Analytic Tools for Locating, Sizing, and Evaluating Electric Vehicle Charging Stations

WA-RD 930.1

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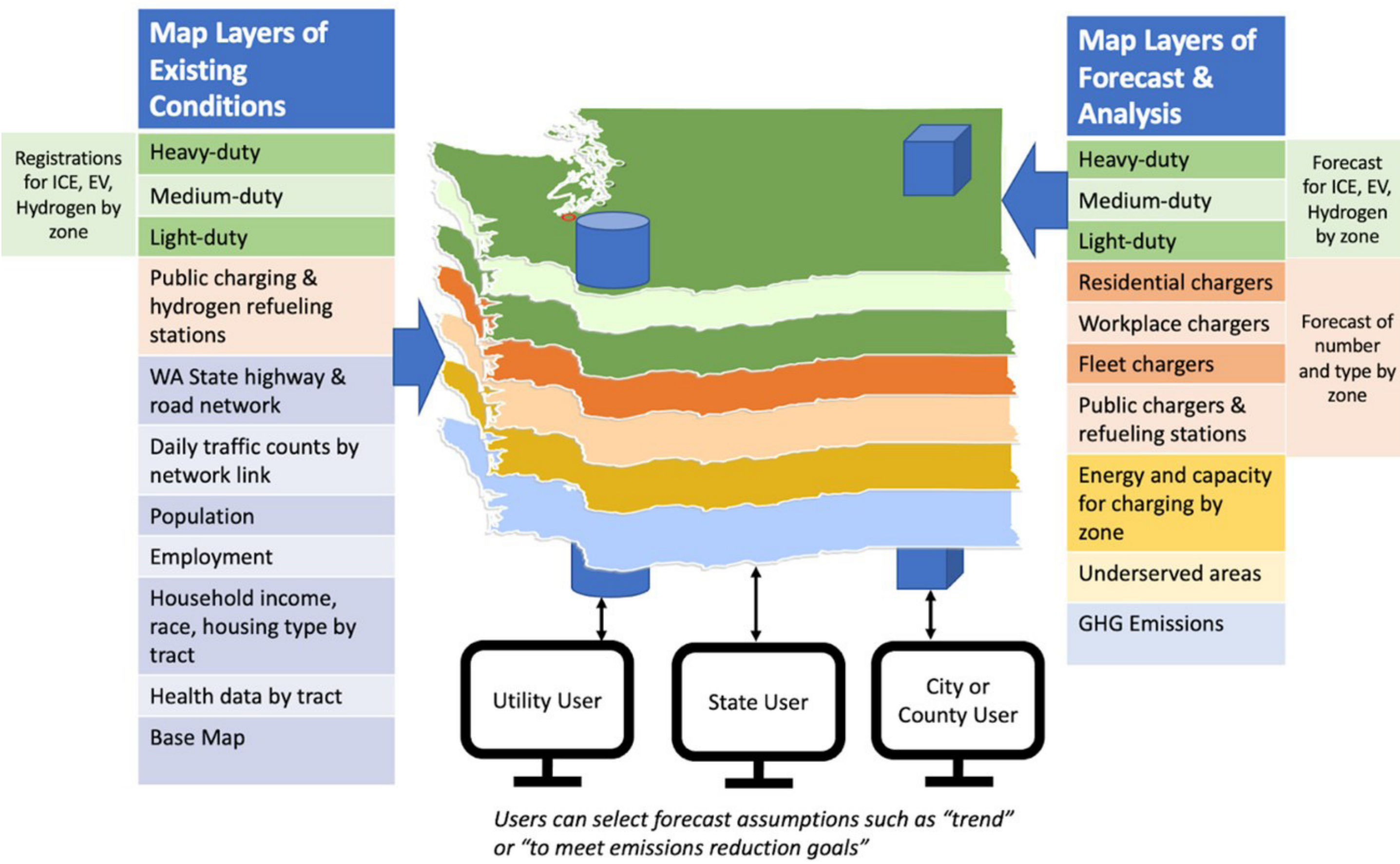

Schematic diagram of requirements for the
Zero-Emission Vehicle Mapping and Forecasting Tool

Washington State Department of Transportation
Office of Research & Library Services

WSDOT Research Report

Research Report
Agreement T1461, Task 88
WSDOT ChargeEval
WA-RD 930.1

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Prepared for
The State of Washington
Department of Transportation
Roger Millar, Secretary

June 2023

TECHNICAL REPORT STANDARD TITLE PAGE

1. REPORT NO. WA-RD 930.1	2. GOVERNMENT ACCESSION NO.	3. RECIPIENT'S CATALOG NO.
4. TITLE AND SUBTITLE ANALYTIC TOOLS FOR LOCATING, SIZING, AND EVALUATING ELECTRIC VEHICLE CHARGING STATIONS		5. REPORT DATE June 2023 6. PERFORMING ORGANIZATION CODE
7. AUTHOR(S) Steffen Coenen, Zack Aemmer, Daniel Malarkey, Don MacKenzie		8. PERFORMING ORGANIZATION REPORT NO.
9. PERFORMING ORGANIZATION NAME AND ADDRESS Washington State Transportation Center University of Washington, Box 359446 University Tower, 4333 Brooklyn Ave NE Seattle, Washington 98195-9446		10. WORK UNIT NO. 11. CONTRACT OR GRANT NO. Agreement T1461, Task 88
12. SPONSORING AGENCY NAME AND ADDRESS Washington State Department of Transportation Transportation Building, MS 47372 Olympia, Washington 98504-7372 14 Doug Brodin, Project Manager, 360-705-7972		13. TYPE OF REPORT AND PERIOD COVERED Research Report 14. SPONSORING AGENCY CODE
15. SUPPLEMENTARY NOTES This study was conducted in cooperation with the University of Washington.		

