and Implications for EV Charging

A significant "duck curve" exists within the solar-rich region such as in the California Independent System Operator (CAISO) for the 2028 scenario. The addition of LDV loads could play a vital role in either exacerbating or reducing evening ramping needs. California load and net load, which is load minus wind and solar generation, looks like a duck, and is called the duck curve, as shown in Figure 6.13. As solar PV installation costs decrease, more rooftop and utility-scale solar PV is expected in the future, which is likely to make the belly of the duck curve dip even lower. It will significantly challenge the ability to reduce the output of thermal plants during the middle of the day and will cause a much higher ramping requirement in the early evening, when fast-ramping and flexible resources are needed to meet the net load curve.

PNNL's study indicates that unmanaged EV charging under the HHND scenario exacerbates the duck curve in two respects: (1) the duck neck becomes steeper, that is, the ramp rate seen in the late afternoon and early evening hours increases by almost 1.4 GW/h (7134 MW/h - 5767 MW/h = 1367 MW/h) with the addition of EV load; and (2) the duck neck become taller, which means that the EV charging peak coincides with the system peak at about 20:00 hours.

A mitigation strategy is managed charging. Assuming the charging infrastructure is in place, managed charging would use the PV generation during the day and thus reduce both the duck head and the steepness of the neck. It would reduce the ramping and reduce the system peak. Figure 6.13 illustrates the effect of unmanaged and managed charging of LDVs and their consequential impacts on the CAISO duck curve for an average winter day.

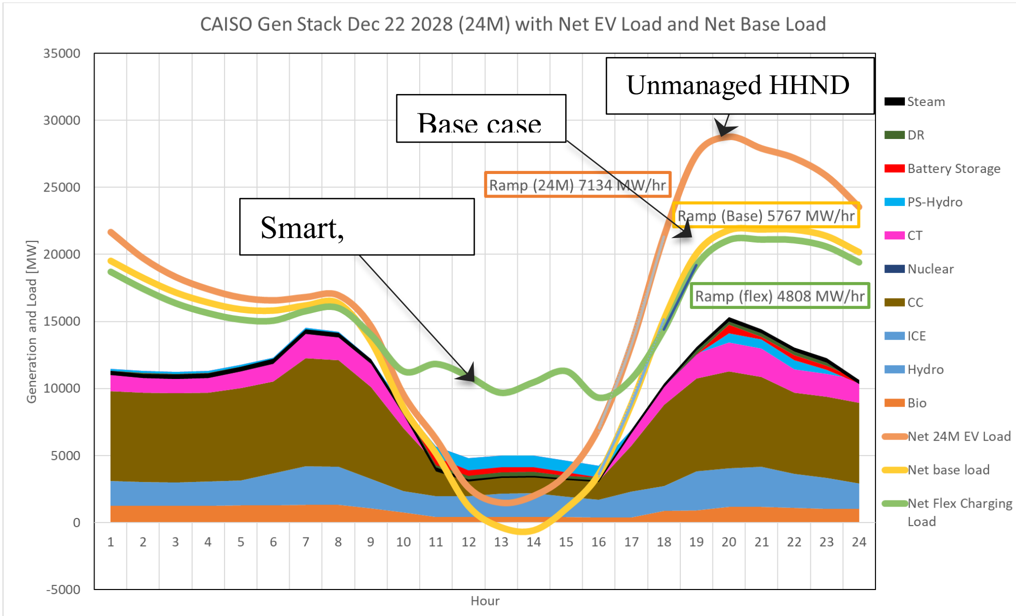

Figure 6.13. CAISO duck-curve impacts with the addition of unmanaged and managed charging of EVs.

An operational benefit that can be gained with the implementation of managed EV charging is the reduction in renewable curtailment during the daylight hours. During the middle of the day, solar generation has pushed net load close to zero, sometimes in the negative range, which means that electricity will either be curtailed or exported out of California. To manage this hourly variability, significant ancillary services, including ramping capability, must be made available. Overgeneration is expected during the middle of the day during the light load seasons (spring and fall), as are likely curtailments of solar generation. To mitigate renewable curtailment, EV charging during the day would reduce or avoid curtailments.

PNNL results indicate, as expected, that EV charging leads to a reduction in solar and wind curtailment across the WECC, as shown in Table 6.3 and Figure 6.14. Charging that coincides with solar generation has the most reduction in curtailment (i.e., daytime/early evening work charging). PNNL's analysis shows that the addition of LDVs can reduce curtailment up to 70%. With the introduction of managed charging, reduction of curtailment increases beyond 70%.

Table 6.3. Curtailment impacts in the 24 million LDV penetration scenario for varying charging scenarios.

Curtailment (MWh)							
	Base	HHND	HHWD	HLND	HLWD	WLND	WLWD
WECC	2,281,029	931,807	1,659,744	863,905	895,102	636,414	570,138
AZ	17,677	6,101	24,584	5,513	7,627	3,027	3,469
CA	1,614,205	543,249	1,210,701	493,810	547,551	295,645	259,863
WA	277,811	173,425	148,299	156,368	136,078	152,121	137,516

% Reduction in Curtailment from Base						
	HHND	HHWD	HLND	HLWD	WLND	WLWD
WECC	-59%	-27%	-62%	-61%	-72%	-75%
AZ	-65%	39%	-69%	-57%	-83%	-80%
CA	-66%	-25%	-69%	-66%	-82%	-84%
WA	-38%	-47%	-44%	-51%	-45%	-51%

The majority of the avoided solar curtailments would occur during low load conditions during the spring and fall seasons (see Figure 6.14).

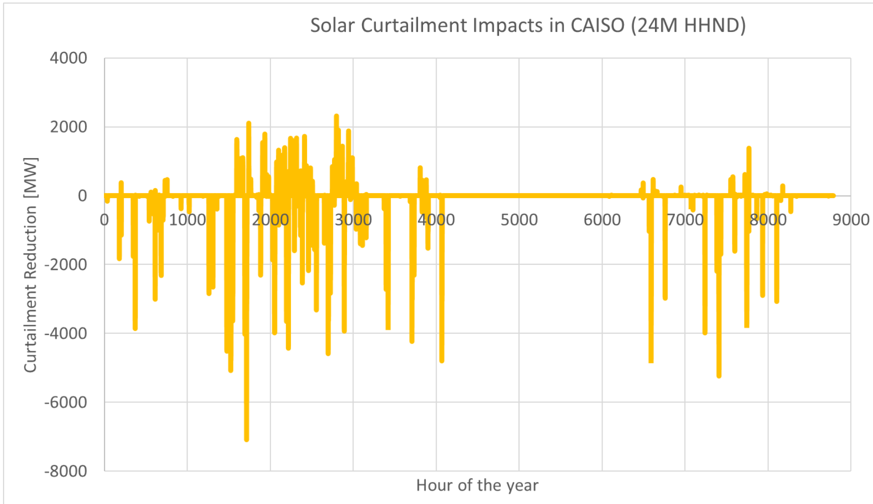

Figure 6.14. Solar curtailment reductions in CAISO in the 24 million LDV unmanaged charging scenario, HHND. Negative values indicate a reduction in curtailment.

6.2.3 Smart (Managed) Charging in Solar-Rich Regions

As mentioned in the previous section, managed, or smart, charging can provide multiple values in solar-rich regions, such as California. These values include (1) reduction of the duck neck's steepness and height, (2) the greatest improvement in renewable curtailment reduction, and (3) increased EV resource adequacy. To further evaluate the benefits of managed charging, the authors modeled managed EV charging as a dispatchable and price-based load that was subject to generation dispatch within the WECC PCM model. They applied an aggressive assumption that 80% of the LDV fleet was sufficiently flexible and that sufficient charging infrastructure was available so that the fleet could be charged anytime during the day. The model would choose the optimal charging time to reduce the system cost. Twenty percent of the LDV fleet was considered constrained to the HHND schedule with no flexibility to manage its charging profile. The production cost model would then seek to dispatch charging that minimized the total system cost.

The results of the managed and unmanaged (HHND) charging are shown in Figure 6.15. The left frame shows that managed charging would occur during the day, ahead of the unmanaged schedule, and that the resulting price response, as expressed in LMP (see Figure 6.15, right frame), shows no negative prices as an indicator of overgeneration and significantly reduced positive price spikes during periods of high demand.

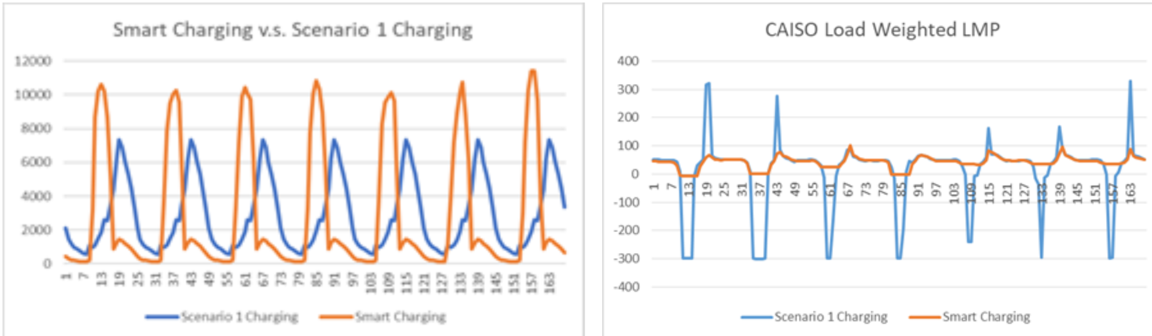

Figure 6.15. Smart charging and Scenario 1 charging and its impacts on price.

Overall, the study indicated the following benefits of managed charging for solar-rich regions such as California:

- The duck-curve neck steepness can be reduced by about 2 GW/h (compared to HHND) and about 1 GW/h (compared to the base case).
- The peak load can be reduced by about 6 GW in the evening, thereby avoiding the use of higher cost CTs.
- Solar curtailment can be reduced. (For the month of July, the authors estimated a reduction of 80 GWh.)
- The production cost for managed charging was improved by 3.5% for the month of July.

These modeling results indicate that smart charging offers several benefits for operation of the bulk power system, in addition to improving resource adequacy in high-penetration scenarios. These results are aligned with several pilot projects across the country that have shown the effectiveness of such techniques in modifying EV charging behavior (Black et al. 2019; DOE 2014; Bauman et al. 2016).

7.0 Washington State Analysis: Illustrative Example at Higher Granularity

Washington State stakeholders expressed interest in understanding potential grid impacts as the EV fleet in Washington State grows and as additional support for transportation of electrification is offered by the state. Washington is the third largest market of EVs in the nation after California and New York.[1]

This section discusses the WECC modeling results from a Washington State perspective. To provide context for the Washington electricity supply landscape, we list the BAs that serve customers in the state. Their approximated areas are shown in Figure 7.1.

• Bonneville Power Administration (BPA)	• Public Utility District No. 1 of Chelan County (CHPD)
• Puget Sound Energy (PSE)	• PUD No. 1 of Douglas County (DOPD)
• Seattle City Light (SCL)	• PUD No. 2 of Grant County (GCPD)
• Avista Corporation (AVA)	• Tacoma Public Utilities (TPWR)

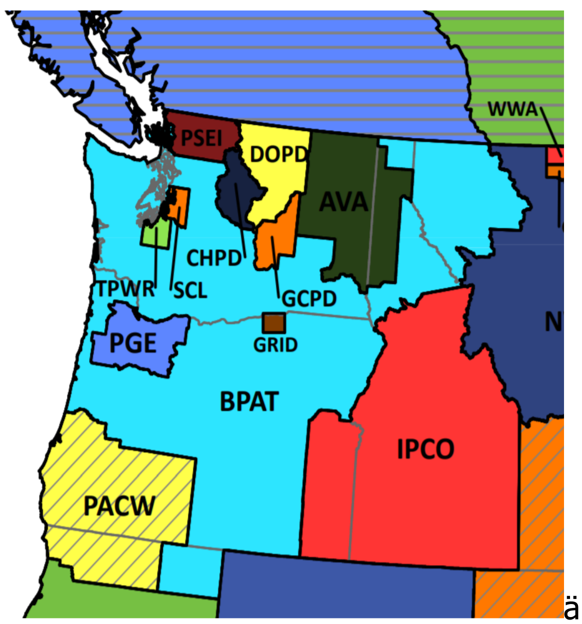

Figure 7.1. Approximated balancing authority boundaries in Washington State (WECC 2018).

7.1 EV Penetration in Washington State

A heat map of electric LDV penetration by counties is displayed in Figure 7.2. Under the 24 million LDV penetration scenario, Washington State was estimated to have an additional electric

[1] Based on sales figures from April 2010 through April 2020. Available at https://www.atlasevhub.com/materials/state-ev-sales-and-model-availability/

LDV penetration of 980,000 by 2028, including the existing 47,000 vehicles[1] already registered. For MDVs, we estimated approximately 4,600 by 2028, and for the HDV charging events we simulated 9 charging hubs along the interstate highway system in Washington State (see Table 7.1 and Table 7.2). The incremental EV load is concentrated in western Washington, where King County, served by both SCL and PSE, contains the highest levels of EV penetration. Detailed county-to-BA mapping can be found in **Error! Reference source not found.**.

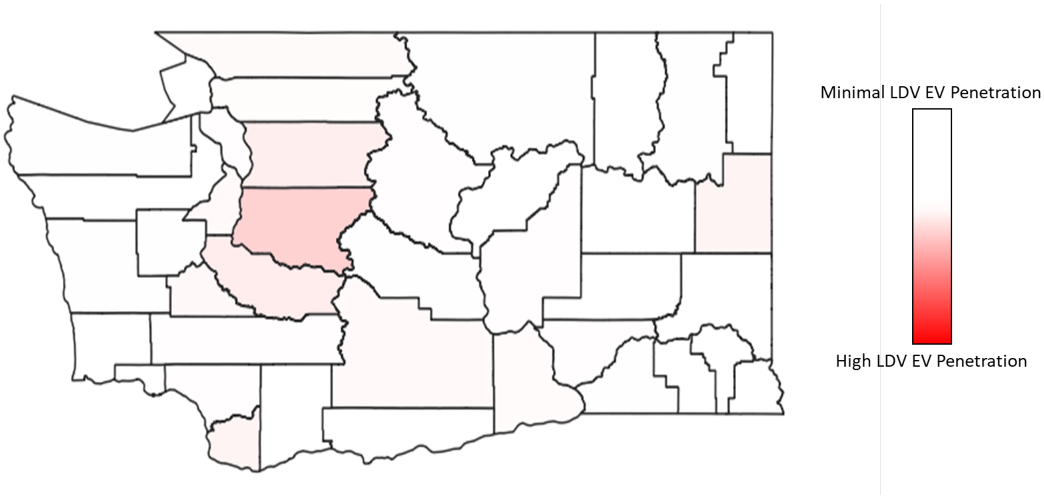

Figure 7.2. Heat map of LDV vehicle penetration by county.

Table 7.1. Washington State 2028 EV penetration assumptions.

	2028 Washington State EV Penetration Assumptions
LDVs	980,000 vehicles
MDVs	4,600 vehicles
HDVs	9 charging hubs

The proportional EV charging load added to each BA can be seen for the charging scenario and most of the charging occurs in the evening (HHND), as shown in Figure 7.3.

Table 7.2. Detailed breakdown of Washington State 2028 EV penetration assumptions.

	LDV		MDV		HDV	
Balancing Authority	No. of Vehicles	Max Charging Capacity (MW) *Unmanaged*	No. of Vehicles	Max Charging Capacity (MW) *Unmanaged*	No. of Stations	Max Charging Capacity (MW) *Unmanaged*

[1] Ibid

AVA	93,959	168	462	7	3	58
BPAT	328,085	580	1,346	21	3	47
CHPD	11,583	21	0	0	1	4
DOPD	12,302	22	0	0	0	0
GCPD	14,387	26	0	0	1	9
PSEI	382,376	682	799	12	0	0
SCL	103,813	185	1,569	24	1	75
TPWR	33,224	59	456	7	0	0
TOTAL	979,729 Vehicles	1,743 MW	4,632 Vehicles	71 MW	9 Stations	193 MW

The proportional EV charging load added to each BA can be seen for the unmanaged (HHND) charging scenario, as shown in Figure 7.3. The aggregated Washington State load stacked by vehicle type is shown in Figure 7.4. Most of the charging occurs in the evening with unmanaged charging.

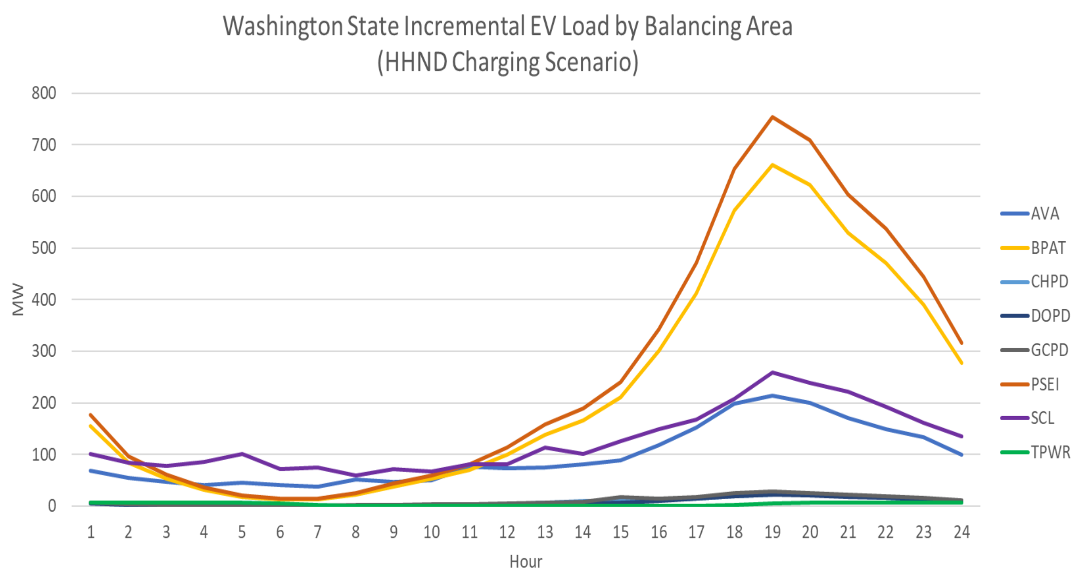

Figure 7.3. Incremental EV loads added to Washington State BAs under the 24 million LDV nationwide penetration scenario (about 1 million LDVs in Washington State). (For Washington, the BPA load represents EV load mapped to Washington State counties only.)

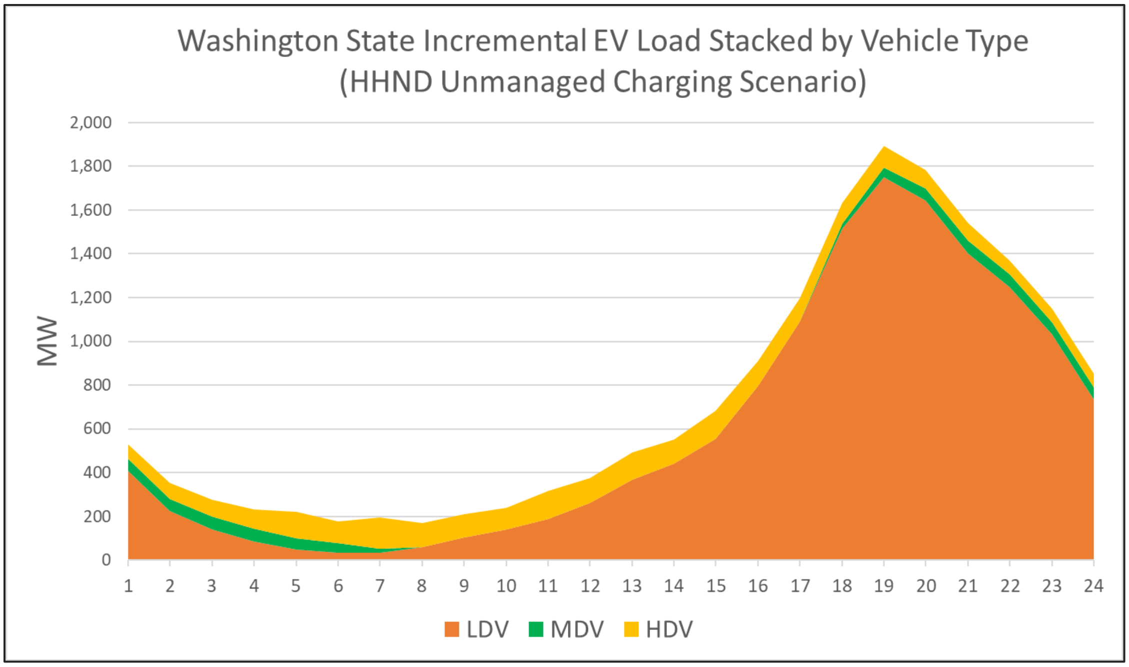

Figure 7.4. Aggregated Washington State Incremental EV loads stacked by vehicle type under the 24 million LDV nationwide penetration scenario (about 1 million LDVs in Washington State).

7.2 Unserved Energy

Figure 7.5 shows unserved energy by BA under increasing LDV penetration with unmanaged charging (HHND). As can be seen, most of the unserved energy would begin within BPA's load territory, because it is the largest load territory in Washington State. As LDV penetration increases, more interesting results begin to appear. Increased unserved energy can be seen to spread into GCPD and AVA located in eastern Washington, followed by PSE, SCL, and TPWR loads located in western Washington, where the majority of the EV load is forecasted to occur. Detailed numbers for unserved energy by BA can be found in **Error! Reference source not found.**.

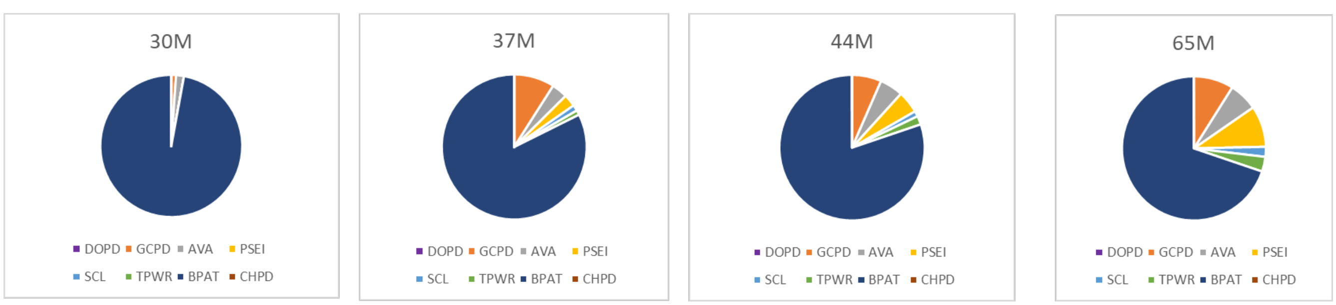

Figure 7.5. Washington State unserved energy by BA and LDV penetration scenario under the HHND charging strategy. For reference, 30 million LDVs nationwide corresponds to about 1.2 million in Washington State, 37 million corresponds to about 1.5 million, 44 million corresponds to about 1.8 million, and 65 million corresponds to about 2.7 million.

The eastern Washington unserved energy seen in these higher LDV penetration scenarios would be caused by resource inadequacy. Much of Washington State's hydropower resources are located in eastern Washington along the Columbia River. As the EV load increases beyond 30 million LDVs nationwide (1.23+ million in Washington State, which is about 50% of today's LDV stock), the flexibility of the Washington State hydropower system and transmission into the region would be the limiting factors relative to supplying additional energy for EV charging in GCPD, AVA, and other eastern Washington BAs.

The western Washington unserved energy seen with these higher LDV penetration scenarios would also be caused by resource inadequacy. The bulk of Washington State's load demand is in western Washington, surrounding the Puget Sound area. As EV load increases beyond 30 million LDVs nationwide, transmission capacity into the region would become a bottleneck, because generation nearby to supply EV charging would not be sufficient.

A deeper dive into generation and transmission constraints within Washington State is explored in the following sections.

7.3 Changes in Generation Dispatch

Section 6.2 contains a brief discussion of how incremental EV load would affect Washington State's generation dispatch. Figure 7.6 highlights seasonal differences not previously discussed. These figures show a generation dispatch delta between the 24 million LDVs penetration scenario and the base case (without additional EVs).

Unlike other regions within WECC, the Washington State load is winter peaking. When comparing the average winter and summer day plots in Figure 7.6, we see higher amounts of hydropower dispatched in winter, despite the EV load remaining consistent throughout the year. There are a couple of reasons for this. First, hydro energy availability is higher during winter than during summer months (NPCC 2019). Secondly, with the increased energy availability of such a low-cost resource during winter months, a higher dependence on Washington State's hydro output to serve incremental EV load outside of Washington State is occurring. Therefore, we see a higher hydropower dispatch delta over an average winter day compared to an average summer day.

Further considerations are needed to investigate whether Pacific Northwest hydropower is flexible enough to be redispatched according to the PCM simulation results attained. Compared to the aggregate hydropower capacity in the Pacific Northwest (PNUCC 2016, E3 2019), the amount of redispatch seen in Figure 7.6 is relatively small and, thus, is not likely to violate and operational limits.

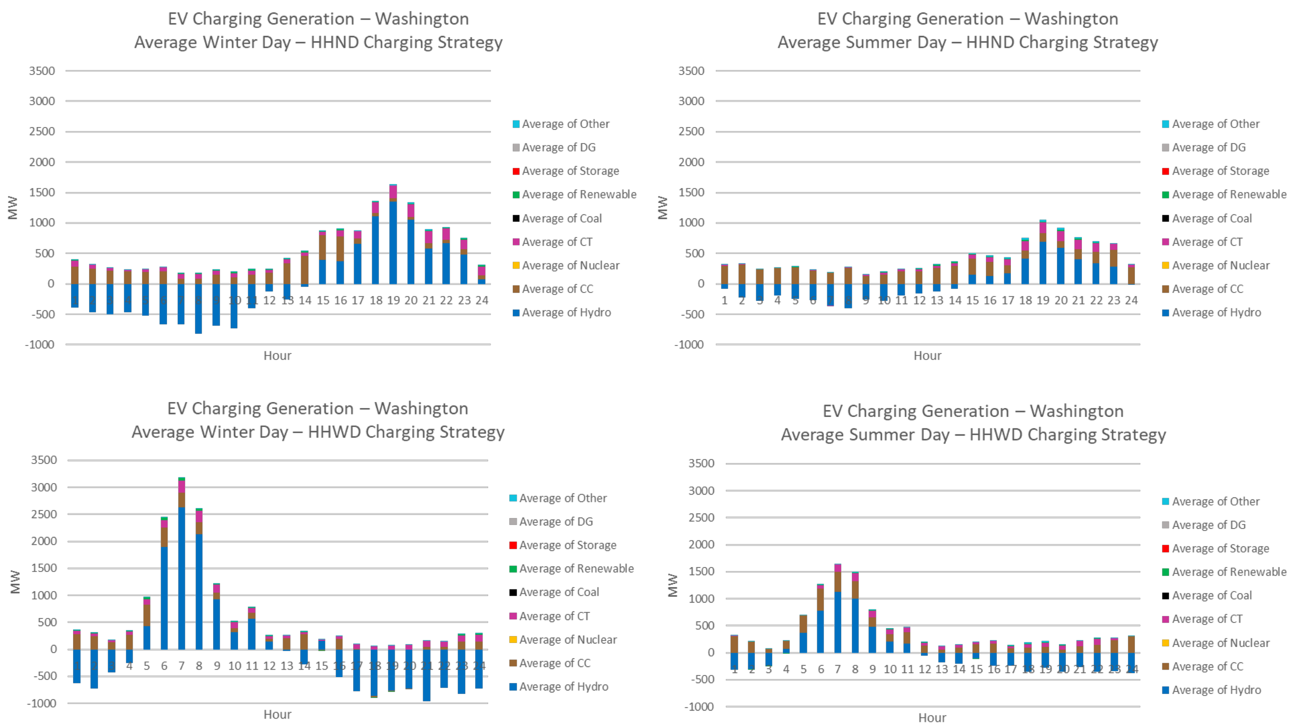

Figure 7.6. Washington State aggregated BA EV charging generation mix.

7.4 Impact on Production Costs and LMP

Under the 24 million LDV nationwide penetration scenario, the highest percentage increase in LMP in Washington State under all charging scenarios is 18% (annual average). The least impact charging scenario occurs under HHWD, when EV load charging is delayed. The highest impact charging scenarios are unmanaged charging (HHND) and work charging scenarios (WLND and WLWD). There are no significant differences in LMP between eastern and western Washington under these conditions.

As LDV penetration increases under unmanaged charging conditions, and generation and transmission resources become increasingly constrained, and LMP in Washington State begins to increase dramatically. Significant impacts begin to occur at 30 million LDVs nationwide. At this point, Washington State would need to consider resource adequacy improvements. The increase in LMP is primarily attributable to transmission congestion during evening peak hours, starting in the summer months under the 24 million LDV penetration scenario. There are no significant differences in LMP between eastern and western Washington under conditions of increasing LDV penetration.

LMP impacts by charging and penetration scenario are shown in Table 7.3, Table 7.4, and Figure 7.7.

Table 7.3. Washington State LMP impacts with 24 million LDV nationwide by charging scenario.

LMP by Charging Scenario($/MWh)							
	Base	HHND	HHWD	HLND	HLWD	WLND	WLWD
WA	22.80	26.77	25.56	26.48	26.38	26.81	26.93
Eastern WA	22.47	26.43	25.25	26.14	26.05	26.48	26.60
Western WA	22.90	26.78	25.61	26.51	26.42	26.85	26.98

% Increase in LMP from Base						
	HHND	HHWD	HLND	HLWD	WLND	WLWD
WA	17%	12%	16%	16%	18%	18%
Eastern WA	17%	12%	16%	16%	18%	18%
Western WA	17%	12%	16%	15%	17%	18%

Table 7.4. Washington State LMP impacts by LDV penetration scenario.

LMP by Penetration Scenario ($/MWh)						
	Base	24M	30M	37M	44M	65M
WA	22.80	26.77	29.17	34.89	44.00	111.31
Eastern WA	22.47	26.60	29.01	34.76	43.93	111.27
Western WA	22.90	26.78	29.17	34.85	43.88	110.78

% Increase in LMP from Base					
	24M	30M	37M	44M	65M
WA	17%	28%	53%	93%	388%
Eastern WA	17%	28%	53%	93%	389%
Western WA	17%	28%	52%	92%	385%

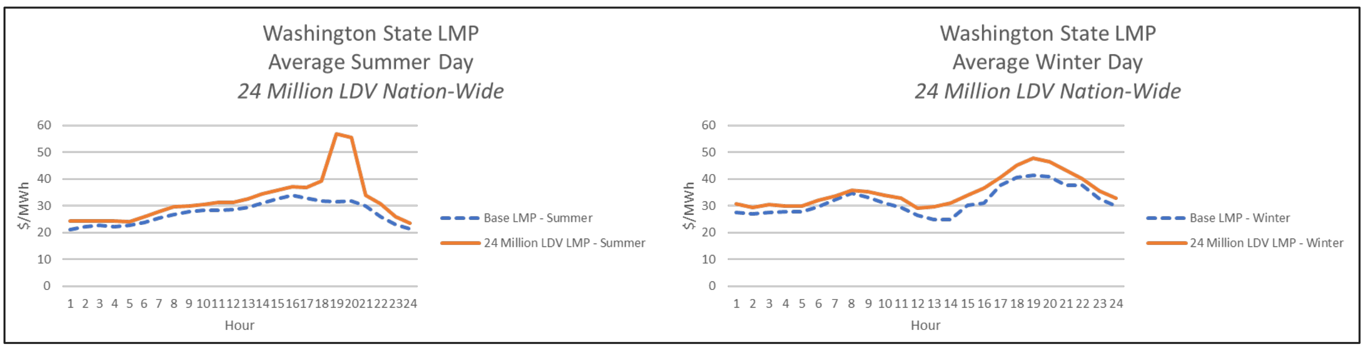

Figure 7.7. Washington State LMP by hour with 24 million LDVs nationwide.

The average production cost impacts are shown in Table 7.5, Table 7.6, and Figure 7.8. In the 24 million LDV nationwide penetration scenario, the charging strategy does not significantly change production cost for individual Washington BAs under generation ownership. However, when LDV penetration increases beyond the 24 million high-penetration scenario, production cost does begin to increase. However, these increases are not as significant as the LMP growth seen in Table 7.4, which again points to transmission being the principal bulk grid bottleneck in Washington State.

Table 7.5. Washington State production cost impacts by charging scenario.

Production Cost by Charging Scenario ($/MWh)							
	Base	HHND	HHWD	HLND	HLWD	WLND	WLWD
WA	5.60	6.09	6.05	6.07	6.08	6.11	6.11
AVA	13.42	14.62	14.67	14.58	14.68	14.63	14.61
PSEI	16.64	17.84	17.71	17.73	17.65	17.77	17.67
TPWR	7.03	7.55	7.44	7.53	7.47	7.55	7.50
BPA	4.19	4.36	4.37	4.37	4.40	4.39	4.42

% Increase from Base						
	HHND	HHWD	HLND	HLWD	WLND	WLWD
WA	9%	8%	8%	8%	9%	9%
AVA	9%	9%	9%	9%	9%	9%
PSEI	7%	6%	7%	6%	7%	6%
TPWR	7%	6%	7%	6%	7%	7%
BPA	4%	4%	4%	5%	5%	6%

Table 7.6. Washington State production cost impacts by LDV penetration scenario.

Production Cost ($/MWh)						
	Base	24M	30M	37M	44M	65M
WA	5.6	6.09	6.16	6.25	6.34	6.63
AVA	13.4	14.6	14.8	14.8	14.9	15.2
PSEI	16.6	17.8	18	18.3	18.5	19.3
TPWR	7.03	7.55	7.65	7.76	7.86	8.11
BPA	4.19	4.36	4.38	4.41	4.45	4.56

% Increase from Base					
	24M	30M	37M	44M	65M
WA	9%	10%	11%	13%	18%
AVA	9%	10%	10%	11%	13%
PSEI	7%	8%	10%	11%	16%
TPWR	7%	9%	10%	12%	15%
BPA	4%	5%	5%	6%	9%

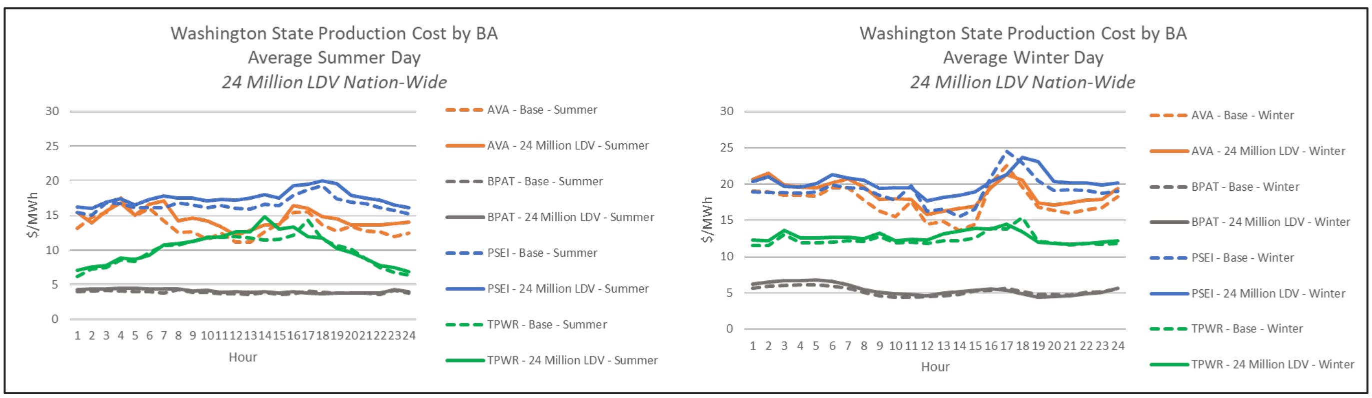

Figure 7.8. Washington State production cost by BA by hour with 24 million LDVs nationwide.

7.5 Impact on Transmission Congestion

Using BPA's defined transmission paths and flowgates, as shown in Figure 7.9, and the PCM analysis performed on the WECC, the authors studied how seasonal flow patterns changed under various LDV penetration scenarios. Unmanaged charging (Figure 4.1) exacerbates the existing evening peak load. Detailed plots showing the seasonal flow patterns for the flowgates identified in Figure 7.9 can be found in **Error! Reference source not found.**.

Under HHND charging assumptions and increasing LDV penetration the following observations can be made under normal system, weather, and water conditions in Washington State:

- Outside of winter months, Seattle area transmission congestion is minimally affected by incremental EV load based on **North of Echo Lake** seasonal flow patterns. However, transmission congestion during winter months may be exacerbated by unmanaged EV charging during evening peak hours.

- Summer through winter flows at the **South of Custer** and **South of Boundary** flowgates indicate increased congestion from Canada into Washington State during evening peak hours under unmanaged EV charging conditions.
- All season flows at the **Cross Cascades North** flowgate indicate higher than normal congestion (eastern Washington to western Washington) during evening peak hours under unmanaged EV charging conditions.
- All season flows at the **Columbia Injection** flowgate capture a shift in Washington hydropower dispatch with the addition of EV load, in which morning hydropower is conserved and then increased in late afternoon to serve the higher evening peak.
- EV load south of Washington contributes to slightly increased congestion on the **South of Allston** flowgate (Washington to Oregon) during evening peak hours under unmanaged EV charging conditions.
- Flows at the **Paul-Raver, Paul-Allston,** and **North of John Day** flowgates indicate less north to south flow (Washington to Oregon) during morning peak hours.

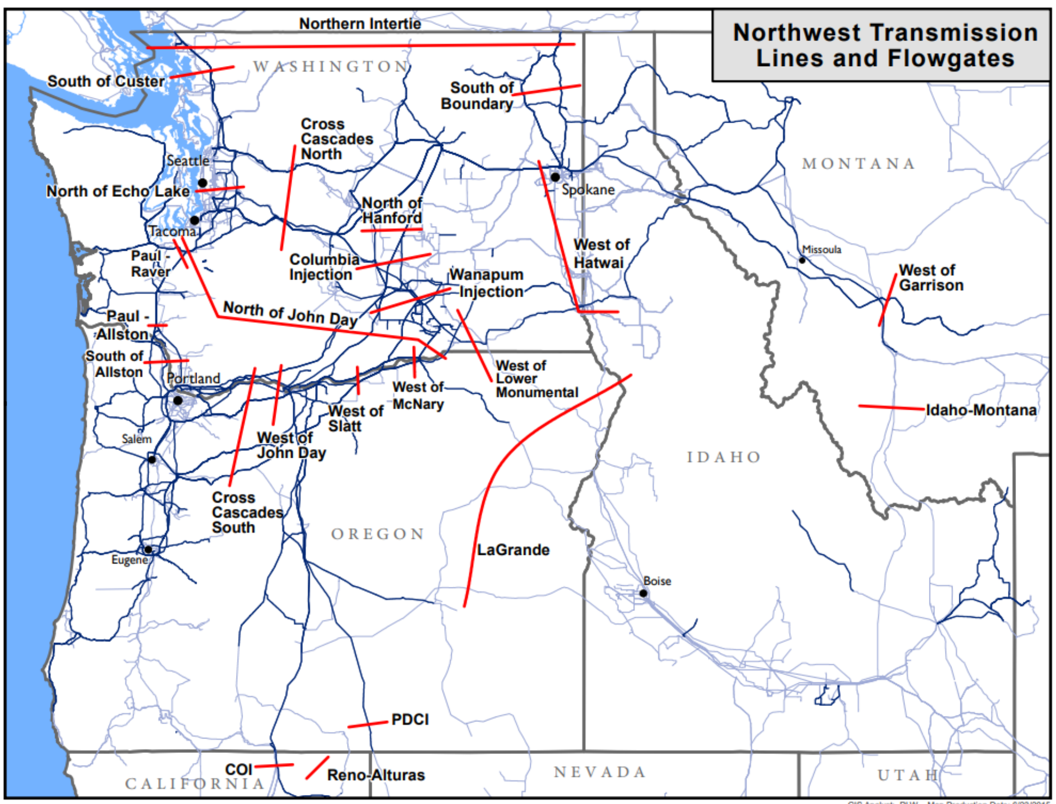

Figure 7.9. BPA flowgate map of major transmission paths in the Pacific Northwest.[1]

[1] BPA (Bonneville Power Administration). 2015. Northwest Transmission Lines and Flowgates. Available at https://transmission.bpa.gov/Business/Operations/Paths/Flowgate%20Map_2015-06-23.pdf

7.6 Summary of EV-at-Scale Impacts for Washington State and Considerations for Future Grid Analyses

The Washington State analysis indicates relatively minimal impact at the bulk power level for Washington State BAs under the high-penetration scenario of 24 million LDVs nationwide or 980,000 LDVs for Washington State, under normal system, weather, and water conditions. Bottlenecks would arise under increasing penetration beyond 1.2 million LDVs, causing some operational challenges and significant changes in generation dispatch and transmission congestion. As discussed in Section 6.1.1, by shifting away from unmanaged charging and encouraging EV smart charging, Washington State could reduce bulk grid reliability impacts and accommodate higher numbers of EVs beyond the 65 million national high-penetration scenario (2.7 million in Washington). Operationally, natural gas CC plants and CTs are likely to provide the additional generation for charging EVs. Power from the hydropower system may need to be redispatched to accommodate the additional peak demand set by EVs. The average production cost implications are relatively small—varying from 4 to 9%—and are primarily caused by additional natural gas generation.

Based on the insights gained from this study, Washington State may want to consider additional analysis to address the following questions:

- Being energy limited, are Washington State's hydropower resources flexible enough to be redispatched (in accordance with Figure 7.6) to supply energy to unmanaged EV load? If not, do Washington State BAs need to invest in alternative resources or non-wire solutions (i.e., energy storage) to supply this energy?
- With increased congestion during evening peak hours on transmission between Canada and Washington, Washington to Oregon, and eastern Washington to western Washington, what solutions could Washington State explore to better manage congestion caused by EV charging?
- How could smart charging technology be best deployed and implemented in Washington State to mitigate bulk grid impacts caused by unmanaged EV load?
- Across a broad range of weather, drought conditions, and system operating conditions, can BAs in Washington State maintain resource adequacy under higher levels of EV penetration?

8.0 Considerations for EV Impact Analyses in Distribution Systems

8.1 Background and Motivation

The main emphasis of this study was centered on system resource adequacy questions that relate to the ability of the grid to generate and transmit electric energy to the load centers for meeting the new EV charging requirements. This resource adequacy study excludes the delivery of the "last-mile" from the bulk power substation to the charging station through mid-voltage distribution circuits. Some of these circuits are very old, particularly in established large urban areas that were designed and built before the advent of air-conditioning many decades ago. With the rapid growth of EVs and particularly with new EV-based services such as ride-hailing and taxi services, there is a growing need for public charging stations that provide fast charging capabilities. Compounding the current EV growth of the LDV segment is the expected growth of MDV and HDV segments in the near future, as evidenced by the recent announcement by Amazon.com Inc. to purchase 100,000 EV delivery trucks from Rivian with delivery expected by 2024.[1] In addition, transit agencies are beginning to transition their diesel bus fleets to EVs to meet state clean fuels targets. These growth trends, particularly for the MDV and HDV segments that feature much larger batteries than LDVs, suggest that charging stations may need to deliver charge rates of 300 kW and higher. Some MDV manufacturers are testing technologies that deliver charging rates of more than 1 MW.

Given the mostly urban locations of vehicle yards of transit agencies and delivery business places, new attention to the need for upgrades of distribution circuits and sub-transmission infrastructure is needed to accommodate the near-term expected charging infrastructure build-out. With the growing need for long-distance driving of EVs and expected new EV-based mobility services in urban centers, the grid planning community recognizes the need to address the future upgrade needs of the distribution systems to accommodate the growing EV charging needs.

The review of upgrade needs is predicated on reliability concerns that the new EV load may pose to the existing distribution circuits beyond the operating conditions for which they were originally designed. Mitigation of the stress during high load conditions is critical for reliable operations of the distribution system. Depending on the nature of the stressors, this mitigation could come in multiple forms: transformer/conductor upgrades, additional voltage support, smart charge management systems, etc. For example, sag in voltage resulting from numerous simultaneous charging events from fast DC charging at a public parking space needs to be resolved by boosting local voltage. Therefore, understanding and quantifying the current or future impact of EV charging on distribution feeder circuits is a critical first step toward resolving the issue. In this section, we discuss a grid analysis based on power flow simulations using GridLAB-D on a simple example. In addition, we lay out a broader distribution system analysis as follow-on work to this study to address the needs for the distribution planning community to be ready for growth in EV charging demands.