16. ABSTRACT

The Washington State Legislature directed the Department of Transportation to develop analytic tools “to enable coordinated, effective, efficient, and timely deployment of charging and refueling infrastructure necessary to support statewide and local transportation electrification efforts that result in emissions reductions” consistent with state goals. This report reviews the available analytic tools for planning electric vehicle (EV) charging infrastructure and makes recommendations on how to meet legislative requirements for mapping and forecasting zero-emission vehicles and recharging equipment. The report presents an approach for generating a ten-year forecast of EV adoption at the census tract level and presents the results of that method. The report also describes an approach to simulating EV charging at public stations that estimates the plug count and power levels needed to meet charging demand with low wait times and the corresponding electric energy and capacity required to serve the charging demand. The report concludes with opportunities for additional research and development to create practical analytic tools that would assist planners and policymakers in making decisions about EV charging investments.

17. KEY WORDS Electric vehicle charging, analytic tools, forecasting, simulation models, queueing models, electric energy, power, and capacity.	18. DISTRIBUTION STATEMENT No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22616

19. SECURITY CLASSIF. (of this report)	20. SECURITY CLASSIF. (of this page)	21. NO. OF PAGES	22. PRICE
None	None	64	

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The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Washington State Department of Transportation or Federal Highway Administration. This report does not constitute a standard, specification, or regulation.

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EXECUTIVE SUMMARY

The Washington State Department of Transportation (WSDOT) contracted with researchers in the University of Washington's Sustainable Transportation Lab (UW) to research and make recommendations on how best to implement the Zero-Emission Vehicle Mapping and Forecasting Tool (ZEV-MFT) required by House Bill 1287 that was signed by Governor Inslee in May 2021.

Findings from a Review of ZEV Infrastructure Studies in Other Jurisdictions

- California, Oregon, British Columbia, Seattle, and Colorado have all recently completed zero-emission vehicle (ZEV) studies that relied primarily on custom analyses to forecast needed infrastructure.
- Though custom analysis was the predominant approach, both California and Oregon used EVI-Pro from the National Renewable Energy Laboratory to develop their forecasts of charging infrastructure for light-duty vehicles.

Findings from a Review of Existing Mapping and Forecasting Tools

- The UW team reviewed seventeen different tools to help states, counties, cities, and tribal governments plan for ZEV infrastructure. Given the nascent stage of the market, all of the available tools carry some risk that the vendor will stop marketing, improving, and providing technical support for their offering.
- None of the tools reviewed by UW could meet the requirements of HB 1287 alone or in combination. Most of the tools forecast light-duty electric vehicles and related infrastructure, a few address medium- and heavy-duty electric vehicles, and none of them forecasts the infrastructure needs of hydrogen ZEV vehicles or the marine and aviation sectors.

Recommendations for the Zero-Emission Vehicle Mapping and Forecasting Tool

- Implement the ZEV-MFT on the ArcGIS Online platform that WSDOT currently licenses from ESRI because the hosted software solution has a multi-year operating history and a demonstrated capacity to serve thousands of users in local governments and utilities with flexible, on-line mapping services.
- Assemble the map layers of existing conditions in Washington state required under HB 1287 from information already available at WSDOT and other state

and federal agencies in a manner consistent with guidance from Office of the Chief Informationn Officer's (OCIO) Geospatial Program Office.

- Contract with public or private entities that have relevant expertise for annual forecasts of zero-emission vehicles and infrastructure in a data standards compliant format that integrates with ArcGIS Online to generate maps and related reports for Washington and its subdivisions.
- WSDOT should plan to spend approximately $8.7 million over five years to build and implement the ZEV-MFT, which would include hiring three full-time staff people to support the project.

Small Area Forecasts of Electric Vehicle Adoption

Subsequent to reviewing the available mapping and forecasting tools, the University of Washington team developed an approach to producing regular small area forecasts of electrc vehicle adoption. Within this report, the term electric vehicle (EV) includes both battery-electric vehicles (BEVs, or all-electric vehicles) and plug-in hybrid electric vehicles (PHEVs). To produce monthly, census tract-level forecasts, the UW team implemented a logistic regression model with a logit-transformed dependent variable representing the EV market penetration. The dependent variable was the electric vehicle share of either new light-duty vehicle sales (sales share) or the light-duty vehicle stock (stock share). The team used these two approaches because charging infrastructure needs are determined by the number of EVs on the road (stock share) while the state's goals (100 percent sales share by 2030 or 2035) are defined in terms of the EV sales share.

Figure ES-1 shows the results from the UW forecast of census tract-level EV stock share in 2035. The figure reveals a strong geographic heterogeneity, as past trends of EV adoption across Washington were used to project the future. Some census tracts are characterized by fast EV adoption pathways, with EV stock shares reaching more than 50 percent and up to 73 percent in the fastest-adopting census tract. On the other hand, there are still tracts with EV shares of less than 0.5 percent in their vehicle stock (white tracts in Figure ES-1), implying an even greater discrepancy between the highest- and lowest-adopting census tracts across Washington than existed in 2022.

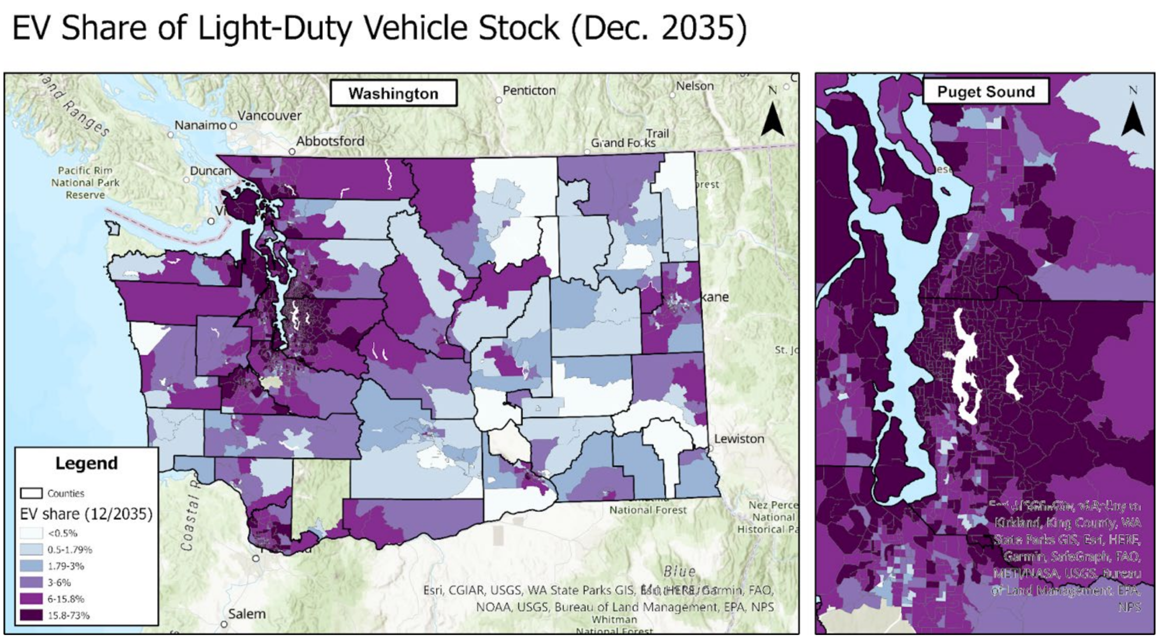

Figure ES-1: Census tract-level map of EV share of light-duty vehicle stock in Washington in 2035 based on forecasting using EV stock share as the dependent variable.

Future Demand from Light-Duty Electric Vehicles at DC Fast Charge Stations

In recent years, federal and state policymakers have directed public funds to WSDOT to make grants to accelerate the construction of DC fast charge stations. WSDOT staff need to make decisions about the locations and plug configurations of charging stations that will receive grant funds. The UW evaluated where stations would be needed and how different station configurations would affect charging times and the potential waiting time for a free plug to start charging. To quantify station-level performance, the team developed a queueing simulation model. The model quantified performance by modeling the interaction between simulated EV drivers and a theoretical charging station with customizable parameters (e.g., plug count, power). Several scenarios were tested to demonstrate the model and estimate station performance under current and future conditions.

Table ES-1 shows, for different levels of average annual daily traffic (AADT), the count of plugs required to keep waiting times below 5 minutes, as well as the number of daily charging sessions, peak power, peak power utilization, total energy provided, and average power utilization. Green cells show scenarios in which the current federal standard of four 150-kW plugs meets the performance metric of 5 minutes or less of delay for more than 95 percent of the vehicles arriving at the station.

Additional Research and Implications for Policy

The census tract-level forecasting results suggest additional areas of research to support the development of mapping and forecasting tools to support the transition to zero-emission vehicles:

- Use census tract-level EV forecasts as an input to estimate future long-distance EV travel demand on state highway links.
- Use census tract-level EV forecsts to estimate charging demand for home, office, and public fast chargers.
- Develop methods for regularly updating the EV forecasts to match ongoing adoption trends.

The EV charging simulation research also suggest areas of additional inquiry that will help planners and policymakers better prepare for new station deployment:

- Model the effects of differences in battery capacity and C-rate on charging times and optimal station configurations.
- Develop vehicle and charging demand forecasts for medium- and heavy-duty vehicles to supplement the analysis of light-duty vehicles

The forecasting and station modeling results also have implications for current grant-making by WSDOT:

- Stations should be planned with the capacity to add more plugs as the size of the EV fleet increases. Sizing utlity connections and conduit to allow the addition of more high capacity plugs may reduce the overall costs of building out charging stations..
- Making grants for rural fast charge stations with fewer than four 150-kW plugs (the federal standard for the National Electric Vehicle Infrastructure (NEVI) program) with the capacity to add new plugs may allow for the best coverage with state dollars.
- Control software that could manage the charging load across all of the plugs at a charging station could significantly lower the electrical capacity requirements and thus the costs of the utility service to the station.

Table ES-1: Simulation results for fast charge stations at different levels of traffic and EV share

Average Annual Daily Traffic	Electric Vehicle Share	1%	10%	25%	50%	75%	100%
30 veh/day	Plugs	1	2	2	2	3	3
	Daily Charging Sessions (veh)	1	1	2	4	6	8
	Peak Power Demand (kW)	150	300	300	300	411	448
	Peak Utilization (%)	1.00	1.00	1.00	1.00	0.91	1.00
	Total Energy Provided (kWh)	14	72	161	382	493	687
	Average Utilization (%)	0.00	0.01	0.02	0.05	0.05	0.06
300 veh/day	Plugs	2	3	4	7	9	10
	Daily Charging Sessions (veh)	1	8	20	40	61	77
	Peak Power Demand (kW)	201	385	599	812	1083	1197
	Peak Utilization (%)	0.67	0.86	1.00	0.77	0.80	0.80
	Total Energy Provided (kWh)	56	696	1783	3494	5383	6895
	Average Utilization (%)	0.01	0.06	0.12	0.14	0.17	0.19
750 veh/day	Plugs	2	4	8	12	16	21
	Daily Charging Sessions (veh)	2	20	50	100	150	194
	Peak Power Demand (kW)	300	515	1068	1471	1810	2235
	Peak Utilization (%)	1.00	0.86	0.89	0.82	0.75	0.71
	Total Energy Provided (kWh)	150	1712	4408	8942	13187	17047
	Average Utilization (%)	0.02	0.12	0.15	0.21	0.23	0.23
1500 veh/day	Plugs	2	7	12	21	29	39
	Daily Charging Sessions (veh)	4	40	99	199	287	391
	Peak Power Demand (kW)	300	863	1421	2276	2847	4058
	Peak Utilization (%)	1.00	0.82	0.79	0.72	0.65	0.69
	Total Energy Provided (kWh)	312	3498	8898	17585	25456	34742
	Average Utilization (%)	0.04	0.14	0.21	0.23	0.24	0.25
2250 veh/day	Plugs	3	9	16	29	42	55
	Daily Charging Sessions (veh)	6	61	147	292	439	575
	Peak Power Demand (kW)	397	1023	2015	3078	4424	5340
	Peak Utilization (%)	0.88	0.76	0.84	0.71	0.70	0.65
	Total Energy Provided (kWh)	561	5385	13073	26094	39093	51152
	Average Utilization (%)	0.05	0.17	0.23	0.25	0.26	0.26
3000 veh/day	Plugs	3	10	21	39	55	70
	Daily Charging Sessions (veh)	8	78	192	389	588	778
	Peak Power Demand (kW)	442	1315	2294	4083	5516	6643
	Peak Utilization (%)	0.98	0.88	0.73	0.70	0.67	0.63
	Total Energy Provided (kWh)	758	6865	17117	34771	52140	69031
	Average Utilization (%)	0.07	0.19	0.23	0.25	0.26	0.27