[1] https://www.theverge.com/2019/9/19/20873947/amazon-electric-delivery-van-rivian-jeff-bezos-order

8.2 Modeling of EV Charging on Distribution Feeder Circuits

The modeling effort reported here was based on three distinct components: (1) the modeling penetration and charging behaviors of EV, (2) the selection and modeling of feeder circuits that best represent real-world systems, and (3) the definition of EV driving patterns to determine energy requirements for EV charging. The example discussed below was based on a synthetic feeder model that PNNL can generate from a large library of real-world feeder models. The feeder model synthesis was based on a few of parameters to lay out a grid topology and define the load scenarios given the customer composition to be served.

8.2.1 Modeling of EV Penetration and Charging Behaviors

The first step in this modeling effort was to downscale the EV penetration projections from the bulk power analysis to the distribution systems level, as shown in Figure 8.1. This needed to be done consistently, so that the sum of all hourly loads in distribution system circuits beneath a bulk power substation represented the same load profile as those used in the bulk power analysis. This was done in two steps. The EV load was first mapped from the BA zone to a transmission (bulk power) network node, and then further mapped down to the distribution system level.

To calculate the number of EVs per feeder circuit, a simple approximation was used: the peak charging load was divided by the average demand from a single L2 charger. Once the numbers of EVs per feeder circuit was calculated they were randomly distributed to houses on the circuit.

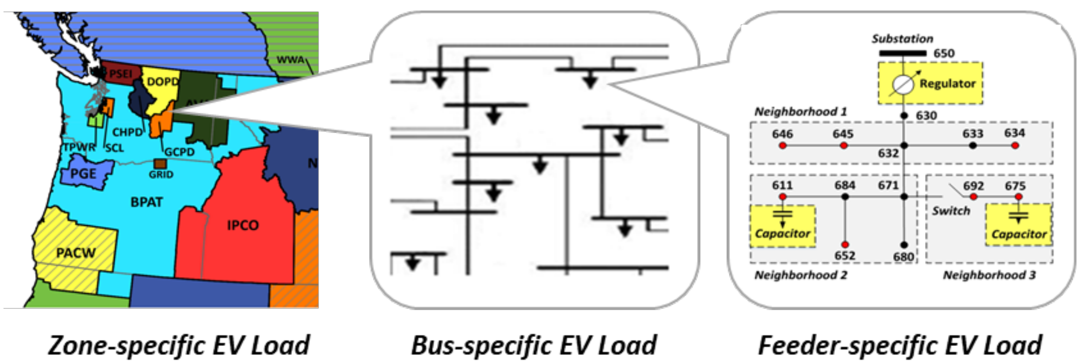

Figure 8.1. Methodology to align bulk grid and distribution feeder EV adoption.

8.2.2 Selection and Modeling of Synthetic Feeder Circuits

There is a lot of diversity in the nature of distribution system circuits across the country. Specifically, the diversity arises from variations in topologies, voltage levels, and load compositions, among other factors. Among the other factors are climate conditions that specify whether heating is done electrically or by a fossil fuel source. Natural gas or oil heating is commonly used in the colder regions of the United States. If heating is done electrically, the individual customer’s load profile is markedly different than that of a customer using natural gas heating. Similarly, in hot and humid climate, air-conditioning will add significantly to the summer load profile.

This makes it challenging to derive meaningful results for distribution system impact analysis, unless the analysis is performed on actual utility feeder circuits. Procuring and processing feeder models from utilities is time-intensive and could not be accommodated within the timeline of this project. As a result, for this project, the distribution system analysis was performed using GridLAB-D's prototypical feeders (Schneider et al. 2008).

The prototypical feeders are collections of synthetic feeder models that represent circuits from five climatic zones in the United States, as shown in Figure 8.2. These zones are temperate, hot/arid, cold, hot/cold, and hot/humid. Actual utility feeder models from these regions were collected, clustered, and reduced to a representative set of 24 circuits that were determined to be typical representations of feeders in these regions across the nation. These 24 circuits were broken into the climatic regions based on the following proportions: temperate region – 5 circuits; cold region – 5 circuits; hot and arid region – 3 circuits; hot and cold region – 3 circuits; hot and humid region – 6 circuits; and one general circuit that is common to all regions. Within the subset of feeder models for each climatic region, the circuits represent urban, suburban, and rural areas, at primary voltages of 12.47 kV, 25 kV, and 35 kV, respectively. Though the circuits were derived from actual utility feeder models, they are completely sanitized and stripped of any details pointing to the real-world circuit.

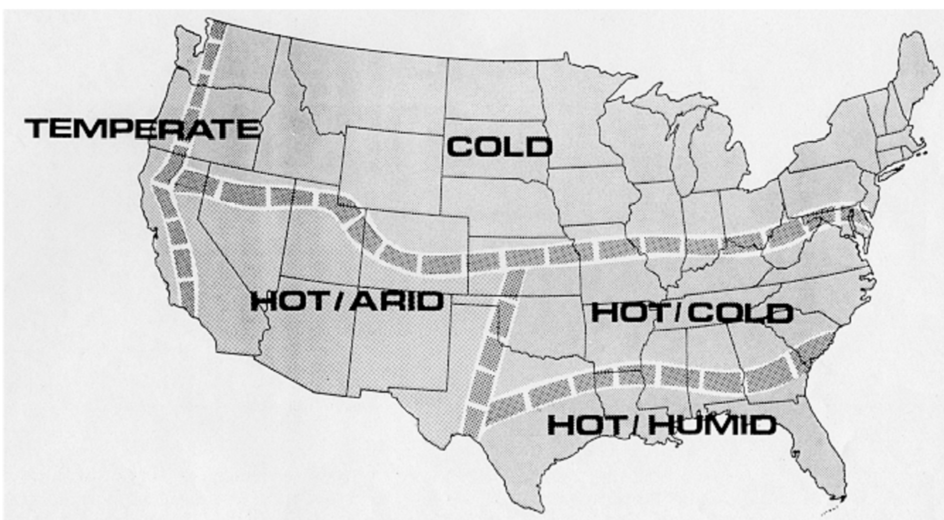

Figure 8.2. Prototypical feeders climatic regions.

The distribution system analysis discussed in this document was performed for a single circuit as an example. The goal was to describe the process of performing a more comprehensive distribution system analysis to provide insights into future planning needs.

The prototypical feeder selected for this example represents the Pacific Northwest climate region with a customer composition typical of a suburban circuit of mainly single-family homes (around 800) and some commercial loads. The substation serving a suburban circuit, with a peak load comparable to the selected prototypical feeder (2.9 MW), was identified from the Pacific Northwest region of the WECC bulk power model. The limits of the substation remained unknown. The EV penetration associated with this substation was determined to be approximately 200 EVs, and the feeder model was appropriately populated using randomly selected locations. The standard GridLab-D EV charging profile was used, which represents an L2 charging at home derived from the National Household Travel Survey, which was similar to but not exactly the same as the HHND load profile used in the bulk power analysis. In addition, we simulated a DC charging load of 1 MW, superimposed over the 200 L2 charging events.

8.2.3 Impact Assessment of EV Charging on Distribution Feeder Circuits

The impact assessment was performed by comparing the results of the feeder with EVs to the base case without EVs. We discuss the results based on three metrics: substation load, primary circuit voltage, and secondary circuit voltage. These three metrics are indicative of any potential reliability concerns based on (1) thermal overloading of any grid assets and (2) American National Standards Institute (ANSI) voltage violations (ANSI 2011).

8.2.3.1 Thermal Overload Potential

Figure 8.3 presents a comparison of substation load with (orange curve) and without EV (blue curve) charging loads, in addition to a red curve that represents just the EV charging load. The peak load in the base case was noted to be ~2.9 MW at 6:13 PM. In the EV case, the 15-minute fast charging event at 10 AM pushes the system load to a new peak value of ~3.25 MW, a 12% increase. Excluding the fast charging event, the system peak is marginally increased to 3.01 MW from at-home, evening L2 charging events. Clearly, the bigger threat to distribution system operation is from DC fast charging events. If the DC fast charging events coincided with system peak, they could potentially push the feeder components closer and beyond their operating limit or rated capacity. This could require an upgrade of feeder infrastructure on the primary circuit. On the other hand, L2 at-home charging events could require an upgrade of the secondary circuit infrastructure. Because these feeder circuits were synthesized, we do not have any information about the capacity limits of individual grid assets. Only real feeder data will reveal if any rated capacity was exceeded.

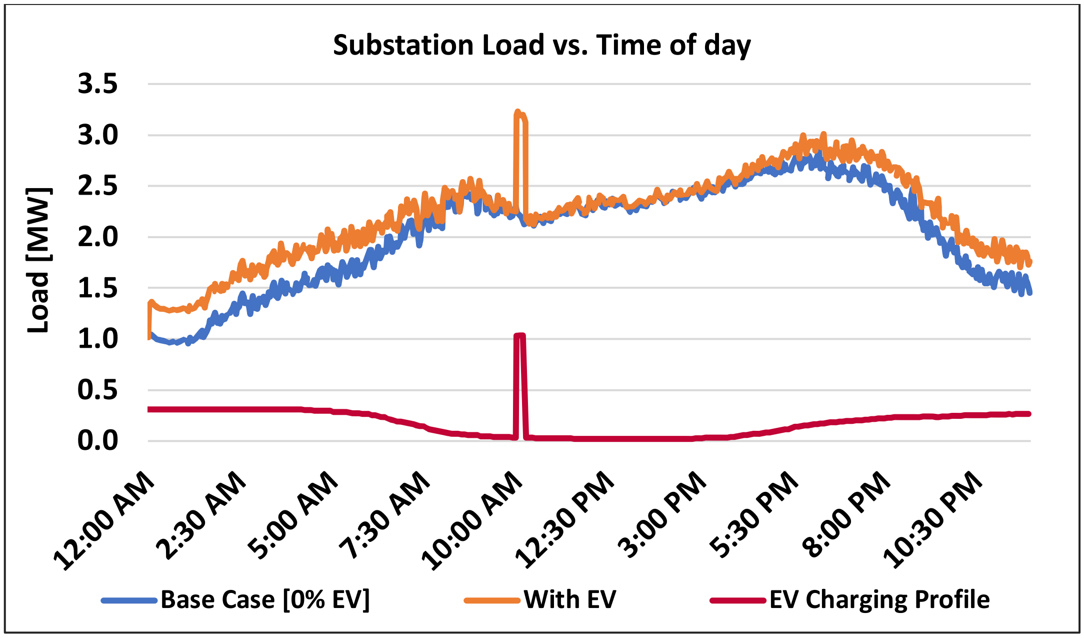

Figure 8.3. Comparison of substation load with and without EV charging.

8.2.3.2 Voltage Violations

Figure 8.4 shows a comparison of the primary circuit voltage with and without EV charging. The biggest impact on the primary circuit voltage is from the fast charging event at 10 AM. However, the drop in voltage of ~25 V is insignificant, and can be handled easily by existing voltage controls in the feeder. The impact of EV charging on the secondary circuit, as shown in Figure 8.5, was also determined to be minimal. Though the results from the test system show a negligible impact on feeder voltage on both the primary and secondary circuits, the result cannot necessarily be generalized to all circuits. For example, EV charging could potentially have an impact on voltage if the charging location is located downstream. Such a scenario could force infrastructure upgrades by way of localized voltage support device installation to improve the voltage profile.

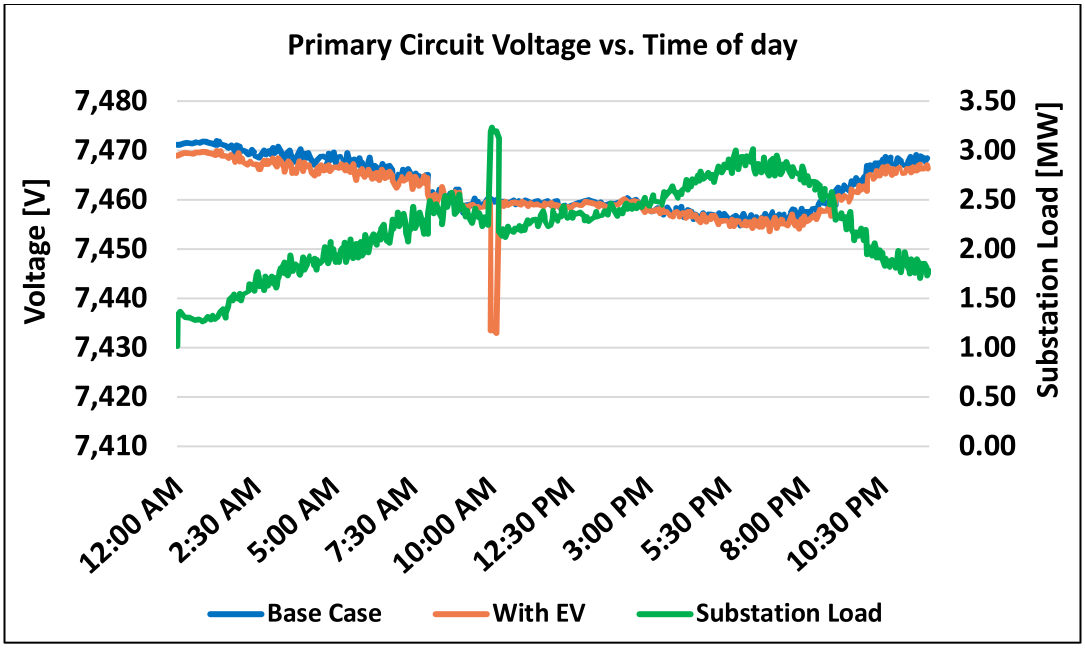

Figure 8.4. Comparison of primary circuit voltage with and without EV charging.

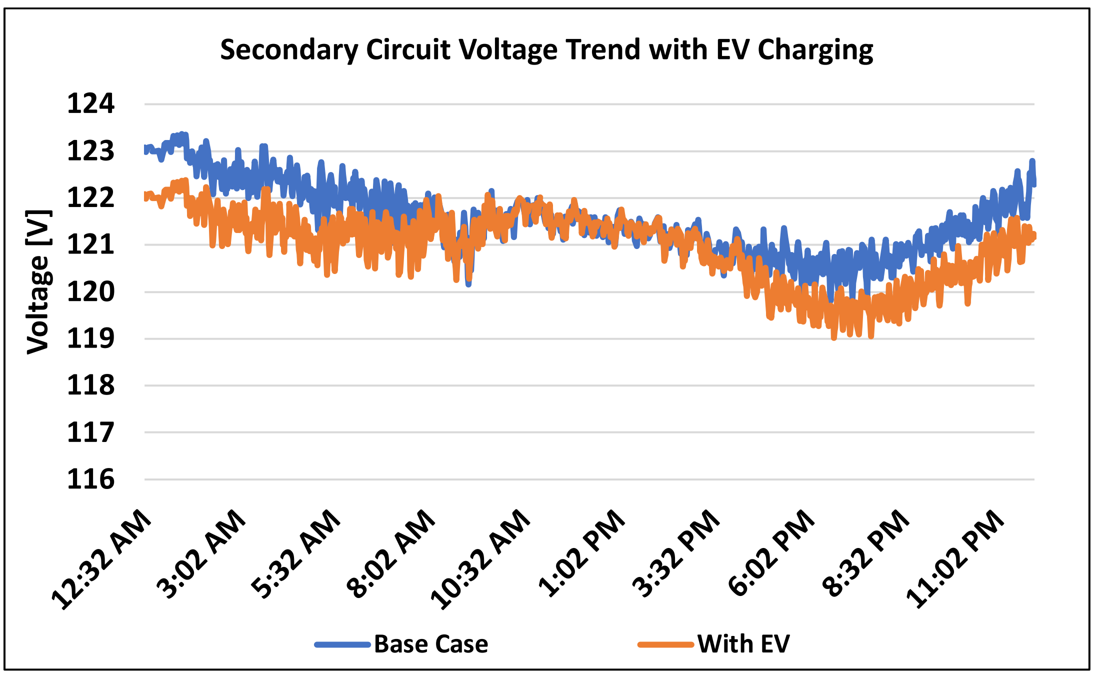

Figure 8.5. Comparison of secondary circuit voltage with and without EV charging. The ANSI standard allows for a ±5% deviation from the nominal voltage of 120 V (ANSI 2011).

8.2.4 Summary of the Distribution System Example

This brief example illustrates the fundamental elements of a distribution system analysis of EV impacts. We used a synthesized feeder model for illustration purposes that lacked size and rating information for all infrastructure assets (transformers, conductors, voltage regulators, capacitor banks). As a consequence, the results should serve as an illustration of the mechanism of how additional EV load may impose stress on the distribution infrastructure and how the stress condition may limit the number of EVs to be serviced.

8.2.5 Considerations for the Distribution System Analyses to Inform the Grid Planning Community

To provide insights into the limiting factors that determine the EV hosting capability of a given feeder, a comprehensive distribution system analysis needs to be performed using real-world feeder data and participation by utility partners. There is no real substitute for real feeder data to reveal the bottleneck conditions that may induce capital investments in upgrading distribution system circuits. Unlike the bulk power EV-at-scale analysis, there is no central entity that owns data about distribution infrastructure other than each individual load-serving entity or utility organization. As a consequence, insights gained by performing a comprehensive distribution system analysis is only valid for the very utility organization for which it was done. Generalizations are not applicable and may lead to wrong conclusions. Therefore, we recommend that any follow-on work for EV impact studies be performed as individual case studies with more than one utility partner. By performing several case studies with real-world data, we may expect some overarching insights to emerge. Unless the analysis is done, it would be too early to predict what the insights might be.

Here are some considerations for in-depth distribution system analyses to explore the EV hosting capabilities of distribution system infrastructure:

1. Work with two to three utility partners from across the nation to perform an EV distribution impact analysis to determine the EV hosting capability for a portfolio of feeders.
2. Perform analysis for several time frames (2025, 2030) and represent some upgrade investments that would occur in the absence of EVs, such as smart grid investments. Include behind-the-meter distribution energy technologies (PV and batteries) that may be installed by the customer, that would affect the analysis.
3. Estimate EV hosting capabilities under LDV, MDV, and HDV penetration scenarios and vary the assumptions for DC charging technologies to represent a spectrum of charging rates and EV use patterns that determine the charging profiles.
4. Estimate how the EV hosting capability may be expanded when using smart or managed charging strategies. Estimate the value of smart charging strategies by deferring capital investments in infrastructure upgrades.
5. Compare the results obtained from the two to three utility partners and discuss the insights learned, which may be of value to the broader community.

9.0 Conclusions and Next Steps

9.1 Conclusions

This EV-at-scale Phase I analysis addressed the following two key questions of interest to DOE related to the impacts of EV at the bulk power level at the time when EVs are deployed at scale:

1. Are there sufficient resources in the U.S. bulk power grid to provide the electricity for charging a growing EV fleet? This question addresses the system adequacy.
2. What are the likely operational changes necessary to accommodate a growing EV fleet? This question addresses changes in
   - generation mix
   - production cost
   - challenges and benefits of accommodating the new EV loads.

Because of the short time frame for the analysis, the national discussion was reduced to a Western grid analysis. Commonly accepted WECC grid data were readily available for use in a future (2028) grid scenario. All the results of this study are based on simulations of the WECC system using ABB's GridView production cost modeling software. Load scenarios were developed with the support by NREL for LDVs. New charging profiles were developed by PNNL for MDVs and HDVs.

It should be noted that this study did not include a capacity expansion analysis that searches for cost-optimal investments of new grid infrastructure given the new EV loads. Instead this study focused on the resource adequacy question of high EV adoption as the WECC grid planners defined the evolution of the bulk power system to the year 2028.

The key outcomes of this EV-at-scale analysis are as follows:

2028 resource adequacy is likely to be sufficient for high EV penetration assumption.

- Under a high-penetration scenario with national electric fleets of ~24 million LDVs, 200,000 MDVs, 150,000 HDVs for a 2028 time frame, we are not expecting resource adequacy issues in the WECC under normal operating conditions (normal system, normal weather, and normal water conditions). The corresponding electric fleet sizes for the WECC footprint are 9 million LDVs, 70,000 MDVs, and 94 HDV charging stations. It is customary for resource adequacy analyses to be performed for normal operating condition. Contingency analyses that test the reliability under outage conditions are only performed for interconnection analyses and special study cases and, thus, were deemed out of scope for this analysis.

EV resource adequacy can be doubled with managed charging strategies.

- The EV resource adequacy for the entire WECC interconnection was estimated for a likely unmanaged charging scenario under which most LDVs were charging at home starting in the evening (HHND). The maximum number of LDVs when projected to the national fleet was about 30 million (national value) or 9 million for the WECC footprint. At that point, insufficient generation and transmission bottlenecks would emerge requiring both transmission and generation expansion. Alternatively, if managed charging was applied by hypothesizing a price-minimization scheme, the EV resource adequacy could be expanded to 65 million (national fleet number) or 19.6 million for the WECC. This suggests a significant opportunity to substitute additional generation and transmission requirements with smart charging strategies and much better utilization of the existing grid.

- At that maximum number of LDVs, the authors found transmission congestion to be the limiting factor, which means that there are some available power plants in the WECC but the electric power could not be delivered to the load centers because of transmission limitations. The largest transmission congestions were in California (Paths 15, 26).

Operational changes can be made to accommodate EVs.

- The additional generation for charging EVs is likely to be provided by natural gas CC plants and CTs predominantly throughout the WECC (85%–89% of all new generation). Storage is used in California to meet the peaks set by EVs. Hydropower generation in Washington State is redispatched to resemble a commonly observed charging/discharge cycle of an energy storage technology. No new hydropower generation is expected because hydropower generation is energy limited—no more water is expected in the Columbia River system.
- All EV charging load is likely to reduce renewable curtailments between 25% and 75% based on when EVs are charged. Managed charging could reduce the curtailment the most by an additional 16%.
- The production cost implications due to the additional load varied from 3% in Arizona, where there is some available coal generation, to 23% in California, where CTs are required to meet the peak load set by EVs.
- Managed charging has significant operational benefits in solar-rich areas such as California. It reduced the duck curve in two ways: (1) it reduced the coincident peak (duck height) and (2) it reduced the ramp requirements in the evening when the sun sets (steepness of the duck's neck).