CHAPTER 1
IMPLEMENTING A MAPPING AND FORECASTING TOOL FOR ZERO-EMISSION VEHICLES AND RELATED INFRASTRUCTURE IN WASHINGTON STATE

MAPPING AND FORECASTING TOOL REQUIREMENTS

The Washington Legislature in 2021 passed HB 1287 that included direction to the Washington State Department of Transportatio (WSDOT) to develop a Zero-Emission Vehicle Mapping and Forecasting Tool (ZEV-MFT) "to enable coordinated, effective, efficient, and timely deployment of charging and refueling infrastructure necessary to support statewide and local transportation electrification efforts that result in emissions reductions" consistent with state goals. The ZEV-MFT will allow WSDOT, other state agencies, electric utilities, local governments, and private infrastructure companies to plan infrastructure for zero-emission vehicles and track progress toward meeting emission reduction targets.

The federal infrastructure bill that President Biden signed on November 15, 2021, includes billions of dollars to fund infrastructure for zero-emission vehicles. The ZEV-MFT will help stakeholders plan for these federal funds and deliver value to Washington's citizens by aiding the selection of the best locations for zero-emission vehicle (ZEV) infrastructure. The tool would help support grant applications, program design, and project development funded by federal programs that include the following:

- US Department of Transportation (USDOT) electric vehicle formula funds: $5 billion
- USDOT zero-emission vehicle discretionary grants: $2.5 million
- USDOT reduction of truck emissions at port facilities: $250 million
- Federal Transit Administration low-no grants for buses and bus facilities: $5.2 billion
- US Department of Energy state energy program formula funds: $500 million
- US Department of Energy alternative fuel public school facilities: $500 million
- Environmental Protection Agency clean school bus program: $5 billion.

The dollar figures above are the total amounts authorized for the programs nationwide.

Figure 1 shows some of the key requirements for the ZEV-MFT detailed in HB 1287. The mapping tool must include data layers of existing conditions shown in the left-hand column, which include the number of registered ZEVs by vehicle class, along with the number of their associated charging and refueling stations. The tool must also include the existing road network, traffic levels, population, employment, health, environmental, and socio-economic data at the level of census tracts.

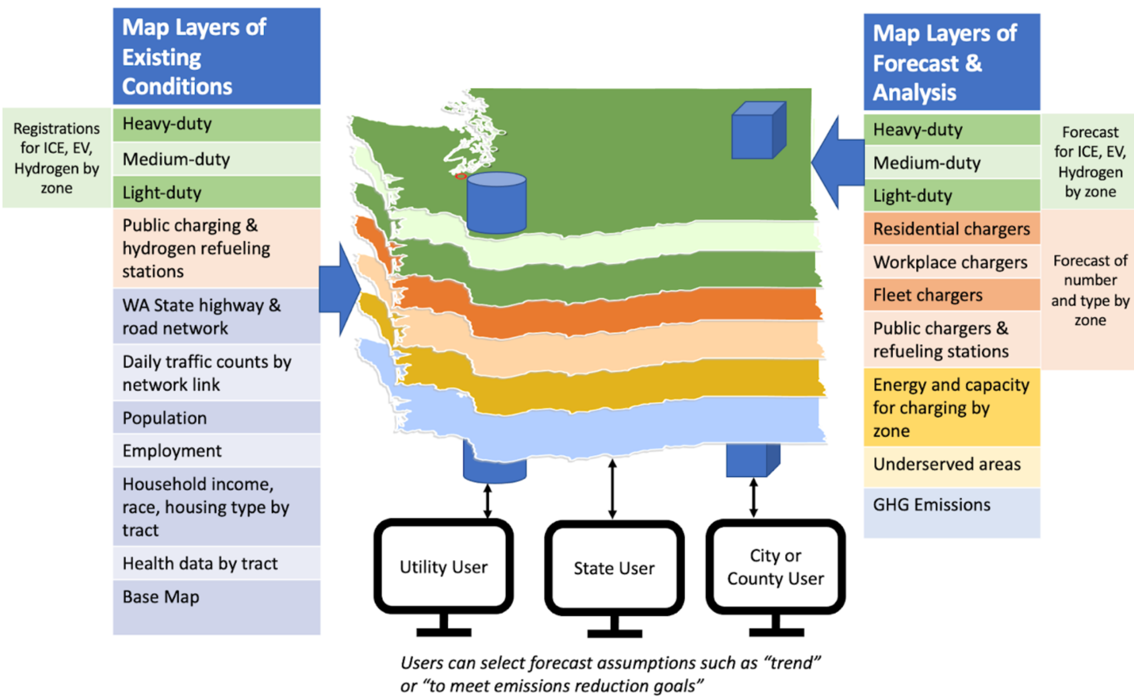

Figure 1. Schematic diagram of requirements for the Mapping and Forecasting Tool

In addition to characterizing present conditions, the ZEV-MFT must also forecast future quantities of vehicles and charging and refueling stations, along with the electricity needed to serve those stations under different scenarios, including a scenario in which the transportation sector meets state goals for greenhouse gas reductions. The tool should allow electric utility users to generate reports on future electric vehicle charging demand to enable effective planning of generation, transmission, and distribution capacity and to aid in the siting of charging facilities. The tool should also allow cities and advocacy groups to analyze existing and projected conditions by subareas to enable timely and equitable distribution of public investments in zero-emission vehicles and charging and refueling stations. The tool should also allow state-level users to evaluate progress toward greenhouse gas reduction goals and provide information on the consequences of potential changes to public policy related to zero-emission vehicles.