In addition, the authors performed an EV-at-scale impact analysis for Washington State using the WECC results and analyzed them for the Washington balancing authorities. The results of this higher resolution analysis are as follows:

- Unmanaged EV resource adequacy for Washington State is approximately 1 million LDVs and 4,600 MDVs under normal system, weather, and water conditions. With managed (smart) charging, the resource adequacy can be increased to 2.7 million LDVs.
- Washington State hydropower resources may need to be redispatched to accommodate unmanaged EV load.
- The average production cost implications of high LDV penetration are minor and vary between 4% and 9% based on the generation mix of the utility organization.
- We recognize congestion in the transmission system that already exists during high loading in the winter. Congestion is likely to be exacerbated with new EV loading with unmanaged charging, because of transfers from Canada to Washington, Washington to Oregon, and eastern Washington to western Washington under normal system, weather, and water conditions.

The illustrative distribution system analysis offered insightful results for Phase II analysis.

An illustrative distribution system analysis was presented that demonstrated the mechanism of how to perform a distribution system analysis and what the expected results and outcomes are. This illustrative example indicated the following:

- Factors most likely to limit the additional growth of EVs are thermal overloading or reaching the rated capacity of grid assets in the distribution system under fast charging conditions.
- Voltage violations may occur under fast charging condition with high ramping loads during fast charging events.

9.2 Next Steps

With the advent of extreme fast charging technology to enable MDV and HDV electrification, there is some concern about the distribution system reliability and need for upgrades. To address this challenge, the authors recommend that a comprehensive distribution system analysis be performed as an extension of the EV bulk power analysis.

To provide insights into the limiting factors that determine the EV hosting capability of a given feeder, comprehensive distribution system analyses need to be performed using real-world feeder data and participation by utility partners. There is no real substitute for real feeder data to reveal the bottleneck conditions that may induce capital investments to upgrade distribution system circuits. Unlike the bulk power EV-at-scale analysis, no central entity owns data about the distribution infrastructure; each individual load-serving entity or utility organization owns these data for their infrastructure. As a consequence, insights gained by performing a comprehensive distribution system analysis are only valid for the very utility organization for which it was done. Generalizations are not applicable and may lead to wrong conclusions. Therefore, the authors recommend that any follow-on work for EV impact studies be performed as individual case studies with more than one utility partner. By performing several case studies with real-world data, they expect that some overarching insights to emerge. Unless such analyses are done, it would be too early to predict what those insights might be.

Considerations for in-depth distribution system analyses to explore the EV hosting capabilities of distribution system infrastructure include the following:

1. Work with two to three utility partners from across the nation to perform an EV distribution impact analysis that would determine the EV hosting capability for a portfolio of feeders.
2. Perform analysis for several time frames (2025, 2030) and represent some upgrade investment scenarios that would occur in the absence of EVs, such as smart grid investments. Include behind-the-meter distribution energy technologies (PV and batteries) that may be installed by the customer that would impact the analysis.
3. Estimate EV hosting capabilities under LDV, MDV, and HDV penetration scenarios and vary the assumptions for DC charging technologies to represent a spectrum of charging rates and EV use patterns that determine the charging profiles.

4. Estimate how the EV hosting capability may be expanded when using smart or managed charging strategies. Estimate the value of smart charging strategies by deferring capital investments of infrastructure upgrades.
5. Compare the results obtained from two to three utility partners and discuss the insights learned, that may be of value to the broader community.

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Appendix A – Selected Medium-Duty Vehicles and Characterization

Model	Class	GVW (lb)	Battery Size (kWh)	Range (miles)	Efficiency (miles/kWh)	Efficiency (kWh/miles)
Streetscooter Work XL with Ford			76	120	1.58	0.63
Lighting Electric Fort F-59		22000	128	110	0.86	1.16
eM2 106 Freightliner/Daimler	3		325	230	0.71	1.41
eCascadia	8		550	250	0.45	2.20
eCanter- Daimler (Europe)		15000	82	80	0.98	1.03
Volvo FL Electric		32000	300	186	0.62	1.61
Chanje V1800 urban average		16000	100	65	0.65	1.54

Appendix B– HDV Model and Algorithm Details

B.1 Selecting the Approximated Map and Highway Network

The map construction started with the Bureau of Transportation Statistics (BTS) reported the top 25 gateway cities for U.S.-International import and export. An additional 31 cities were included subjectively to represent locations where major interstate highway interchanges exist. The approximated interstate highway network was constructed by connecting each of the 56 cities to at least two of the nearest cities, and additional roads were created to assure that the highway network realistically captured U.S. highways mostly traveled on by heavy-duty vehicles (HDVs), as reported in the BTS data.

It is worth noting that when qualitatively compared to the charging station locations, the map used for the HDV fleet model is in a strong agreement with respect to the road networks along which stations are placed and the distances between stations proposed by the Electrify America plan (Electrify America 2018). As illustrated in Figure B.1, the same number of charging stations are placed between Salt Lake City and Seattle. Similarities are particularly true for the northeastern, southern, and midwestern regions. In fact, for these regions, the HDV model map shows additional station locations and even additional roads not covered by Electrify America. Other disagreements between the maps along the western states (especially California) indicate a higher density of station locations offered by the Electrify America plan. However, the HDV fleet model allows for an unlimited number of charging ports at each station to accommodate varying levels of high traffic, thus interpreting the charging profiles from each station to be a local averaged representation contributing to the corresponding balancing authority in which it resides.

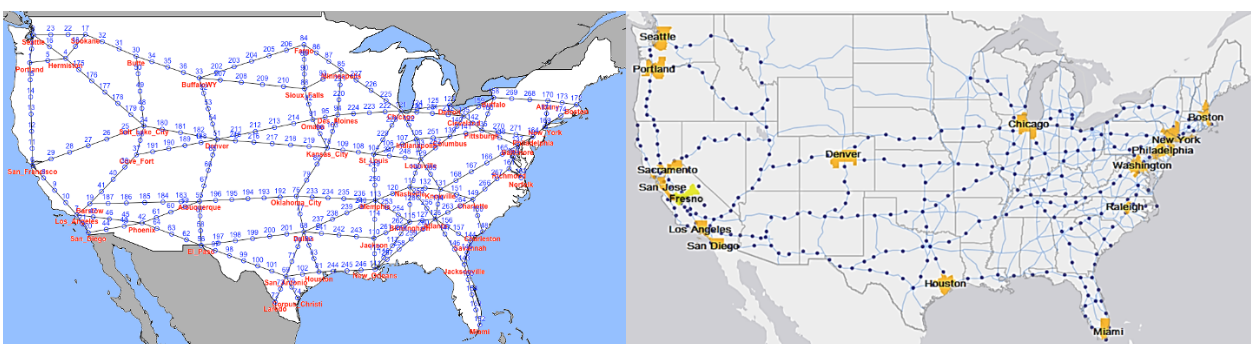


Figure B.1. A comparison between the map of charging locations used in the HDV model simulation (left) and the map of charging station proposed by Electrify America in 2018 (right) (Electrify America 2018)

B.2 Charging Stations

Roadside charging stations were placed along the approximated road network. First, a charging station was placed in each city. Next, charging stations were placed along roads such that they were equally spaced on their respective roads, while assuring they were no more than 100 miles apart.

Charging stations were assumed to have an unlimited number of charging ports available. This was reasonable, because an individual charging station in this model could represent multiple stations in a local region, such that the accumulated number of charging ports was abundant enough so that stopping trucks did not have to encounter a wait for available ports. Of the available ports, every station was assumed to allow for three different speeds: slow (50 kW), medium (350 kW), and fast (2 MW). The slow charging ports were assumed to accommodate long resting periods for drivers, and the fast ones were for those solely stopping for charging purposes.

B.3 Determining HDV Driving Routes

Optimal routes between cities used during the simulation were predetermined, including the charging stations encountered en route. Thus, once a pair of starting and destination cities was determined, the corresponding route was already available. For a given starting city, the route to the next destination was chosen according to the driving distance. Route distance information was provided by the BTS report in the form of freight tonnage and the distance it traveled (BTS 2017). This information was used to create a probability distribution from which route distances were sampled. Upon selecting a route distance, destination city choices were reduced to the subset of cities that were the selected distance away from the given starting city. Of these possibilities, the route destination cities were sampled based on two criteria: the amount of import and export through that city (if it was on the list of 25 gateway cities), and the population of the respective metro area. This way, gateway cities had an advantage of being selected as a destination compared to other major cities that did not serve as trade gateways. Also, small cities with less than 500,000 population were omitted from serving as truck route destinations, because their purpose was served for the realistic representation of the highway network.

B.4 Truck Driver Scenarios

Two truck driver scenarios were considered in this model: (1) a single driver that had to stop for U.S. Department of Transportation (DOT)-regulated short and long breaks, and most HDV battery charging took place during these rest stops; and (2) double drivers, which allowed one driver to take required rests while the other continued the route, so stops were made only when HDV battery charging was needed. The latter case may overlook some DOT rest regulations that dictate some resting periods to allow for drivers to leave the truck. However, the double driver scenario was included to also represent cases where trucks stay on the road as consistently as possible, and it could be argued that a different driver crew could relieve driver pairs that require prolonged resting periods off the road.

Single drivers followed these requirements for how to select resting periods according to the Federal Motor Carrier Safety Administration (FMCSA) guidelines (FMCSA 2013):

- <u>11-Hour Driving Limit</u>: May drive a maximum of 11 hours after 10 consecutive hours off duty.
- <u>14-Hour Limit</u>: May not drive beyond the 14th consecutive hour after coming on duty, following 10 consecutive hours off duty. Off-duty time does not extend the 14-hour period.

- Rest Breaks: May drive only if 8 hours or less have passed since end of the driver's last off-duty or sleeper berth period of at least 30 minutes.
- 60/70-Hour Limit: May not drive after 60/70 hours of being on duty in 7/8 consecutive days. A driver may restart a 7/8 consecutive day period after taking 34 or more consecutive hours off duty.

The last rule was not enforced in our simulations, because the total simulation time was limited to 1 week (7 days).

B.5 Simulating Trucks on the Road

Trucks were simulated one at a time. First, the type of driver scenario was chosen for the simulated truck. A starting city was randomly sampled using only the 25 gateway cities, with probabilities based only on the amount of import into each city. The simulation started at 6:00 AM local time, relative to the sampled starting city. A route to a destination city was determined according to the description above. Upon encountering each charging station, a decision was made to stop based on resting and charging needs prior to continuing on the route to the next station. Recall that resting requirements were dictated by the driver type for this truck. Charging usage and the type of port used were tracked for each charging station throughout the simulation. Every time a truck stopped for any kind of charging, it was assumed that the battery was brought up to full charge.

Trucks were assumed to travel at a constant speed of 50 mph. All trucks had a battery capacity of 1500 kWh, and performance was set to 0.33 miles/kWh. Once a truck reached the route destination, the truck battery was re-charged, and a new destination city and route were chosen. Trucks continued on consecutive routes until the simulation time was reached. The simulation was repeated for 35,000 trucks.

B.6 Accumulating Simulation Results

Charging usage at each station was tracked in 15-minute intervals, including the charging port speeds used. The typical day usage was calculated by averaging the results at each time step over the 7-day simulation period. Because latitude and longitude coordinates were available for each charging station, various types of local and regional subdivisions could be made. In the results shown here, charging profiles were accumulated across different time zones. The final results calculated the total wattage used during each hour, as well as the number of trucks stopped to charge for different charging speeds.

B.7 Summary of Model Assumptions

To develop the domain for the simulated model, a simplified map of continental U.S. cities was selected to serve as the nodes of an artificial road network. The simplified map consisted of 56 U.S. cities. Of these, 25 cities are the top U.S.-International trade freight gateways representing major locations for import and export (BTS 2017). These major port cities serve as the preferred starting and destination points when simulating truck routes. The remaining cities are selected subjectively for their locations serving as a significant interchanges along major interstate highways with high average daily long-haul truck traffic (BTS 2017). Care was taken to choose cities that were located no less than 100 miles apart. Doing so captured an approximated but realistic representation of the U.S. interstate highway network.

Roadside charging stations were placed along the approximated roadmap, and a ubiquitous number of charging ports were made available for use by any number of trucks. This allowed for each charging station location to represent a local total as needed, similar to how multiple gas stations can be located at a single intersection. Each station had slow, medium, and fast charging ports available. The model assumed that a driver would use the slowest port that could bring the truck battery to full charge within the time allowed for by the minimum required resting period.

The model considered two types of driver scenarios: a single driver scenario requires a driver to stop at charging station locations for required resting periods; and a double driver scenario allows for one driver to rest while the other drives, thus allowing for stops to be solely for charging purposes.

Driving routes were selected by randomly choosing a starting city, based on import/export tonnage through that city and the population in the respective metro area. Next, a route distance range was sampled, drawing from distance distributions reported in BTS data. This generated route distances mostly under 500 miles, but still allowed for longer, even cross-country routes to be possible. Once a distance was determined, destination cities falling within the distance range from the starting city were selected using similar biasing criteria as the starting city selection. Stops for resting and charging needs were simulated along this route. Upon reaching the destination, the truck was re-charged, and a new route was selected. This process was repeated until 1 week of simulation time was completed.

The trucks used in this simulation were each assumed to have a 1500 kWh battery capacity. Trucks were assumed to travel at a constant speed of 50 mph. The truck performances were uniformly set to 0.33 miles/kWh, which dictated the battery depletion and charging needs.

Some model variables could be modified to change or scale the simulation results. First, the spacing of charging stations could be increased to allow for a courser grained approximation. Doing so would force the final load requirements to be averaged more generally across balancing authorities (BAs). Using the smaller spacing in the implementation presented here added to the complexity of the model with fewer stations being used, but it allowed for a better localization of distributing energy load from BAs to the nearest charging stations. Next, the number of trucks on the road served as a variable that could effectively scale the final results. Results seemed to converge after 25,000 trucks, which was further verified by counting the number of times a city was chosen as a destination; adding more trucks to the simulation had little effect on changing this distribution. Thus, a scalar multiple of the charging profiles would be all that is needed to represent the presence of a larger number of trucks on the road. Finally, varying truck battery capacity and performance could generate more variety in charging station usage, while simultaneously representing different freight loads that would be carried on HDVs along their routes.

Appendix C– County to Balancing Authority Mapping for All of the Western Electricity Coordinating Council

The table below contains the county to balancing authority mapping used in this analysis.

State	County	Balancing Authority	Percentage of LDV in State Total
ARIZONA	COCONINO	AZPS	2.08%
ARIZONA	MARICOPA	AZPS	59.95%
ARIZONA	NAVAJO	AZPS	1.76%
ARIZONA	YAVAPAI	AZPS	4.00%
ARIZONA	YUMA	AZPS	3.43%
ARIZONA	GREENLEE	PNM	0.17%
ARIZONA	GILA	SRP	0.89%
ARIZONA	PINAL	SRP	5.29%
ARIZONA	COCHISE	TEPC	2.25%
ARIZONA	PIMA	TEPC	13.16%
ARIZONA	SANTA CRUZ	TEPC	1.33%
ARIZONA	APACHE	WALC	1.08%
ARIZONA	GRAHAM	WALC	0.56%
ARIZONA	LA PAZ	WALC	0.40%
ARIZONA	MOHAVE	WALC	3.65%
CALIFORNIA	EL DORADO	BANC	0.55%
CALIFORNIA	SACRAMENTO	BANC	4.08%
CALIFORNIA	ALAMEDA	CISO	3.99%
CALIFORNIA	ALPINE	CISO	0.00%
CALIFORNIA	AMADOR	CISO	0.12%
CALIFORNIA	BUTTE	CISO	0.56%
CALIFORNIA	CALAVERAS	CISO	0.17%
CALIFORNIA	COLUSA	CISO	0.07%
CALIFORNIA	CONTRA COSTA	CISO	3.00%
CALIFORNIA	DEL NORTE	CISO	0.06%
CALIFORNIA	FRESNO	CISO	2.34%
CALIFORNIA	GLENN	CISO	0.09%
CALIFORNIA	HUMBOLDT	CISO	0.38%
CALIFORNIA	INYO	CISO	0.06%
CALIFORNIA	KERN	CISO	2.13%
CALIFORNIA	KINGS	CISO	0.33%
CALIFORNIA	LAKE	CISO	0.21%
CALIFORNIA	LASSEN	CISO	0.07%
CALIFORNIA	MADERA	CISO	0.38%
CALIFORNIA	MARIN	CISO	0.70%
CALIFORNIA	MENDOCINO	CISO	0.29%
CALIFORNIA	MODOC	CISO	0.03%
CALIFORNIA	MONO	CISO	0.04%

State	County	Balancing Authority	Percentage of LDV in State Total
CALIFORNIA	MONTEREY	CISO	1.11%
CALIFORNIA	NAPA	CISO	0.39%
CALIFORNIA	NEVADA	CISO	0.31%
CALIFORNIA	ORANGE	CISO	8.33%
CALIFORNIA	PLACER	CISO	1.08%
CALIFORNIA	PLUMAS	CISO	0.07%
CALIFORNIA	SAN BENITO	CISO	0.17%
CALIFORNIA	SAN BERNARDINO	CISO	5.50%
CALIFORNIA	SAN DIEGO	CISO	8.95%
CALIFORNIA	SAN FRANCISCO	CISO	1.48%
CALIFORNIA	SAN JOAQUIN	CISO	1.92%
CALIFORNIA	SAN LUIS OBISPO	CISO	0.76%
CALIFORNIA	SAN MATEO	CISO	2.14%
CALIFORNIA	SANTA BARBARA	CISO	1.09%
CALIFORNIA	SANTA CLARA	CISO	4.96%
CALIFORNIA	SANTA CRUZ	CISO	0.70%
CALIFORNIA	SHASTA	CISO	0.49%
CALIFORNIA	SIERRA	CISO	0.01%
CALIFORNIA	SISKIYOU	CISO	0.13%
CALIFORNIA	SOLANO	CISO	1.26%
CALIFORNIA	SONOMA	CISO	1.38%
CALIFORNIA	STANISLAUS	CISO	1.39%
CALIFORNIA	SUTTER	CISO	0.27%
CALIFORNIA	TEHAMA	CISO	0.18%
CALIFORNIA	TRINITY	CISO	0.04%
CALIFORNIA	TULARE	CISO	1.13%
CALIFORNIA	TUOLUMNE	CISO	0.17%
CALIFORNIA	VENTURA	CISO	2.23%
CALIFORNIA	YOLO	CISO	0.55%
CALIFORNIA	YUBA	CISO	0.20%
CALIFORNIA	IMPERIAL	IID	0.64%
CALIFORNIA	RIVERSIDE	IID	6.03%
CALIFORNIA	LOS ANGELES	LDWP	24.57%
CALIFORNIA	MARIPOSA	TIDC	0.06%
CALIFORNIA	MERCED	TIDC	0.66%
COLORADO	ADAMS	PSCO	9.00%
COLORADO	ALAMOSA	PSCO	0.31%
COLORADO	ARAPAHOE	PSCO	11.04%
COLORADO	BACA	PSCO	0.10%

State	County	Balancing Authority	Percentage of LDV in State Total
COLORADO	BENT	PSCO	0.09%
COLORADO	BOULDER	PSCO	5.24%
COLORADO	BROOMFIELD	PSCO	1.17%
COLORADO	CLEAR CREEK	PSCO	0.24%
COLORADO	COSTILLA	PSCO	0.09%
COLORADO	CROWLEY	PSCO	0.07%
COLORADO	DENVER	PSCO	11.26%
COLORADO	DOUGLAS	PSCO	5.82%
COLORADO	EL PASO	PSCO	11.79%
COLORADO	ELBERT	PSCO	0.65%
COLORADO	GILPIN	PSCO	0.16%
COLORADO	HUERFANO	PSCO	0.15%
COLORADO	JEFFERSON	PSCO	10.05%
COLORADO	LAS ANIMAS	PSCO	0.32%
COLORADO	LINCOLN	PSCO	0.13%
COLORADO	MORGAN	PSCO	0.65%
COLORADO	OTERO	PSCO	0.37%
COLORADO	PROWERS	PSCO	0.25%
COLORADO	PUEBLO	PSCO	2.89%
COLORADO	ARCHULETA	WACM	0.30%
COLORADO	CHAFFEE	WACM	0.44%
COLORADO	CHEYENNE	WACM	0.05%
COLORADO	CONEJOS	WACM	0.19%
COLORADO	CUSTER	WACM	0.12%
COLORADO	DELTA	WACM	0.68%
COLORADO	DOLORES	WACM	0.05%
COLORADO	EAGLE	WACM	1.12%
COLORADO	FREMONT	WACM	0.85%
COLORADO	GARFIELD	WACM	1.25%
COLORADO	GRAND	WACM	0.36%
COLORADO	GUNNISON	WACM	0.34%
COLORADO	HINSDALE	WACM	0.02%
COLORADO	JACKSON	WACM	0.04%
COLORADO	KIOWA	WACM	0.04%
COLORADO	KIT CARSON	WACM	0.20%
COLORADO	LA PLATA	WACM	1.10%
COLORADO	LAKE	WACM	0.17%
COLORADO	LARIMER	WACM	5.96%
COLORADO	LOGAN	WACM	0.41%
COLORADO	MESA	WACM	2.81%
COLORADO	MINERAL	WACM	0.02%
COLORADO	MOFFAT	WACM	0.28%
COLORADO	MONTEZUMA	WACM	0.54%

State	County	Balancing Authority	Percentage of LDV in State Total
COLORADO	MONTROSE	WACM	0.87%
COLORADO	OURAY	WACM	0.11%
COLORADO	PARK	WACM	0.45%
COLORADO	PHILLIPS	WACM	0.11%
COLORADO	PITKIN	WACM	0.41%
COLORADO	RIO BLANCO	WACM	0.15%
COLORADO	RIO GRANDE	WACM	0.27%
COLORADO	ROUTT	WACM	0.53%
COLORADO	SAGUACHE	WACM	0.14%
COLORADO	SAN JUAN	WACM	0.02%
COLORADO	SAN MIGUEL	WACM	0.17%
COLORADO	SEDGWICK	WACM	0.06%
COLORADO	SUMMIT	WACM	0.63%
COLORADO	TELLER	WACM	0.54%
COLORADO	WASHINGTON	WACM	0.13%
COLORADO	WELD	WACM	5.95%
COLORADO	YUMA	WACM	0.24%
IDAHO	BENEWAH	AVA	0.68%
IDAHO	BONNER	AVA	3.02%
IDAHO	KOOTENAI	AVA	9.98%
IDAHO	LATAH	AVA	1.95%
IDAHO	BOUNDARY	BPAT	0.81%
IDAHO	CLEARWATER	BPAT	0.52%
IDAHO	LEWIS	BPAT	0.22%
IDAHO	NEZ PERCE	BPAT	2.56%
IDAHO	SHOSHONE	BPAT	0.84%
IDAHO	ADA	IPCO	23.89%
IDAHO	ADAMS	IPCO	0.31%
IDAHO	BLAINE	IPCO	1.64%
IDAHO	BOISE	IPCO	0.58%
IDAHO	BUTTE	IPCO	0.19%
IDAHO	CAMAS	IPCO	0.08%
IDAHO	CANYON	IPCO	11.52%
IDAHO	CASSIA	IPCO	1.52%
IDAHO	CUSTER	IPCO	0.33%
IDAHO	ELMORE	IPCO	1.61%
IDAHO	GEM	IPCO	1.22%
IDAHO	GOODING	IPCO	1.04%
IDAHO	IDAHO	IPCO	1.17%
IDAHO	JEROME	IPCO	1.56%
IDAHO	LEMHI	IPCO	0.58%
IDAHO	LINCOLN	IPCO	0.36%
IDAHO	MINIDOKA	IPCO	1.47%

State	County	Balancing Authority	Percentage of LDV in State Total
IDAHO	OWYHEE	IPCO	0.87%
IDAHO	PAYETTE	IPCO	1.48%
IDAHO	TWIN FALLS	IPCO	4.97%
IDAHO	WASHINGTON	IPCO	0.67%
IDAHO	VALLEY	IPCO	0.82%
IDAHO	BANNOCK	PACE	4.59%
IDAHO	BEAR LAKE	PACE	0.45%
IDAHO	BINGHAM	PACE	2.86%
IDAHO	BONNEVILLE	PACE	6.31%
IDAHO	CARIBOU	PACE	0.50%
IDAHO	CLARK	PACE	0.05%
IDAHO	FRANKLIN	PACE	0.88%
IDAHO	FREMONT	PACE	0.84%
IDAHO	JEFFERSON	PACE	1.76%
IDAHO	MADISON	PACE	1.69%
IDAHO	ONEIDA	PACE	0.33%
IDAHO	POWER	PACE	0.54%
IDAHO	TETON	PACE	0.74%
MONTANA	FLATHEAD	BPAT	10.60%
MONTANA	LAKE	BPAT	3.13%
MONTANA	LINCOLN	BPAT	1.97%
MONTANA	MINERAL	BPAT	0.46%
MONTANA	SANDERS	BPAT	1.27%
MONTANA	BEAVERHEAD	NWMT	0.90%
MONTANA	BIG HORN	NWMT	1.56%
MONTANA	BROADWATER	NWMT	0.64%
MONTANA	CARBON	NWMT	1.20%
MONTANA	CASCADE	NWMT	6.73%
MONTANA	CHOUTEAU	NWMT	0.59%
MONTANA	DEER LODGE	NWMT	1.06%
MONTANA	GALLATIN	NWMT	9.18%
MONTANA	GLACIER	NWMT	1.40%
MONTANA	GOLDEN VALLEY	NWMT	0.10%
MONTANA	GRANITE	NWMT	0.55%
MONTANA	JEFFERSON	NWMT	1.22%
MONTANA	JUDITH BASIN	NWMT	0.22%
MONTANA	LEWIS AND CLARK	NWMT	6.68%
MONTANA	MADISON	NWMT	0.97%
MONTANA	MEAGHER	NWMT	0.20%
MONTANA	MISSOULA	NWMT	10.00%
MONTANA	MUSSELSHELL	NWMT	0.52%

State	County	Balancing Authority	Percentage of LDV in State Total
MONTANA	PARK	NWMT	1.73%
MONTANA	PONDERA	NWMT	0.62%
MONTANA	POWELL	NWMT	0.58%
MONTANA	RAVALLI	NWMT	4.16%
MONTANA	SILVER BOW	NWMT	2.82%
MONTANA	STILLWATER	NWMT	1.01%
MONTANA	SWEET GRASS	NWMT	0.37%
MONTANA	TETON	NWMT	0.69%
MONTANA	TREASURE	NWMT	0.34%
MONTANA	WHEATLAND	NWMT	0.20%
MONTANA	YELLOWSTONE	NWMT	13.49%
MONTANA	BLAINE	WAUW	0.75%
MONTANA	CARTER	WAUW	0.18%
MONTANA	CUSTER	WAUW	1.11%
MONTANA	DANIELS	WAUW	0.21%
MONTANA	DAWSON	WAUW	0.87%
MONTANA	FALLON	WAUW	0.34%
MONTANA	FERGUS	WAUW	1.17%
MONTANA	GARFIELD	WAUW	0.15%
MONTANA	HILL	WAUW	1.48%
MONTANA	LIBERTY	WAUW	0.18%
MONTANA	MC CONE	WAUW	0.24%
MONTANA	PETROLEUM	WAUW	0.05%
MONTANA	PHILLIPS	WAUW	0.55%
MONTANA	POWDER RIVER	WAUW	0.19%
MONTANA	PRAIRIE	WAUW	0.14%
MONTANA	RICHLAND	WAUW	1.53%
MONTANA	ROOSEVELT	WAUW	1.01%
MONTANA	ROSEBUD	WAUW	0.83%
MONTANA	SHERIDAN	WAUW	0.46%
MONTANA	VALLEY	WAUW	0.81%
MONTANA	WIBAUX	WAUW	0.12%
MONTANA	TOOLE	WWA	0.47%
NEBRASKA	CHASE	WACM	0.29%
NEBRASKA	HAYES	WACM	0.05%
NEBRASKA	DUNDY	WACM	0.13%
NEBRASKA	HITCHCOK	WACM	0.21%
NEVADA	CARSON CITY	NEVP	2.46%
NEVADA	CHURCHILL	NEVP	1.13%
NEVADA	CLARK	NEVP	67.73%
NEVADA	DOUGLAS	NEVP	2.41%
NEVADA	ELKO	NEVP	2.21%
NEVADA	ESMERALDA	NEVP	0.06%

State	County	Balancing Authority	Percentage of LDV in State Total
NEVADA	EUREKA	NEVP	0.10%
NEVADA	HUMBOLDT	NEVP	0.80%
NEVADA	LANDER	NEVP	0.27%
NEVADA	LINCOLN	NEVP	0.22%
NEVADA	LYON	NEVP	2.55%
NEVADA	MINERAL	NEVP	0.21%
NEVADA	NYE	NEVP	2.10%
NEVADA	PERSHING	NEVP	0.22%
NEVADA	STOREY	NEVP	0.22%
NEVADA	WASHOE	NEVP	16.89%
NEVADA	WHITE PINE	NEVP	0.41%
NEW MEXICO	DONA ANA	EPE	10.25%
NEW MEXICO	EDDY	EPE	3.20%
NEW MEXICO	OTERO	EPE	3.04%
NEW MEXICO	BERNALILLO	PNM	28.81%
NEW MEXICO	CATRON	PNM	0.24%
NEW MEXICO	CHAVES	PNM	2.94%
NEW MEXICO	CIBOLA	PNM	1.02%
NEW MEXICO	COLFAX	PNM	0.70%
NEW MEXICO	CURRY	PNM	2.25%
NEW MEXICO	DE BACA	PNM	0.11%
NEW MEXICO	GRANT	PNM	1.56%
NEW MEXICO	GUADALUPE	PNM	0.24%
NEW MEXICO	HARDING	PNM	0.05%
NEW MEXICO	HIDALGO	PNM	0.24%
NEW MEXICO	LEA	PNM	3.66%
NEW MEXICO	LINCOLN	PNM	1.17%
NEW MEXICO	LOS ALAMOS	PNM	1.03%
NEW MEXICO	LUNA	PNM	1.29%
NEW MEXICO	MC KINLEY	PNM	2.72%
NEW MEXICO	MORA	PNM	0.30%
NEW MEXICO	QUAY	PNM	0.49%
NEW MEXICO	RIO ARRIBA	PNM	2.03%
NEW MEXICO	ROOSEVELT	PNM	0.88%
NEW MEXICO	SAN JUAN	PNM	5.81%
NEW MEXICO	SAN MIGUEL	PNM	1.44%
NEW MEXICO	SANDOVAL	PNM	7.06%
NEW MEXICO	SANTA FE	PNM	8.88%
NEW MEXICO	SIERRA	PNM	0.67%
NEW MEXICO	SOCORRO	PNM	0.88%
NEW MEXICO	TAOS	PNM	1.94%
NEW MEXICO	TORRANCE	PNM	0.88%
NEW MEXICO	UNION	PNM	0.22%

State	County	Balancing Authority	Percentage of LDV in State Total
NEW MEXICO	VALENCIA	PNM	4.01%
OREGON	BAKER	BPAT	0.46%
OREGON	BENTON	BPAT	1.97%
OREGON	CLATSOP	BPAT	1.04%
OREGON	COLUMBIA	BPAT	1.46%
OREGON	CROOK	BPAT	0.71%
OREGON	DESCHUTES	BPAT	5.26%
OREGON	GILLIAM	BPAT	0.06%
OREGON	GRANT	BPAT	0.22%
OREGON	HARNEY	BPAT	0.22%
OREGON	JEFFERSON	BPAT	0.63%
OREGON	KLAMATH	BPAT	1.80%
OREGON	LAKE	BPAT	0.24%
OREGON	LANE	BPAT	8.82%
OREGON	LINCOLN	BPAT	1.30%
OREGON	LINN	BPAT	3.25%
OREGON	MORROW	BPAT	0.34%
OREGON	SHERMAN	BPAT	0.07%
OREGON	TILLAMOOK	BPAT	0.78%
OREGON	UMATILLA	BPAT	1.96%
OREGON	UNION	BPAT	0.69%
OREGON	WALLOWA	BPAT	0.23%
OREGON	WASCO	BPAT	0.72%
OREGON	WHEELER	BPAT	0.05%
OREGON	MALHEUR	IPCO	0.75%
OREGON	COOS	PACW	1.70%
OREGON	CURRY	PACW	0.69%
OREGON	DOUGLAS	PACW	2.97%
OREGON	JACKSON	PACW	5.49%
OREGON	JOSEPHINE	PACW	2.40%
OREGON	CLACKAMAS	PGE	10.13%
OREGON	HOOD RIVER	PGE	0.71%
OREGON	MARION	PGE	8.29%
OREGON	MULTNOMAH	PGE	16.81%
OREGON	POLK	PGE	1.97%
OREGON	WASHINGTON	PGE	13.22%
OREGON	YAMHILL	PGE	2.60%
SOUTH DAKOTA	LAWRENCE	WACM	2.97%
SOUTH DAKOTA	PENNINGTON	WACM	12.46%
SOUTH DAKOTA	CUSTER	WACM	1.15%

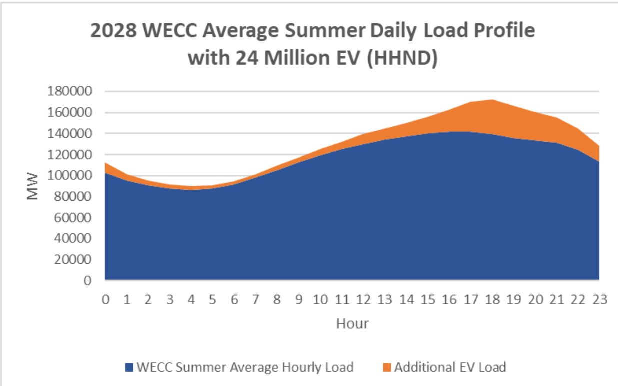
State	County	Balancing Authority	Percentage of LDV in State Total
SOUTH DAKOTA	FALL RIVER	WACM	1.02%
TEXAS	EL PASO	EPE	2.86%
TEXAS	HUDSPETH	EPE	0.01%
TEXAS	CULBERSON	EPE	0.01%
UTAH	BEAVER	PACE	0.28%
UTAH	BOX ELDER	PACE	2.17%
UTAH	CACHE	PACE	3.61%
UTAH	CARBON	PACE	0.80%
UTAH	DAGGETT	PACE	0.05%
UTAH	DAVIS	PACE	10.66%
UTAH	DUCHESNE	PACE	0.83%
UTAH	EMERY	PACE	0.42%
UTAH	GARFIELD	PACE	0.19%
UTAH	GRAND	PACE	0.43%
UTAH	IRON	PACE	1.76%
UTAH	JUAB	PACE	0.48%
UTAH	KANE	PACE	0.31%
UTAH	MILLARD	PACE	0.56%
UTAH	MORGAN	PACE	0.48%
UTAH	PIUTE	PACE	0.06%
UTAH	RICH	PACE	0.10%
UTAH	SALT LAKE	PACE	36.41%
UTAH	SAN JUAN	PACE	0.40%
UTAH	SANPETE	PACE	1.04%
UTAH	SEVIER	PACE	0.89%
UTAH	SUMMIT	PACE	1.91%
UTAH	TOOELE	PACE	2.50%
UTAH	UINTAH	PACE	1.30%
UTAH	UTAH	PACE	16.61%
UTAH	WASATCH	PACE	1.25%
UTAH	WASHINGTON	PACE	5.90%
UTAH	WAYNE	PACE	0.13%
UTAH	WEBER	PACE	8.48%
WASHINGTON	FERRY	AVA	0.12%
WASHINGTON	LINCOLN	AVA	0.21%
WASHINGTON	PEND OREILLE	AVA	0.23%
WASHINGTON	SPOKANE	AVA	6.64%
WASHINGTON	STEVENS	AVA	0.79%
WASHINGTON	WHITMAN	AVA	0.52%
WASHINGTON	ADAMS	BPAT	0.31%
WASHINGTON	ASOTIN	BPAT	0.29%
WASHINGTON	BENTON	BPAT	2.76%

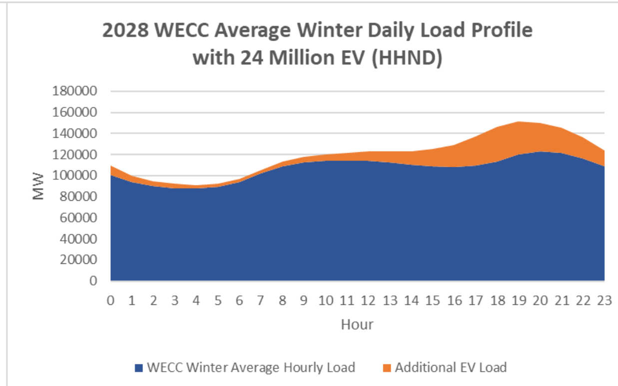
State	County	Balancing Authority	Percentage of LDV in State Total
WASHINGTON	CLALLAM	BPAT	1.14%
WASHINGTON	CLARK	BPAT	6.27%
WASHINGTON	COLUMBIA	BPAT	0.06%
WASHINGTON	COWLITZ	BPAT	1.57%
WASHINGTON	FRANKLIN	BPAT	1.31%
WASHINGTON	GARFIELD	BPAT	0.04%
WASHINGTON	GRAYS HARBOR	BPAT	1.09%
WASHINGTON	ISLAND	PSEI	1.30%
WASHINGTON	JEFFERSON	BPAT	0.53%
WASHINGTON	KITSAP	PSEI	3.72%
WASHINGTON	KITTITAS	PSEI	0.66%
WASHINGTON	KLICKITAT	BPAT	0.37%
WASHINGTON	LEWIS	BPAT	1.30%
WASHINGTON	MASON	BPAT	1.03%
WASHINGTON	PACIFIC	BPAT	0.35%
WASHINGTON	SAN JUAN	PSEI	0.31%
WASHINGTON	SKAMANIA	BPAT	0.18%
WASHINGTON	SNOHOMISH	BPAT	10.74%
WASHINGTON	THURSTON	PSEI	4.25%
WASHINGTON	WAHKIAKUM	BPAT	0.07%
WASHINGTON	WALLA WALLA	BPAT	0.79%
WASHINGTON	YAKIMA	BPAT	3.67%
WASHINGTON	CHELAN	CHPD	1.20%
WASHINGTON	DOUGLAS	DOPD	0.58%
WASHINGTON	OKANOGAN	DOPD	0.69%
WASHINGTON	GRANT	GCPD	1.49%
WASHINGTON	SKAGIT	PSEI	2.03%
WASHINGTON	WHATCOM	PSEI	3.14%
WASHINGTON	KING	SCL	10.72%
WASHINGTON	KING	PSEI	16.09%
WASHINGTON	PIERCE	PSEI	8.01%
WASHINGTON	PIERCE	TPWR	3.43%
WYOMING	FREMONT	PACE	6.35%
WYOMING	LINCOLN	PACE	3.35%
WYOMING	PARK	PACE	5.45%
WYOMING	SUBLETTE	PACE	2.02%
WYOMING	SWEETWATER	PACE	7.56%
WYOMING	TETON	PACE	4.40%
WYOMING	UINTA	PACE	3.69%
WYOMING	ALBANY	WACM	4.93%
WYOMING	BIG HORN	WACM	2.34%
WYOMING	CAMPBELL	WACM	8.26%
WYOMING	CARBON	WACM	2.78%

State	County	Balancing Authority	Percentage of LDV in State Total
WYOMING	CONVERSE	WACM	2.62%
WYOMING	CROOK	WACM	1.48%
WYOMING	GOSHEN	WACM	2.22%
WYOMING	HOT SPRINGS	WACM	0.88%
WYOMING	JOHNSON	WACM	1.62%
WYOMING	LARAMIE	WACM	16.38%
WYOMING	NATRONA	WACM	13.34%
WYOMING	NIOBRARA	WACM	0.50%
WYOMING	PLATTE	WACM	1.86%
WYOMING	SHERIDAN	WACM	5.19%
WYOMING	WASHAKIE	WACM	1.44%
WYOMING	WESTON	WACM	1.36%

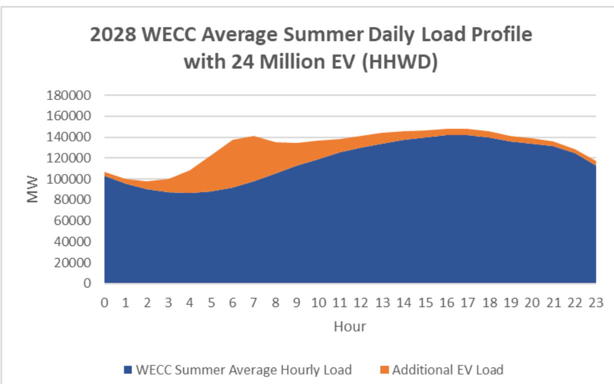
Appendix D – 2028 WECC Load Profiles

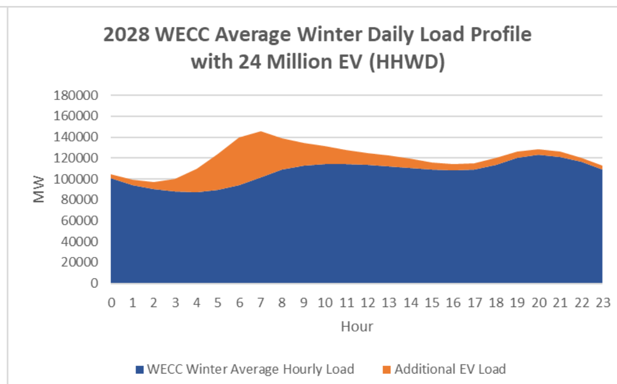
24 Million EV: Home High power No Delay (HHND)



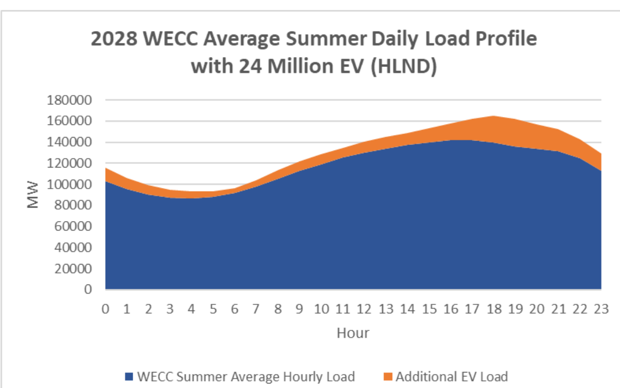


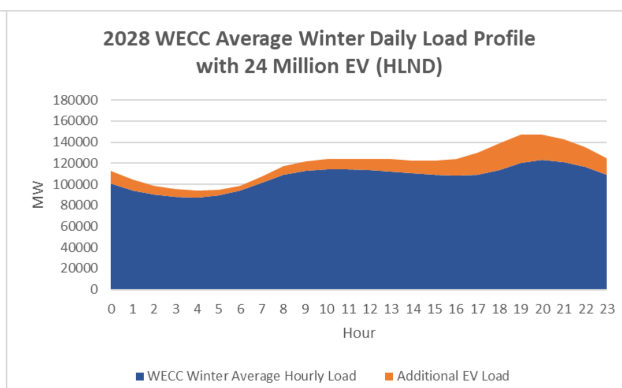
24 Million EV: Home High power With Delay (HHWD)



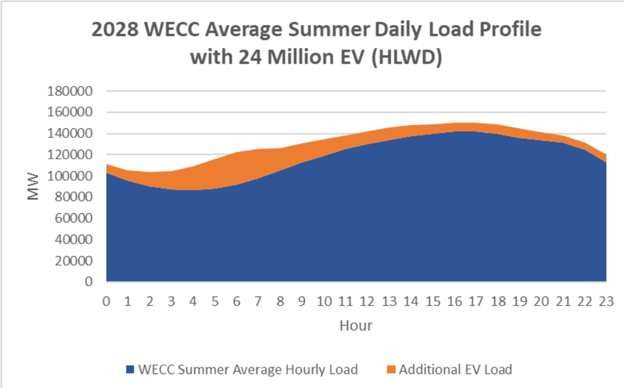


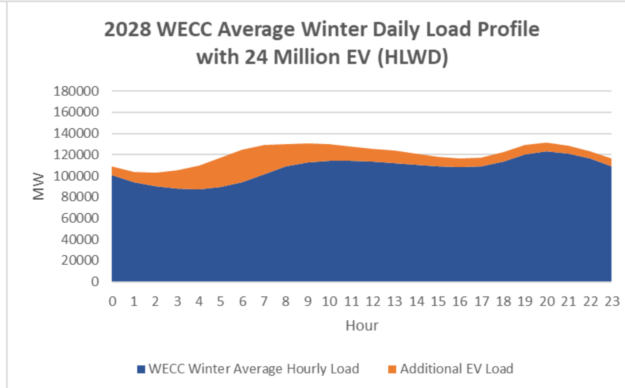
24 Million EV: Home Low power No Delay (HLND)