RESEARCH PROGRAM

The Innovative Partnerships Office at WSDOT contracted with the Sustainable Transportation Lab under the leadership of Professor Don MacKenzie at the University of Washington to answer three related research questions:

1. What tools and approaches to forecasting ZEVs and their related infrastructure have California, Oregon, and other jurisdictions used to develop policies and plans?
2. Do any of the existing tools offered in the market have a track record of meeting requirements close to those in HB 1287, either alone or in combination?
3. What options does WSDOT have for meeting the mapping and forecasting requirements of HB 1287 with high confidence and at reasonable cost?

Over ten weeks in the fall of 2021, the research team evaluated seventeen tools related to ZEV forecasting and planning and reviewed thirteen different studies that estimated future needs for charging and refueling infrastructure. The team also met with leaders in the WSDOT information technology group to discuss their capabilities, experience with geographic information system (GIS) platforms, and recommendations for implementing the ZEV-MFT.

RECENT STUDIES TO PLAN FOR ZEV INFRASTRUCTURE NEEDS

Washington's state and provincial partners on the Pacific Coast (California, Oregon, and British Columbia) each issued reports in 2021 that projected the need for electric vehicle charging infrastructure within their boundaries. These three studies, along with similar reports from Colorado, the City of Seattle, Princeton University, and a consultant team working on behalf of the three Western states provided a snapshot of the state of practice for mapping and forecasting the demand for ZEV infrastructure in 2021 (Table 1). Several key insights emerged from a review of these reports:

- All of the studies relied primarily on custom analysis to estimate future demand for ZEV infrastructure.
- EVI-Pro from the National Renewable Energy Laboratory was used by both Oregon and California to forecast infrastructure needed for light-duty vehicles.
- Most of the studies focused on light-duty electric vehicles; California and the consortium of Western states also estimated demand for medium- and heavy-duty electric vehicles.
- None of the studies specifically forecasted demand for the public transit agency, maritime, or aviation uses that HB 1287 directs Washington's state agencies to consider as a potential application of the tool.
- Washington's neighbors focused their infrastructure forecasts on electric rather than hydrogen vehicles. Given current trends, hydrogen will lag behind electricity for on-road uses, but hydrogen may gain market share over time for on-road, maritime, and aviation uses.

Table 1. Recent ZEV infrastructure needs assessments in Western jurisdictions

Study Name and Date	**Forecasting Tools Used**
Assembly Bill 2127-Electric Vehicle Charging Infrastructure Assessment Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030, California Energy Commission, July 2021.	EVI-Pro, EVI-RoadTrip, HEVI-LOAD
British Columbia Public Light-Duty Zero-Emission Vehicle Infrastructure Study, Province of British Columbia, May 2021.	Custom analysis
Colorado charging infrastructure needs to reach electric vehicle goals, International Council on Clean Transportation, February 2021.	Custom analysis
City charging infrastructure needs to reach electric vehicle goals: The case of Seattle, International Council on Clean Transportation, January 2021.	Custom analysis
Net-Zero America: Potential Pathways, Infrastructure, and Impacts, E. Larson, et al., Princeton University, 29 October 2021.	Custom analysis
Transportation Electrification Infrastructure Needs Analysis (TEINA) for Oregon, Kittleson, RMI, HDR and Forth, June 2021.	EVI-Pro, Custom analysis
West Coast Clean Transit Corridor Initiative, Interstate 5 Corridor, California, Oregon, Washington. HDR, et al., June 2020	Custom analysis

EXISTING MAPPING AND FORECASTING TOOLS

Table 2 summarizes the names and capabilities of the existing tools we reviewed, and Figure 2 evaluates each tool against some of the key requirements identified in HB 1287 and in stakeholder conversations conducted by the Washington State University Energy Office. This long list of potential tools reflects a high level of innovation and a large number of recent entrants that are typical of an emerging market. National labs and universities are conducting research and developing tools that are making their way into the private market of consulting firms and non-profits that provide planning and program services to state and local governments.

Table 2. Existing ZEV forecasting tools

Tool Sponsor/Developer	**Key Characteristics**
BEAM Lawrence Berkeley National Laboratory (LBNL)	• Agent-based, regional transportation model that can site charging. infrastructure based on projected per-hour and per-county demand. • So far only applied on the scale of a metropolitan region (e.g., San Francisco Bay Area). • Free access to software repository; usage is non-interactive and requires executing software code.
Caret Center for Sustainable Energy	• Platform to forecast and evaluate the impacts of different user-defined EV incentive programs. • Applied in several incentive programs of states and regions around the world. • Proprietary software and modeling approach; online user interface.
Charge4All Arup	• Suitability software that identifies high-level prioritization areas for electric vehicle supply equipment (EVSE) and street-level curbside suitability. • So far only applied to Southern California. • Proprietary software and modeling approach; online GIS-based user interface.
ChargEVal University of Washington	• Decision support system for public fast-charging EVSE for Washington. • Estimates the potential utilization for a chosen charging location and predicts other key metrics. • Free access to software; restricted access to online user interface.
E-DRIVE M.J. Bradley & Associates, Georgetown Climate Center, Ceres	• Prioritization tool that identifies the suitability of all census tracts in the U.S. for public fast-charging EVSE deployment. • Estimates based on user-defined weights applied to several metrics. • Free access; online interactive user interface.
Electric Bus Planning Framework M.J. Bradley & Associates	• Framework to determine the capital and operating requirements for the electrification of transit buses, includes necessary charging infrastructure. • Applied to several public metropolitan transit agencies.