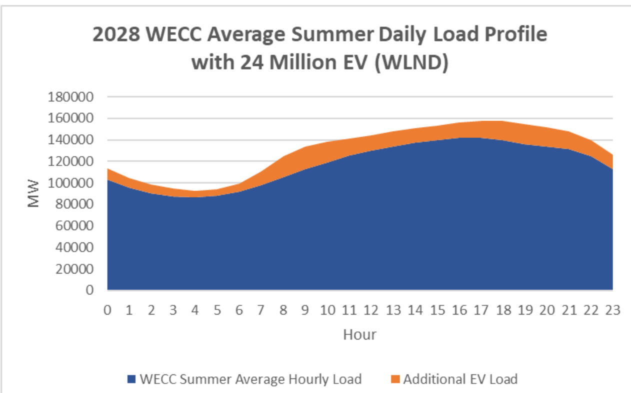


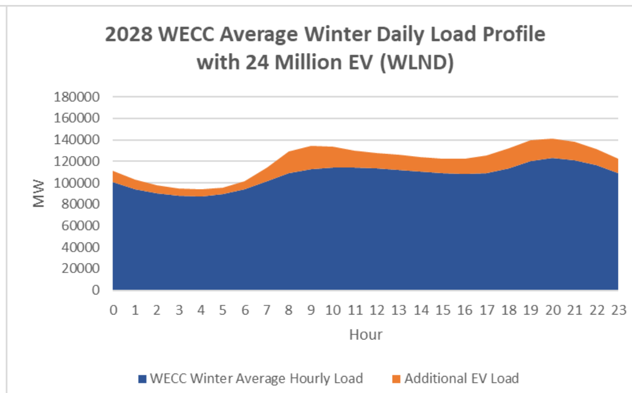
24 Million EV: Home Low power With Delay (HLWD)



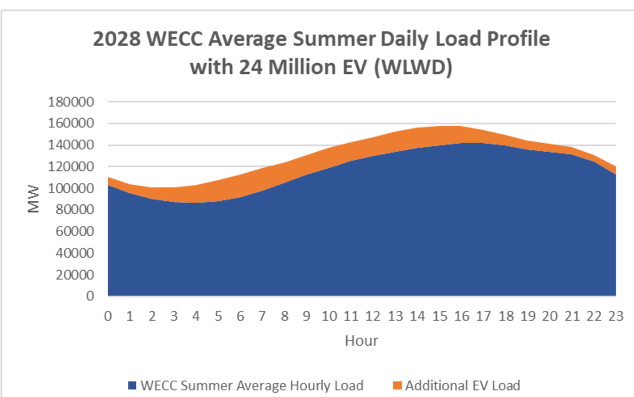


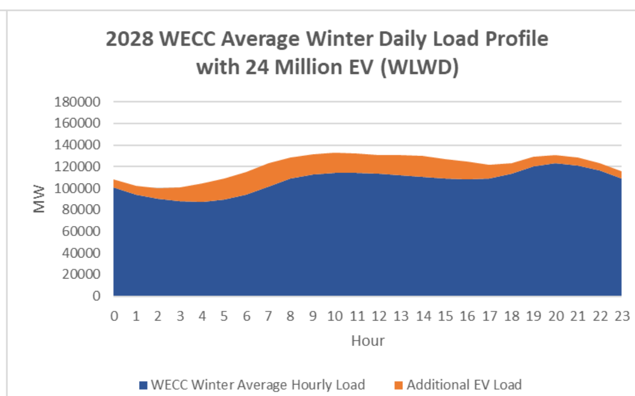
24 Million EV: Work Low power No Delay (WLND)





24 million EV: Work Low power With Delay (WLWD)





Appendix E – Regional Distribution of Unserved Energy over Various LDV Penetration Scenarios

Regional distribution of unserved energy over various light-duty vehicle (LDV) penetration scenarios is shown in the table below. These results are based on production cost model simulations using the Home High power No Delay (HHND) charging scenario.

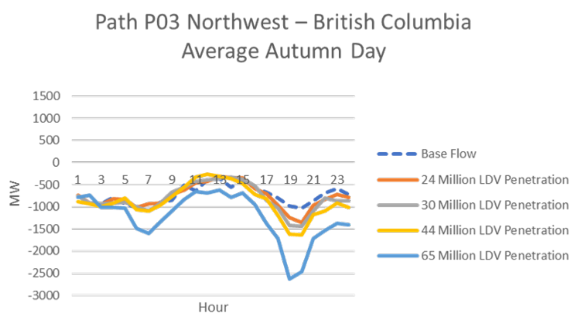
Balancing authorities with locations in Washington State are highlighted in yellow. The top rows are summary rows for the selected states of Arizona, California, and Washington, as well as remaining states in the WECC (Others).

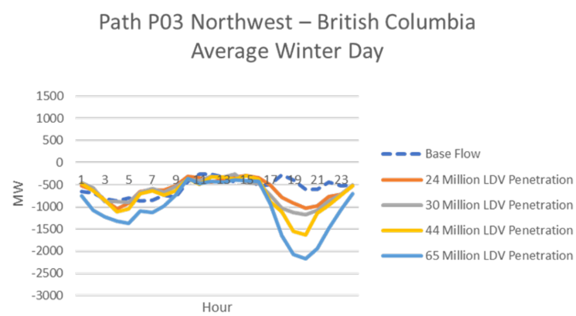
Unserved Energy (MWh)						
Area	**Base**	**24M**	**30M**	**37M**	**44M**	**65M**
WECC	0	3,602	21,501	97,514	309,658	2,771,530
AZ	0	467	2,525	14,620	42,422	271,148
CA	0	3,023	15,582	58,766	169,683	1,444,379
WA	0	-	789	5,385	23,161	361,142
OTHER	0	113	2,606	18,743	74,391	694,862
AESO	0	-	-	-	-	-
CISC	0	617	2,234	8,028	20,756	132,954
CISD	0	252	1,232	5,273	13,669	96,523
DOPD	0	-	-	-	-	-
EPE	0	-	-	239	1,323	11,867
GCPD	0	-	9	504	1,602	34,574
IID	0	486	1,439	6,286	18,025	142,214
IPFE	0	-	41	311	1,272	8,395
IPMV	0	-	15	92	442	2,613
IPTV	0	-	205	614	2,432	16,995
LDWP	0	-	-	427	6,893	336,478
AVA	0	-	15	198	1,268	24,804
NEVP	0	-	215	882	2,744	17,235
NWMT	0	72	612	2,905	7,868	64,258
PACW	0	-	-	-	-	-
PAID	0	-	-	-	-	-
PAUT	0	-	361	1,638	6,015	36,444
PAWY	0	-	11	191	679	11,737
PGE	0	-	50	1,083	4,031	52,454
PNM	0	-	383	3,148	13,722	83,935
PSCO	0	-	-	566	3,637	61,219
PSEI	0	-	-	153	1,206	35,706
AZPS	0	140	586	2,477	5,624	21,595
SCL	0	-	-	73	292	8,651
SPPC	0	-	395	2,770	9,631	76,667
SRP	0	-	662	6,976	21,263	159,114

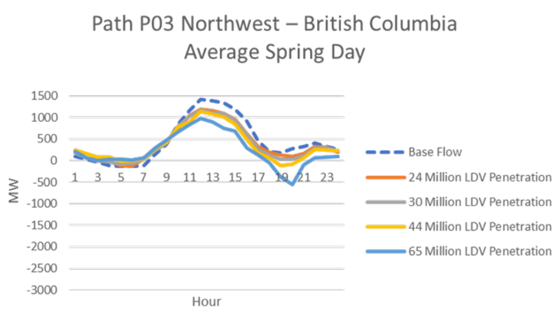
Unserved Energy (MWh)						
Area	**Base**	**24M**	**30M**	**37M**	**44M**	**65M**
TEPC	0	327	1,277	4,955	14,856	84,377
TIDC	0	107	531	1,836	5,290	32,101
TPWR	0	-	-	58	469	12,797
WALC	0	-	-	212	679	6,063
WACM	0	-	58	1,970	8,521	105,535
WAUW	0	4	10	30	68	1,617
BPAT	0	-	780	4,596	19,585	269,224
BANC	0	20	332	1,196	3,144	42,858
VEA	0	-	-	-	-	-
TH_PV	0	-	-	-	-	-
TH_Mead	0	-	-	-	-	-
TH_Malin	0	-	-	-	-	-
BCHA	0	-	-	834	7,498	107,407
CFE	0	37	235	1,273	3,241	11,680
CHPD	0	-	-	-	8	190
CIPB	0	338	3,233	11,358	36,361	275,655
CIPV	0	1,203	6,581	24,362	65,545	385,595

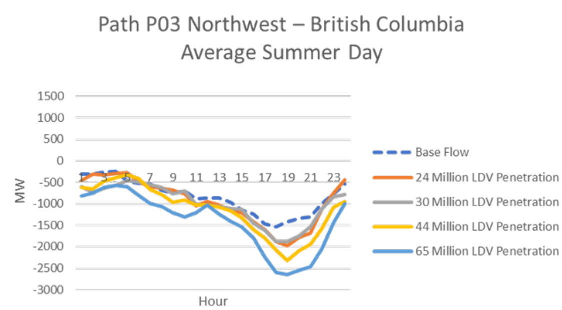
Appendix F – Plots Showing Seasonal Flows Under Increasing LDV Penetration for the WECC Paths

Path 3 Northwest to British Columbia

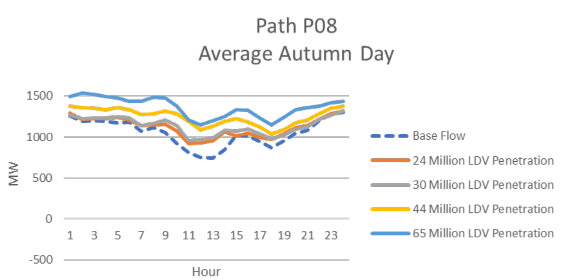


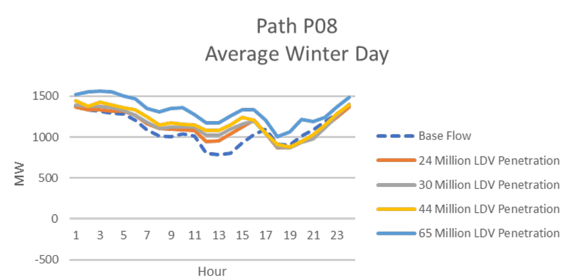


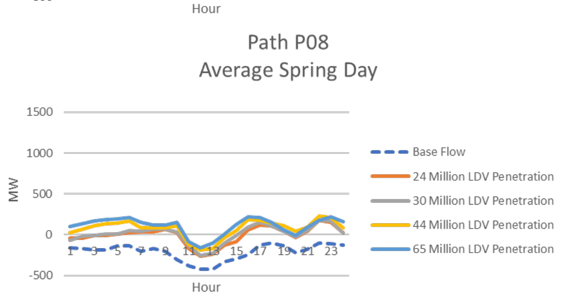


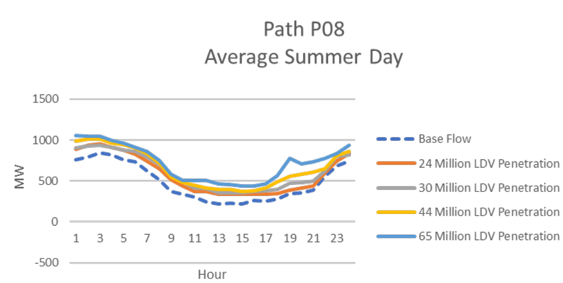


Path 8 Montana to Northwest

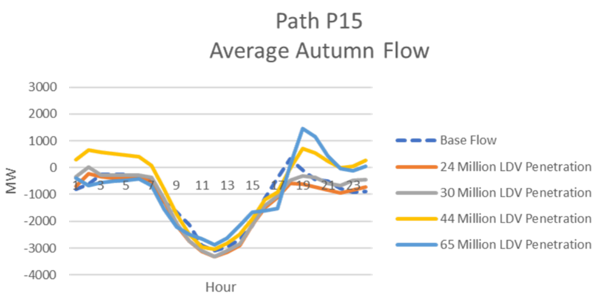


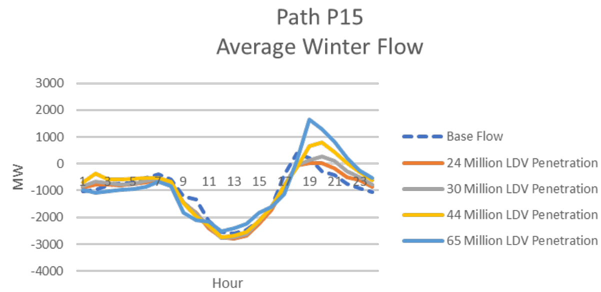


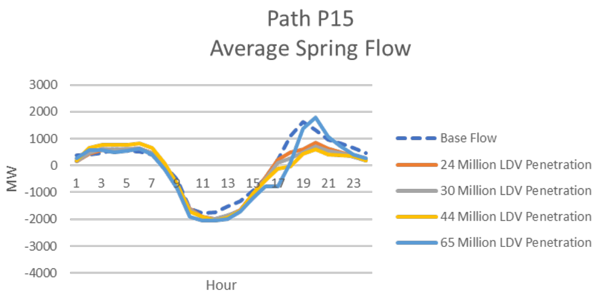


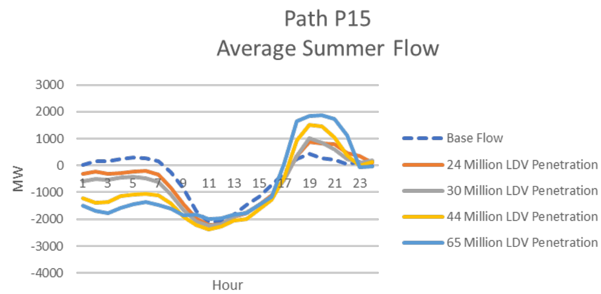


Path 15 Midway – Los Banos

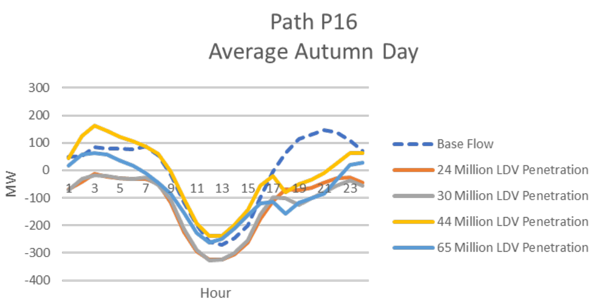


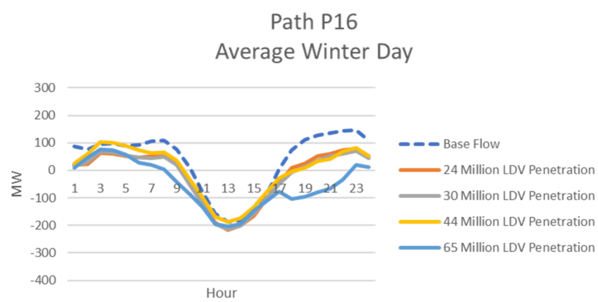


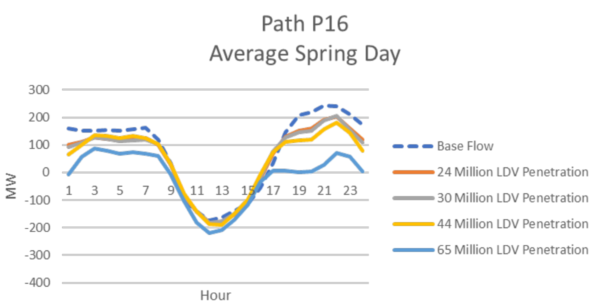


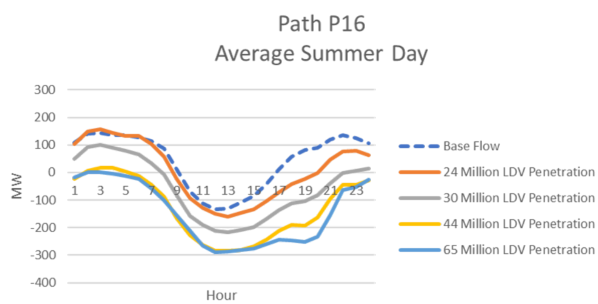


Path 16 Idaho – Sierra

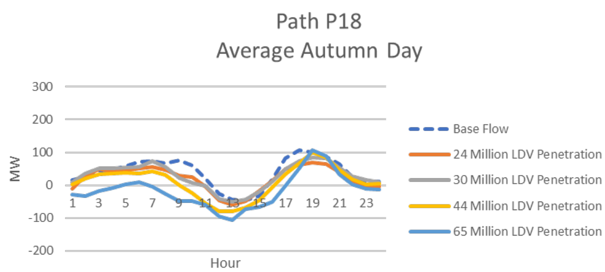


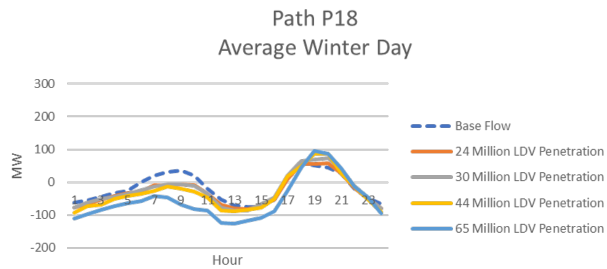


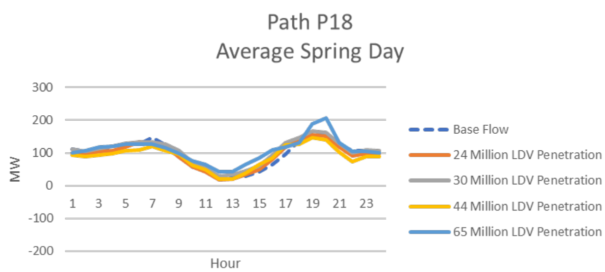


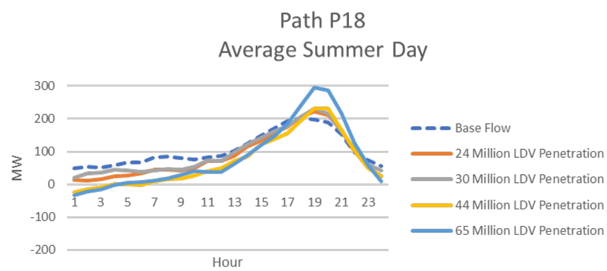


Path 18 Montana to Idaho

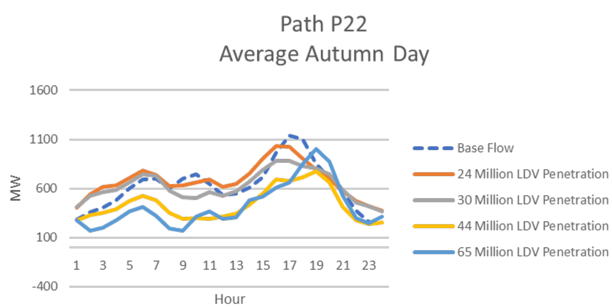


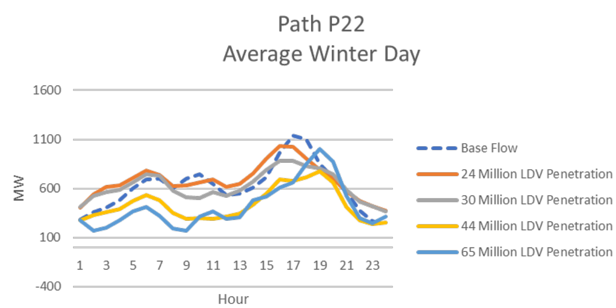


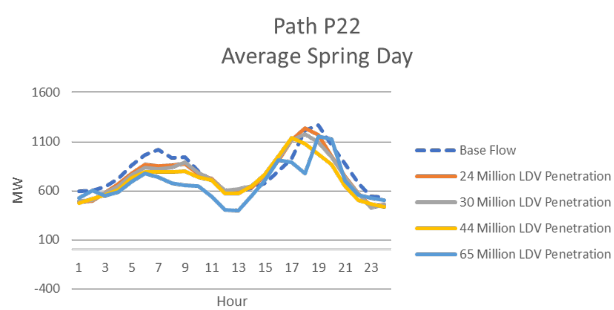


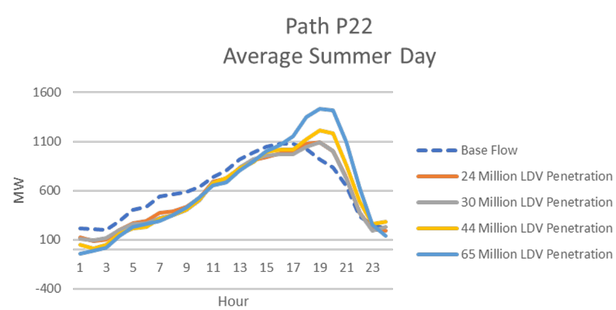


Path 22 Southwest of Four Corners

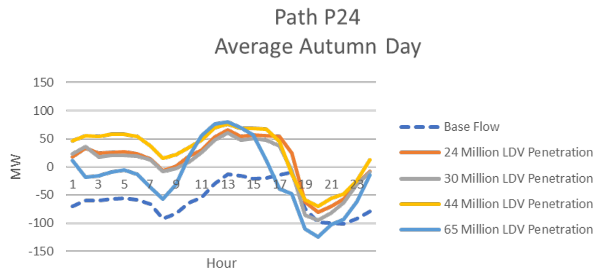


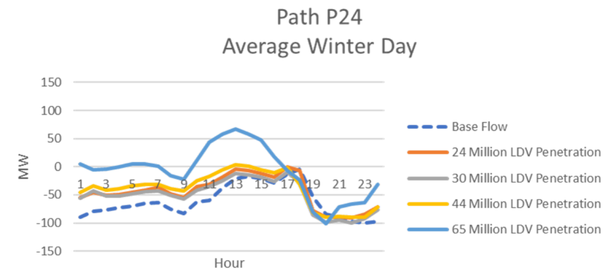


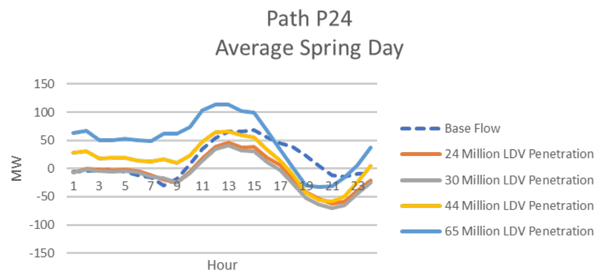


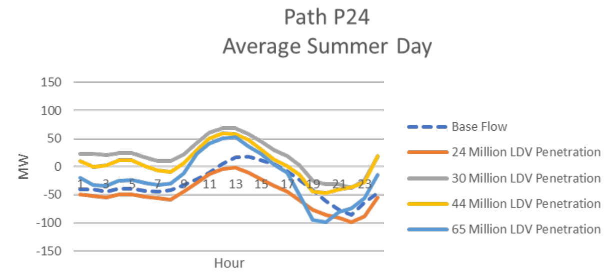


Path 24 PG&E – Sierra

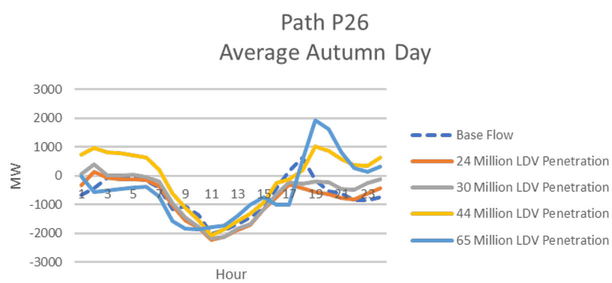


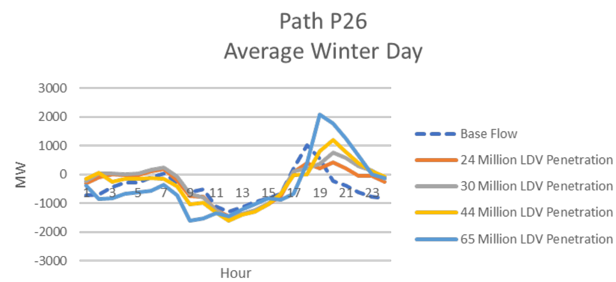


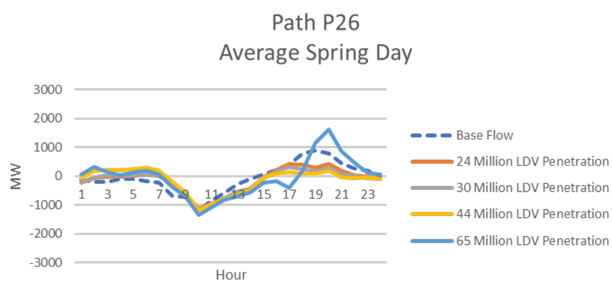


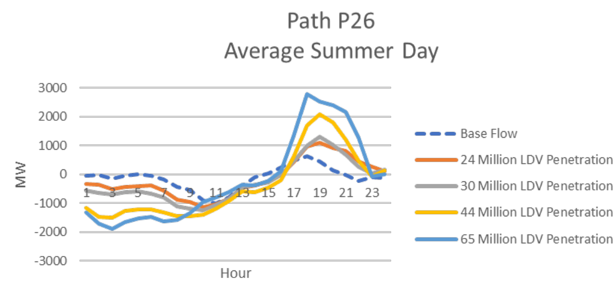


Path 26 Northern – Southern California

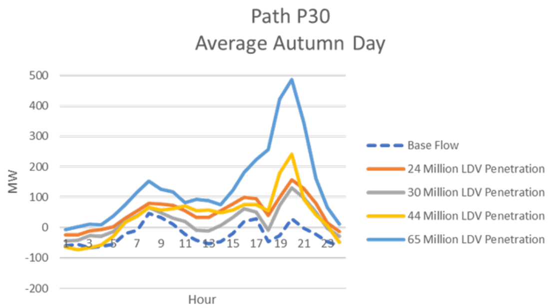


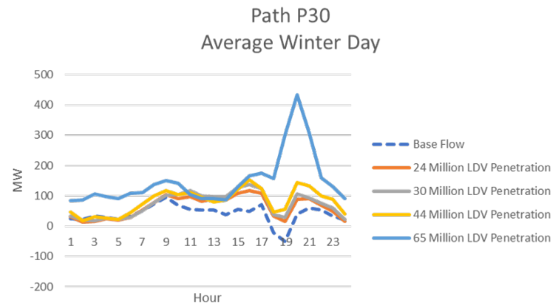


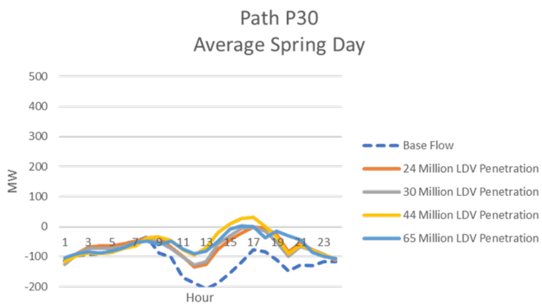


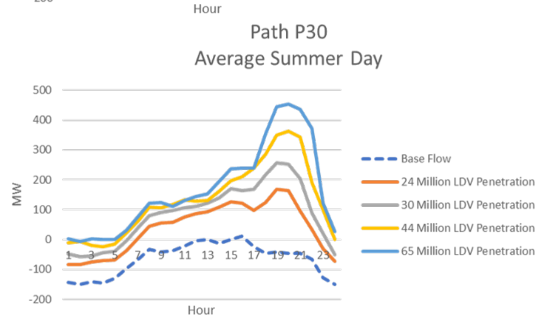


Path 30 TOT 1A

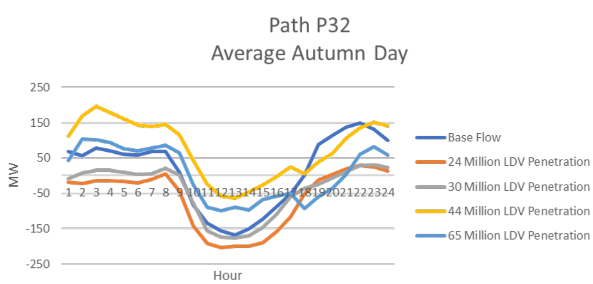


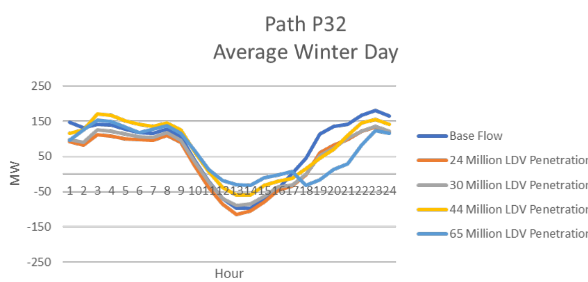


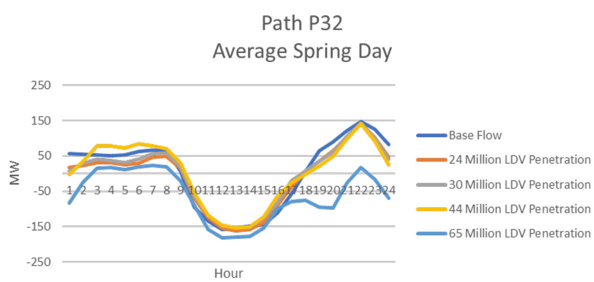


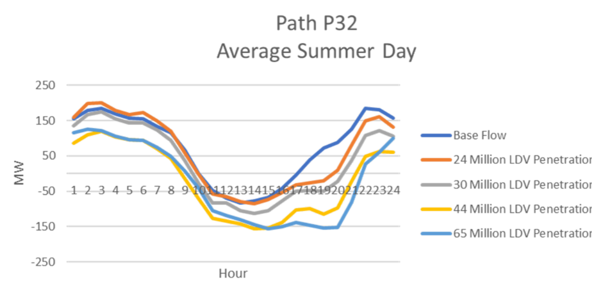


Path 32 Pavant Inter-Mountain – Gonder

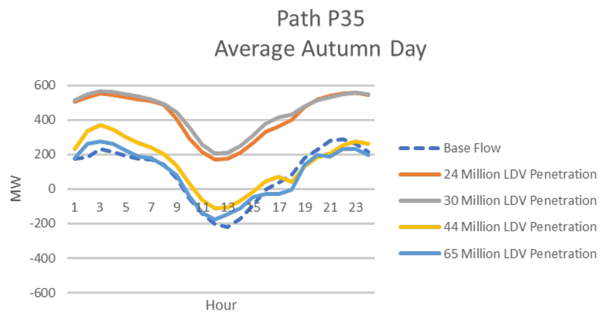


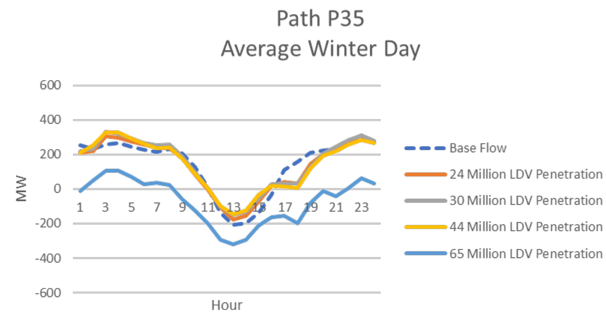


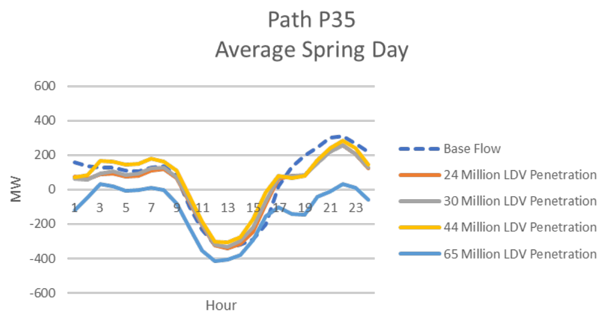


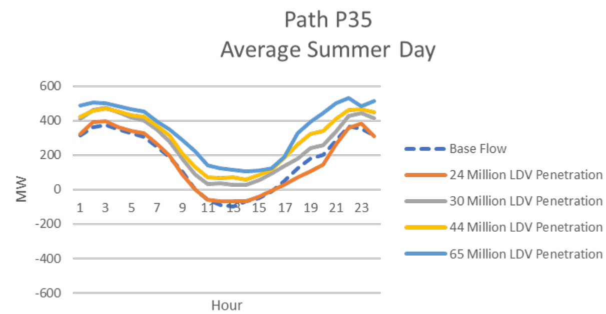


Path 35 TOT 2C

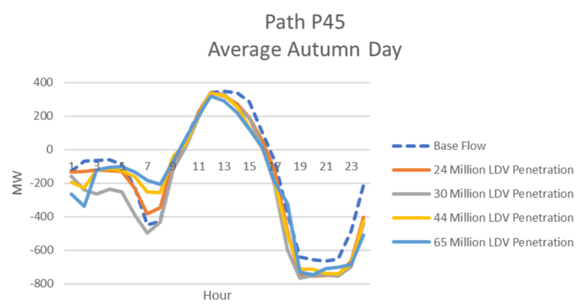


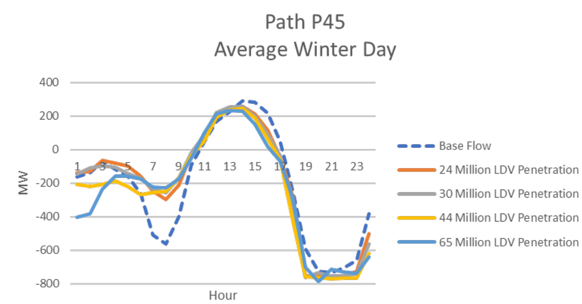


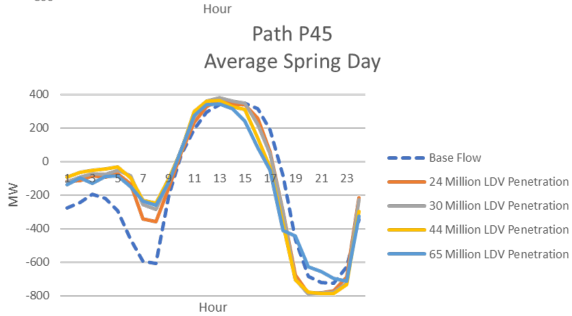


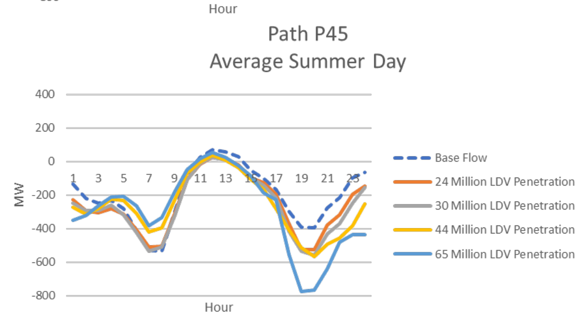


Path 45 SDG&E – CFE

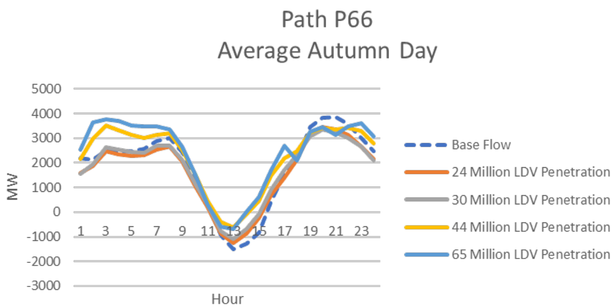


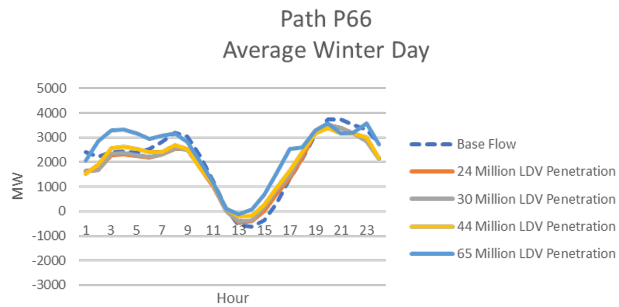


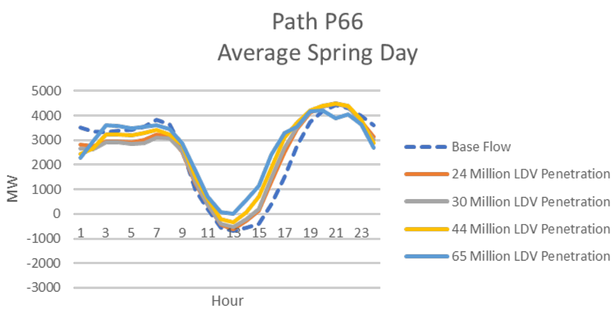


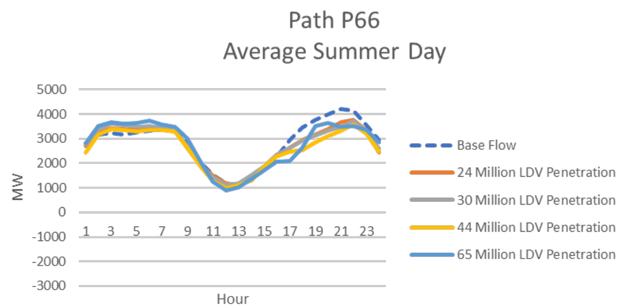


Path 66 California Oregon Intertie





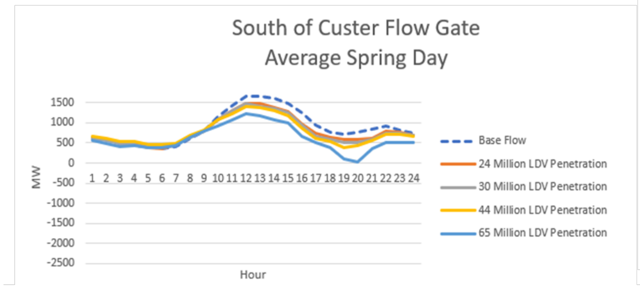


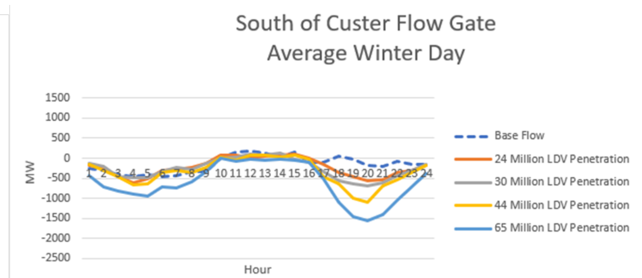


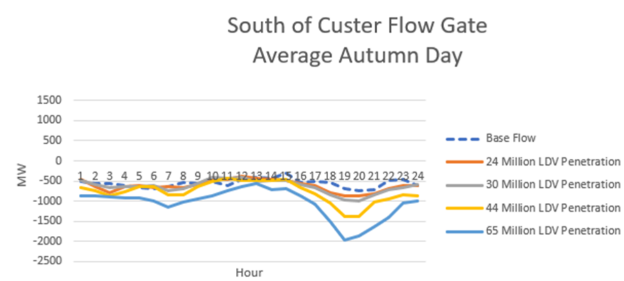
Appendix G – Washington State Flowgate Impacts

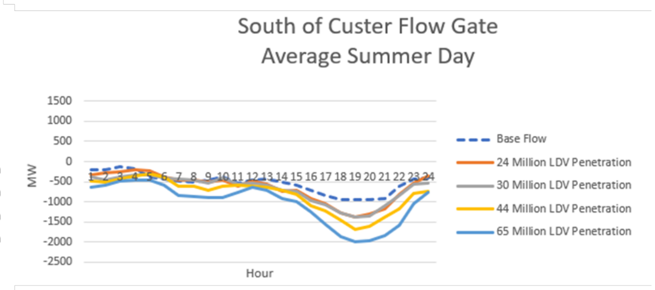
This appendix contains seasonal flows for Bonneville Power Administration (BPA) impacting Washington State under increasing light-duty vehicle penetration scenarios nationwide. Hourly flowgate conditions for BPA are provided below.

South of Custer Flowgate (South to North)

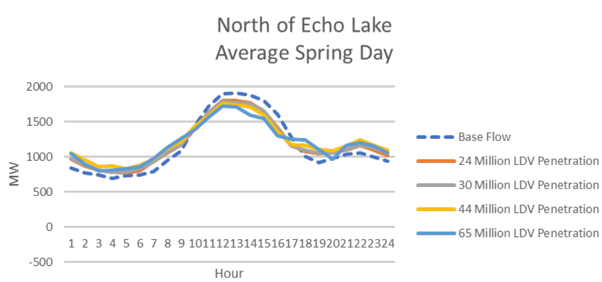


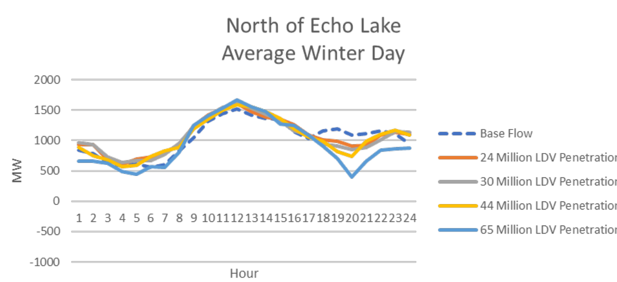


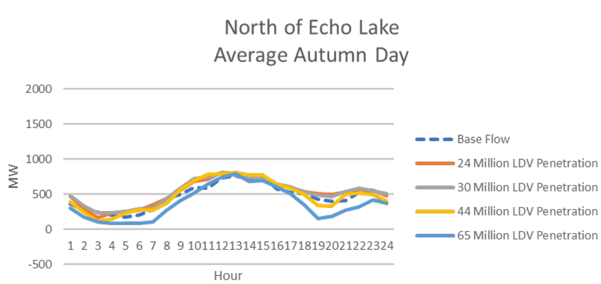


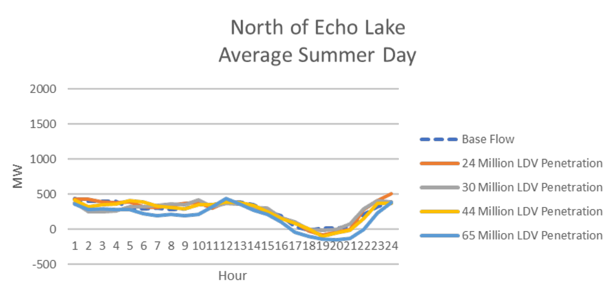


North of Echo Lake Flowgate

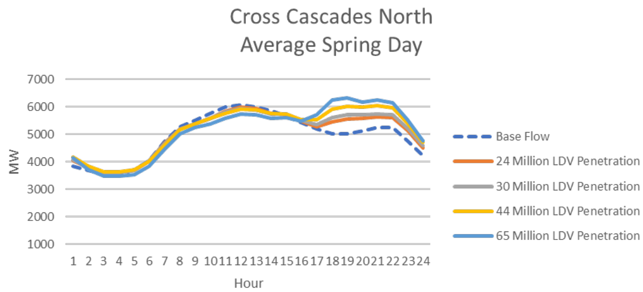


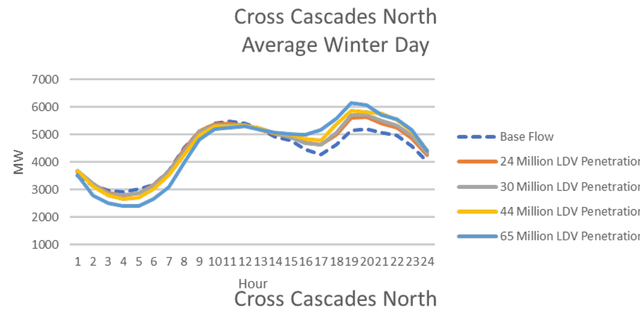


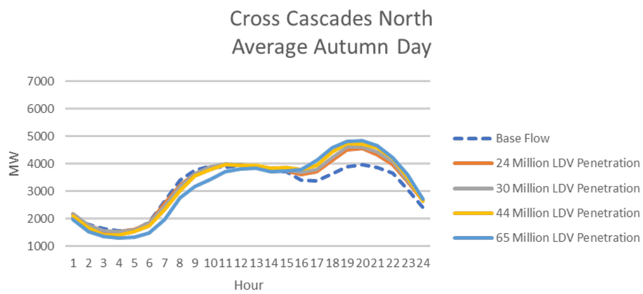


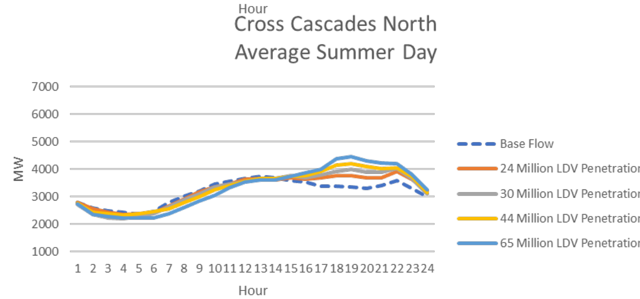


Cross Cascades North Flowgate (East to West)