Tool Sponsor/Developer	**Key Characteristics**
	• Proprietary modeling approach used for consulting to transit agencies; extent and design of user interface not reviewed.
Energy Zones Mapping Tool Argonne National Lab (ANL)	• Mapping tool to identify energy resource areas and corridors in the US based on 360 layers that include various demographic and environmental data. • Recently added exemplary EVSE models (corridor, urban, rural) that output suitability scores for 250x250-m cells. • Free access (after registration); online GIS user interface.
EV-CB Framework M.J. Bradley & Associates	• Framework to project societal costs and benefits of scenarios of EV adoption and charging patterns. • Applied to several states. • Proprietary modeling approach used for consulting purposes; spreadsheet-based tool, extent and design of user interface not reviewed.
EValuateCO Atlas Public Policy	• Dashboard on the current and past market within the state (EV adoption, demographics, and charging infrastructure). • So far only applied to Colorado. • Free access; online dashboard.
EVI-X/EVI-Pro National Renewable Energy Laboratory (NREL)	• Comprehensive modeling suite to inform the development of large-scale EVSE deployment on a city level or county level. • Applied by California and Oregon for their recent EV charging needs assessments. • Proprietary software available under public license; requires executing software code.
GIS EV Planning Toolbox UC Davis	• Forecasting tool to provide workplace and public charging demand on a census block group level based on user-defined EV market sizes. • Applied by metropolitan planning organizations in California and Pennsylvania/New Jersey. • Restricted access to modeling approach; GIS-based user interface.
HEVI-LOAD Lawrence Berkeley National Laboratory (LBNL)	• Model to project regional charging infrastructure needs for public, shared private, and private charging of medium- and heavy-duty electric vehicles. • Applied in California for its 2030 EV charging needs assessment (for the medium and heavy-duty sector). • Software under development and not available online; extent and design of user interface not reviewed.
ILIT M.J. Bradley & Associates, Georgetown Climate Center	• Prioritization tool that identifies the suitability of all census tracts in 14 northeastern states for public fast-charging EVSE deployment. • Estimates based on user-defined weights applied to several metrics. • Free access; online user interface and an interactive GIS data visualization.
PEV-CDM University of Vermont	• Research-focused framework aiming to produce hourly EV charging demands based on real-world travel patterns. • Result of research at the University of Vermont, so far only applied to Quebec. • Restricted access to software; usage is non-interactive and requires executing software code.

Tool Sponsor/Developer	**Key Characteristics**
REVISE-II Oak Ridge National Laboratory (ORNL)	• Optimization tool for where and when new charging stations should be deployed, including the allocated capacity. • So far only reflects inter-city (county-to-county) highway travel. • Free access to software repository; usage is mostly non-interactive and requires executing software code.
StreetLight Data StreetLight Data	• Data provision software to analyze and rank charger site selections on a city level (or smaller) based on travel, traveler, visibility, and charging load metrics. • So far only applied to a city (Santa Clara, Calif.). • Proprietary software; online user interface.
UrbanFootprint UrbanFootprint	• Data provision software to quantify and analyze various impacts of user-defined land-use scenarios in cities. • No direct forecasts of EV charging demand. • Proprietary software; online GIS-based user interface.

Because of the early stage of the market, all of the currently available tools carry some risk that the sponsoring entity may not support them over time, as no clear market leaders have yet emerged. If there were a market leader for forecasting charging infrastructure for light-duty vehicles, it would be EVI-Pro, the tool developed by NREL and used by the states of California and Oregon. However, according to staff at NREL, even this tool has yet to be formally licensed to any entities outside the national labs for commercial use. Moreover, light-duty vehicles are just one of four vehicle types for which HB 1287 requires mapping and forecasting. A quick scan across the rows in Figure 2 reveals that none of the tools reviewed meets all the requirements of HB 1287 alone or in combination. Most of the tools forecast light-duty electric vehicles and related infrastructure, a few address medium- and heavy-duty electric vehicles, and none of them forecasts hydrogen vehicles and refueling infrastructure nor do they forecast maritime and aviation needs.

Figure 2. Existing ZEV forecasting tools scored on HB 1287 requirements

	Accessible to the general public	Non-proprietary forecasts	Applied in Western states	Commercially ready	Includes required WA data				Includes vehicle types and their respective infrastructure				Subarea demand forecast	Forecasts kW & kWh for utilities	Projects ZEV # for climate goals	Includes public transport	Includes maritime & aviation
					Travel	Demographic	Socioeconomic	Environmental	Light EV	Medium EV	Heavy EV	Any hydrogen					
BEAM	3	1	3	2	3	3	3	3	1	3	3	3	2	2	3	2	3
Caret	2	2	2	1	2	2	2	3	1	3	3	3	1	1	2	3	3
Charge4All	2	3	3	1	3	2	2	3	1	3	3	3	2	1	3	3	3
ChargEVal	3	1	2	3	1	3	3	3	1	3	3	3	3	1	3	3	3
E-DRIVE	1	2	3	1	2	1	1	1	1	3	3	3	2	3	3	3	3
Electric Bus Planning Framework	3	1	3	3	3	3	3	3	3	3	2	3	2	2	3	1	3
Energy Zones Mapping Tool	1	2	2	1	2	1	1	1	2	3	3	3	2	2	3	3	3
EV-CB Framework	3	3	3	3	3	3	3	3	2	3	3	3	3	2	2	3	3
EValuateCO	1	3	2	2	3	1	1	3	1	3	3	3	2	2	3	3	3
EVI-X/EVI-Pro	3	2	1	2	3	2	3	3	1	2	2	3	2	2	3	3	3
GIS EV Planning Toolbox	2	2	2	3	3	2	2	3	1	3	3	3	1	1	3	3	3
HEVI-LOAD	3	1	1	2	3	3	3	3	3	1	1	3	2	2	2	1	3
ILIT	1	2	3	1	2	1	1	1	1	3	3	3	2	3	3	3	3
PEV-CDM	3	1	3	3	3	2	2	3	1	3	3	3	1	1	2	3	3
REVISE-II	3	1	3	2	2	3	3	3	1	3	3	3	2	2	3	3	3
StreetLight Data	3	2	3	2	3	2	2	3	1	3	3	3	2	1	3	3	3
UrbanFootprint	1	2	3	1	2	1	1	1	2	3	3	3	2	2	2	2	3