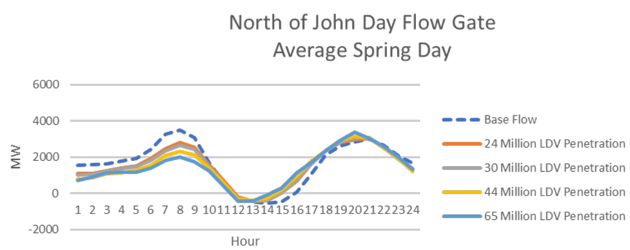


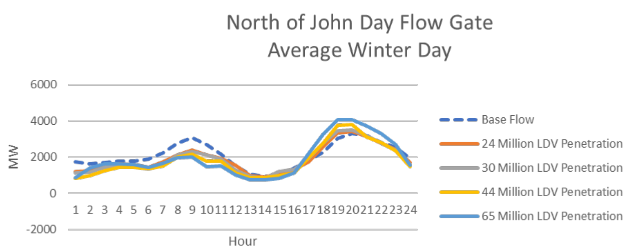


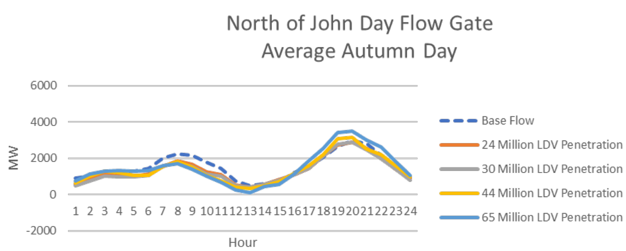


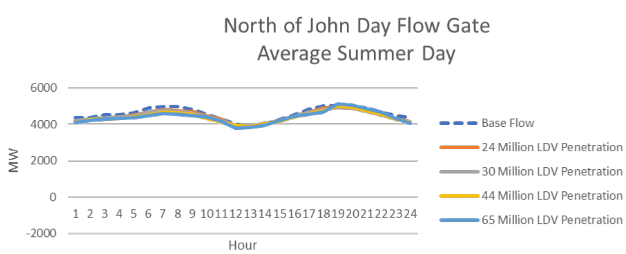


North of John Day Flowgate (North to South)

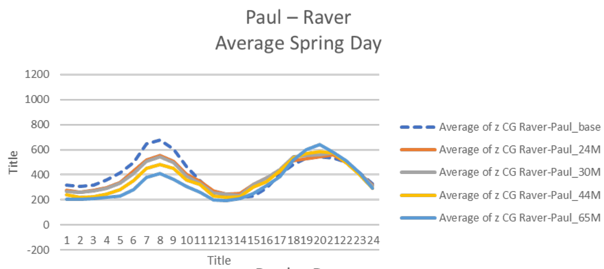


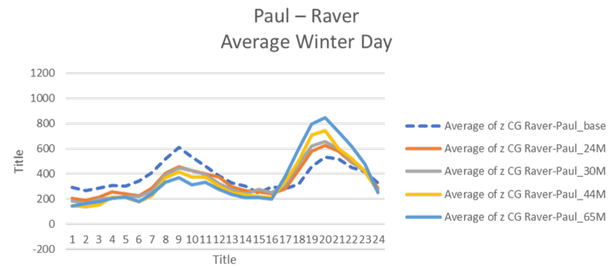


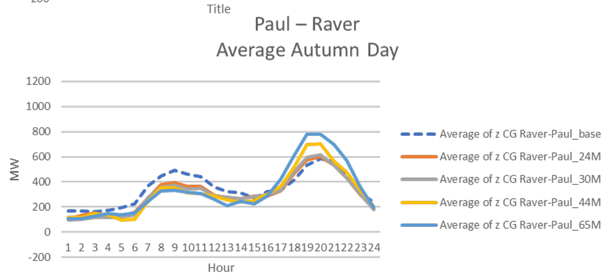


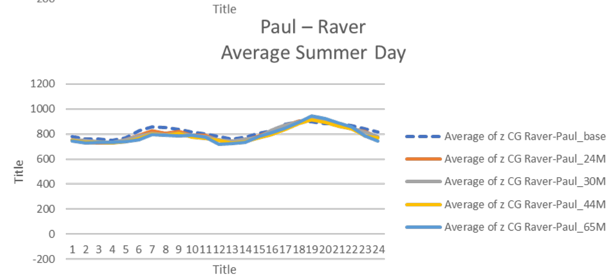


Paul – Raver Flowgate (North to South)

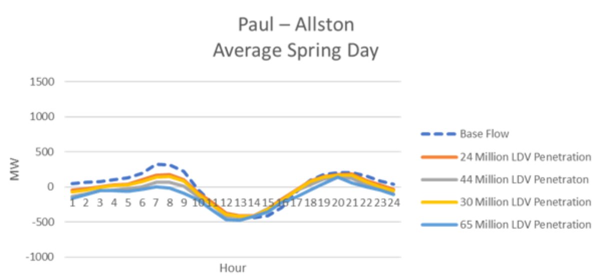


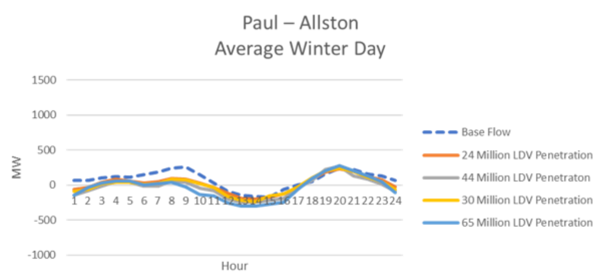


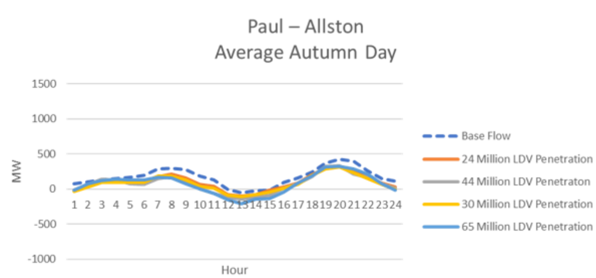


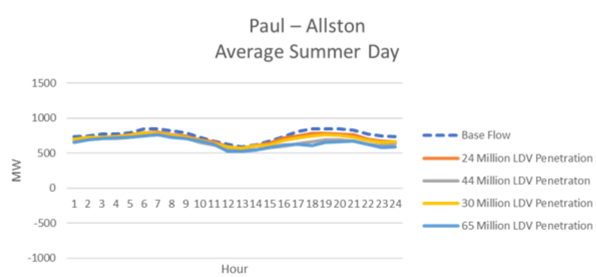


Paul – Allston Flowgate (North to South)

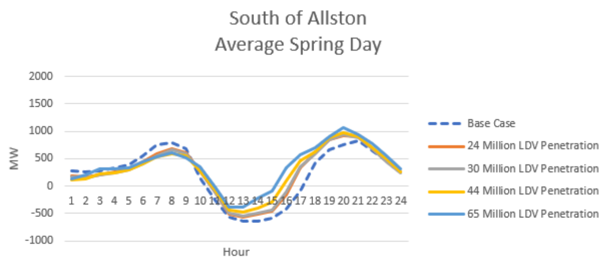


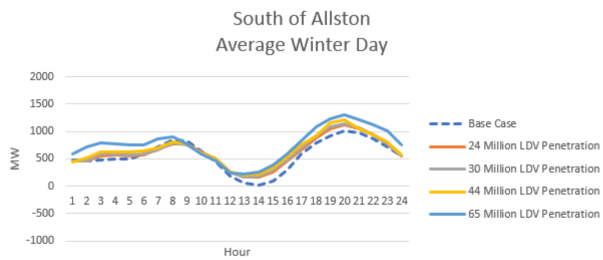


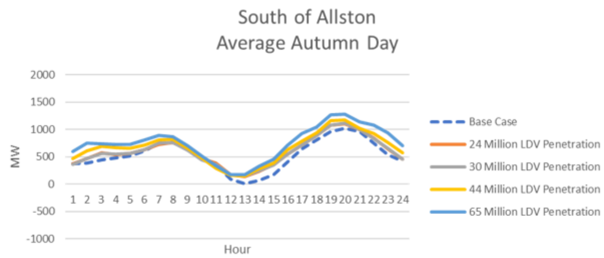


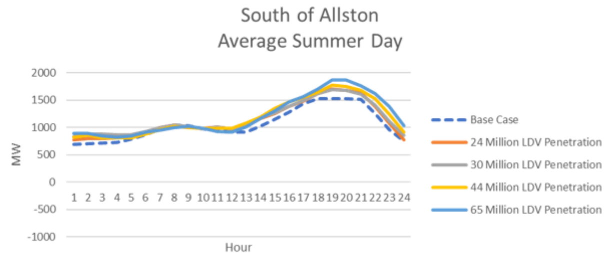


South of Allston Flowgate (North to South)

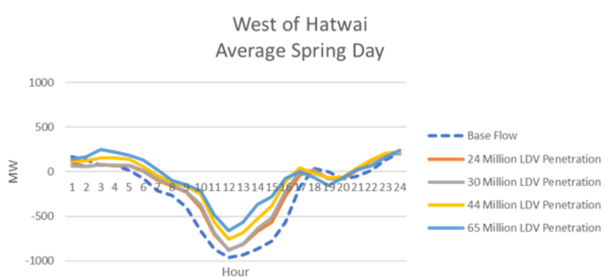


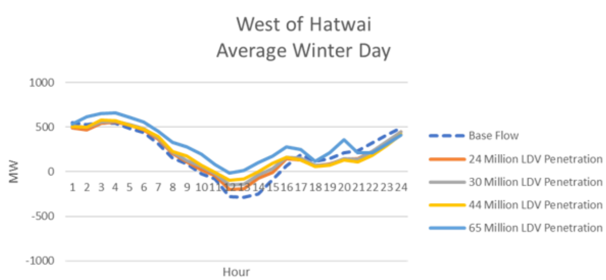


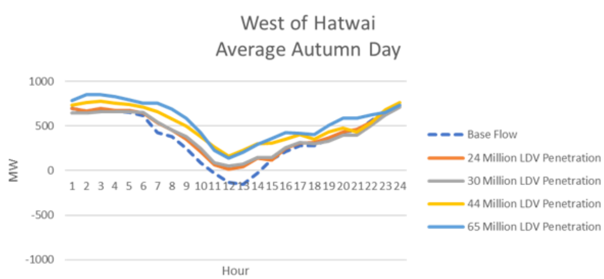


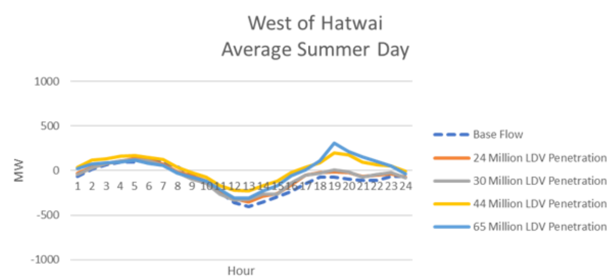


West of Hatwai Flowgate

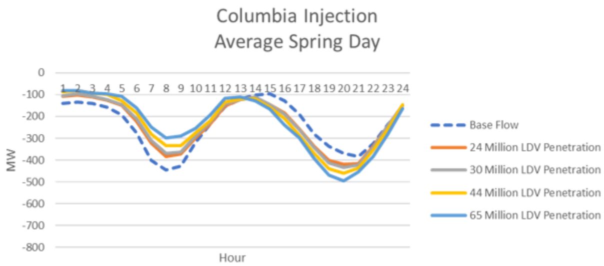


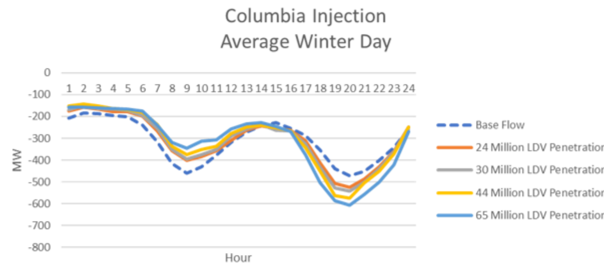


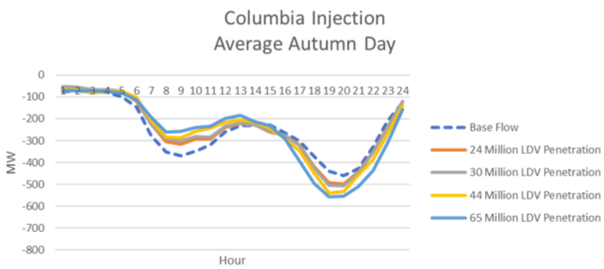


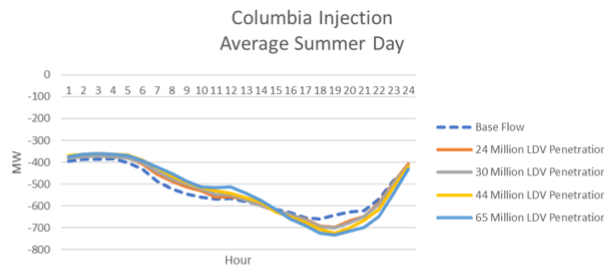


Columbia Injection Flowgate

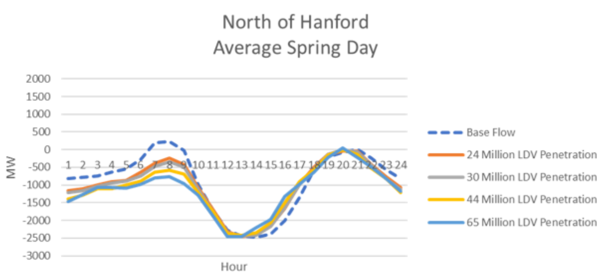


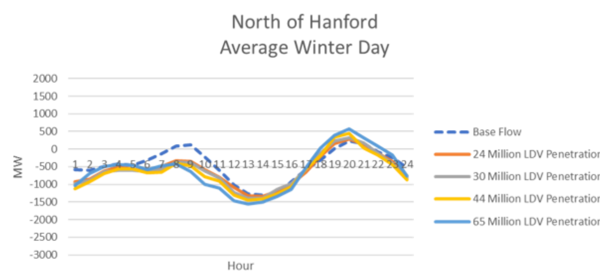


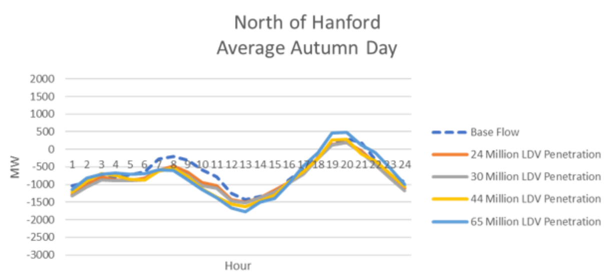


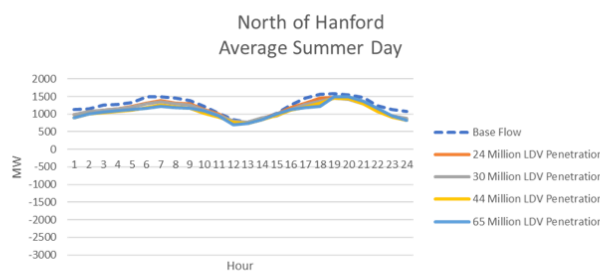


North of Hanford Flowgate

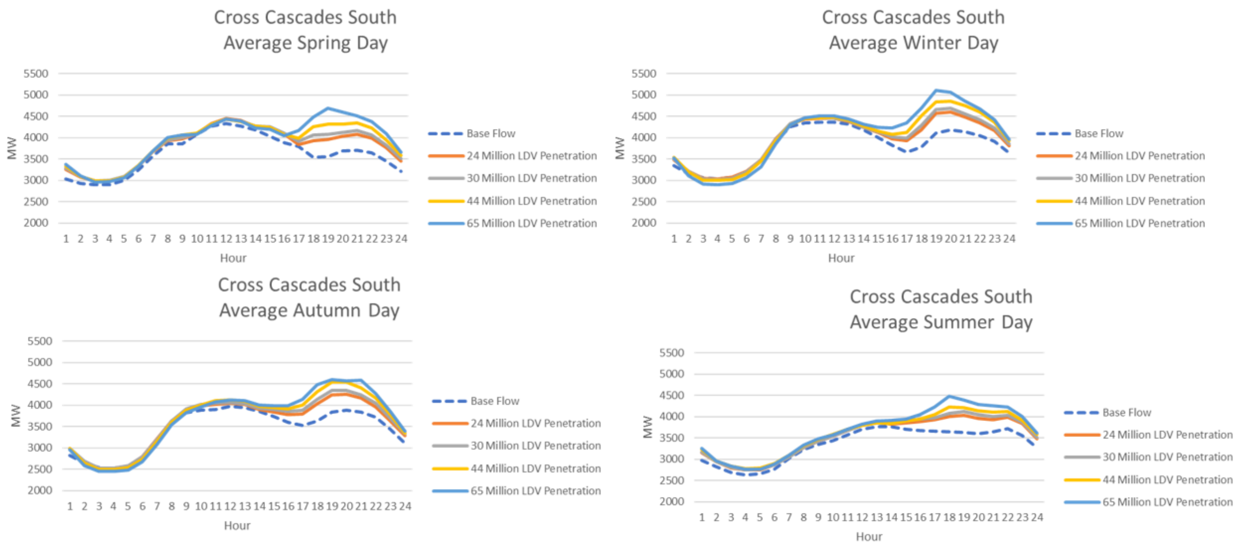




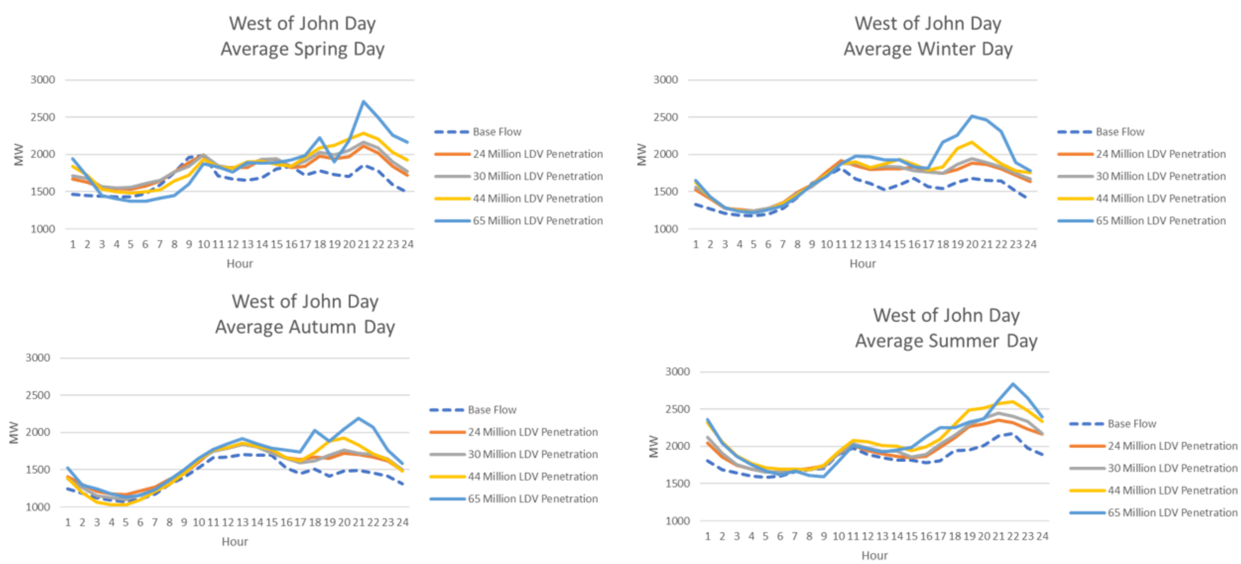




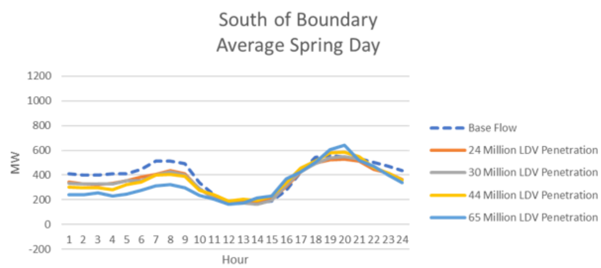
Cross Cascades South Flowgate

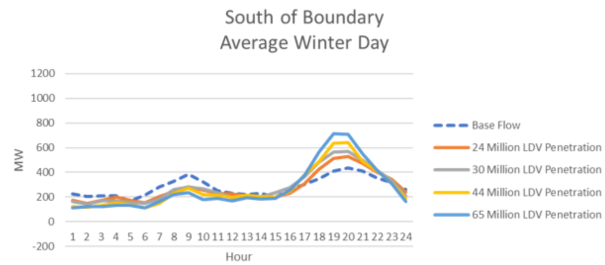


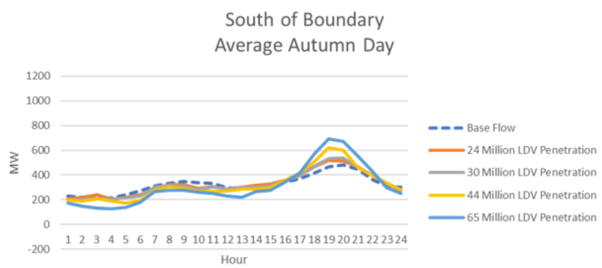
West of John Day Flowgate

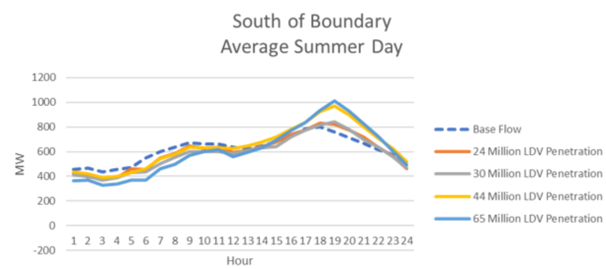


South of Boundary Flowgate (North to South)









West of Monumental Flowgate