Fullfills requirement...

fully or mostly.	1
only in parts.	2
not at all.	3

WSDOT'S EXISTING ONLINE MAPPING PLATFORM

WSDOT, in coordination with the state's Office of the Chief Information Officer, has adopted ArcGIS as its standard geographic information system or electronic mapping platform. WSDOT has a license from the firm ESRI to operate the ArcGIS Online system for a wide range of public uses that can be found at https://wsdot.maps.arcgis.com/home/index.html.

Many of the data layers of existing conditions, shown on the left side of Figure 1, are already available on WSDOT's mapping sites, including the state highway network, traffic counts, public health data, city and county boundaries, and population. Other ArcGIS map layers of existing conditions are readily available from other jurisdictions such as the U.S. Census and the federal Department of Energy. ArcGIS Online is a proven platform for WSDOT, and applications like WSDOT's Community Planning Portal are accessed thousands of times each month by planners and analysts in local government.

PROCUREMENT OPTIONS

Our research team identified three options for WSDOT to procure the ZEV-MFT:

- **Option 1**: Contract for a turnkey solution hosted by the vendor.
- **Option 2:** Host the tool using WSDOT's ArcGIS Online license and contract for the annual forecast layers shown on the right side of Figure 1.
- **Option 3:** Host the tool using WSDOT's ArcGIS Online license and hire new WSDOT staff to generate the annual forecast layers forecasts shown on the right side of Figure 1.

We compared these options across the five evaluative criteria shown in Table 3. Option 1 would have the highest vendor costs and the lowest staff costs; Option 3 would have the highest staff costs and the lowest vendor costs. We cannot say which option would have the lowest combined vendor and staff costs. The risk of vendor lock-in and getting stuck with a stranded mapping and forecasting technology is highest with Option 1, although vendor selection criteria could mitigate this risk. We scored Options 2 and 3 high on the platform's track record, given the proven success of ArcGIS Online across state and local governments in Washington. We recommend Option 2 because it would build on WSDOT's existing ArcGIS Online platform and data sets and then would allow WSDOT to periodically contract for forecasts from the country's leading experts on ZEV infrastructure requirements. We acknowledge that Option 1 might prove more attractive to WSDOT, especially if the IT personnel and institutional resources to support Option 2 were scarce.

Table 3. Procurement options scored on evaluative criteria

Option	Vendor Costs	WSDOT Staff Costs	Vendor Lock-In Risk	Stranded Technology Risk	Platform's Track Record
1. Turnkey	High	Low	High	High	Short
2. Contract for Forecasts	Medium	Medium	Low	Low	Long
3. Staff for Forecasts	Low	High	Low	Low	Long

COST ESTIMATES

To estimate the costs of delivering the ZEV-MFT over five years, we spoke with representatives from the states of Oregon and California about their recent costs to develop reports on ZEV infrastructure needs and with WSDOT IT staff. We also spoke with potential private vendors willing to provide a turnkey solution for the tool. In developing our cost estimates we considered that neither Oregon nor California developed infrastructure forecasts for hydrogen, public transportation, aviation, or marine uses in their reports, nor did they produce a public facing mapping tool with subarea forecasts. We also noted that some of the required data for developing useful forecasts might have to be purchased from private data sources. As shown in Table 4, the five-year budget for Option 2 would be \$6.2 million, which would include hiring three new full-time equivalent positions at WSDOT. WSDOT should expect the tool setup and forecasting services to take 18 to 24 months after contract signing to complete the first version of the tool, which would likely not include all of the features called for in the legislation.

The Princeton University Net-Zero America report published in October 2021 estimated that Washington would need to invest \$856 million in public charging stations in the 2020s and 2030s to achieve net zero emissions by 2050 under a high electrification scenario. The five-year cost of the mapping and forecast tool would be less than 1 percent of this projected investment in public charging stations. By helping stakeholders make better decisions about infrastructure location that resulted in faster adoption of ZEV vehicles and higher utilization of public charging infrastructure, the ZEV-MFT would more than pay for itself.

Table 4. Five-year budget for the Mapping and Forecasting Tool using Option 2

Cost Categories	FTE	FY 23	FYs 23-25	FYs 25-27	5-Year Total
Detailed vendor scope of work with contract IT business analyst		75,000			75,000
Develop long-term data management plan with contract IT business analyst		75,000			75,000
Contracted Services to deliver M&F Tool over 24 months		1,500,000	1,500,000		3,000,000
Contracted Services to update M&F Tool every year			750,000	1,500,000	2,250,000
WSDOT ArcGIS Seat seats		1,000	2,000	2,000	5,000
Annual cloud/hosting costs		75,000	150,000	150,000	375,000
License data from private vendors		100,000	200,000	200,000	500,000
WSDOT Staffing					0
Transportation Specialist 4	1.0	144,517	296,259	303,665	744,441
Transportation Technical Engineer	1.0	168,009	344,419	353,030	865,458
IT Data Management - Journey	0.5	79,697	163,380	167,464	410,541
IT System Admin - Journey	0.5	79,697	163,380	167,464	410,541
Total	3.0	2,297,921	3,569,437	2,843,623	8,710,981

More budget detail is in Appendix C

WORK PLAN

WSDOT's work plan for the ZEV-MFT should include the steps listed in Table 5.

Table 5. One-year work plan

Tasks	Time Frame
1. Use WSDOT's existing research contract with the University of Washington to prototype forecast elements of the ZEV-MFT.	Summer & Fall 2022
2. Hire project staff.	Summer 2022
3. Contract with an IT business analyst to help develop a scope of work for contracted services.	Summer 2022
4. Contract with an IT business analyst to develop a long-term data management plan.	Summer 2022
5. Select Option 1, 2 or 3 to implement the tool.	Fall 2022
6. Acquire additional ArcGIS seats and services from ESRI.	Fall 2022
7. Develop an RFQ/RFP to select one entity to provide forecast and analysis layers and develop routines that generate custom reports for different user types from those layers.	Fall 2022
8. Select an entity to provide annual forecasts of on-road light-, medium-, and heavy-duty vehicles and their composition by internal combustion engine, electric, and hydrogen, their associated charging and refueling infrastructure, the associated greenhouse gas and criteria pollutant emissions, spatial analysis of underserved areas, electric energy and capacity required by subarea, and potentially also the ZEV infrastructure requirements of public transit, marine, and aviation uses.	Fall 2022
9. Develop an advisory working group, including representatives from Commerce, Ecology, Office of Equity, the Utilities and Transportation Commission, Public Utility District association, investor-owned utilities, private charging network operators, public fleet operators, and clean transportation advocates to help establish priorities and provide feedback on early implementations of the tool.	Fall 2022
10. Develop a technical working group that includes representatives from universities, national labs, and consulting firms to review and comment on the forecast methods and results.	2023
11. Develop and implement a regular schedule of stakeholder outreach and engagement.	2023

The Legislature gave WSDOT an unprecedented assignment in HB 1287. None of the existing tools for helping states plan for ZEV infrastructure comes close to providing the functionality envisioned in the bill's description of the mapping and forecasting tool. Fortunately, WSDOT can build on the recent work of its neighboring states and province to identify the best practices to forecast charging and refueling infrastructure. WSDOT can also leverage its own experience with online mapping systems to assemble geographic information that is accessible to the public. By making information available to a wide range of stakeholders including utilities, cities, counties, tribes, and community groups, WSDOT's ZEV-MFT project will help inform more effective public investment decisions as our transportation system shifts away from fossil fuels toward low carbon alternatives.

CHAPTER 2
SMALL AREA FORECAST OF ELECTRIC VEHICLE ADOPTION IN WASHINGTON STATE

BACKGROUND

WSDOT's Innovative Partnerships Office contracted with the University of Washington's Sustainable Transportation Lab to develop light-duty electric vehicle registration forecasts by census tract for the coming years. This chapter describes the data sources and methods used for this task and presents the results obtained from the analysis work. In addition to this report, the Sustainable Transportation Lab has made the results from the different forecast approaches available to WSDOT in a CSV format.

Electric vehicle adoption is increasing in Washington state. Electric vehicles comprised 6.7 percent of all new light-duty vehicle registrations in Washington in the first nine months of 2022 (*1*). They also made up about 1.8 percent of the light-duty vehicle stock in Washington as of September 2022 (*2*). While EV adoption rates are increasing, they also vary widely across the state. King County is home to a quarter of all of Washington's light-duty vehicles but more than half of the state's EVs. The flip side of higher EV adoption in King County is low EV adoption in many rural counties. In September 2022, 10 percent of all census tracts in Washington still had fewer than 10 EVs registered. This strong geographic heterogeneity in EV adoption across Washington will likely persist until zero-emission vehicle sales mandates force lagging areas to catch up.

The adoption of EVs in the next two decades will be shaped by policies recently set by the Washington legislature: a target of 100 percent electric vehicle share of new light-duty vehicle sales by 2030 (*3*) and a requirement in Washington's Clean Vehicles Program for zero-emission vehicles to make up 100 percent of new sales starting in model year 2035 (*4*). Given the differences in EV adoption rates by subarea over the last decade, the regulatory requirement of 100 percent EV sales by 2035 will depend on customer preferences in some areas more than in others. In addition, EV adoption rates in different subareas will depend on local as well as national policies and incentives.

The forecasts presented in this chapter are based on the EV adoption trends in each census tract in Washington over the past 12 years. They do not account for potential future policy interventions, including Washington's regulatory ban on the sale of new light-duty vehicles with internal combustion engines in 2035. These forecasts are best understood as likely pathways of EV adoption by census tract if past trends prevail and are most useful for understanding how EV adoption will vary by locale. Whether a particular census tract hits an EV stock share of 20 percent in ten or thirteen years matters less for planning than knowing that one census tract is forecast to have twice the EV charging demand of another. By projecting plausible estimates of EV adoption by census tract, our forecasts can help state and local governments, electric utilities, property owners, and private charging companies make more informed decisions about where to invest to ensure adequate charging capacity for EV drivers in the future.

DATA AND METHODS

Data Sources

This section presents and references the various datasets used to forecast EV adoption across Washington by census tract. Not all of the listed data sources were used to produce the EV forecasts presented in the next chapter, but the datasets were used for model development and the comparison of different model configurations (as presented later).

For the purpose of this project, data were taken as of September 2022. In the future, the analysis and forecasting framework can be updated with more recent data, especially on EV and light-duty vehicle registration transactions.

Vehicles

The forecasted variable in this work is the electric vehicle market share of all light-duty vehicles, for each step in time and in each census tract in Washington, expressed as either the stock share or sales share. The former describes the share of EVs among the currently registered light-duty vehicle stock (i.e., the vehicles on the road), whereas the latter represents the share of EVs among new light-duty vehicle sales (i.e., the new vehicles entering the vehicle stock). Both quantities relate to each other. One can translate a forecast of annual new electric vehicle sales into a forecast of the total vehicle stock by using a fleet turnover model that appropriately accounts for vehicle entry into and retirement from the vehicle stock. This is done using Argonne National Laboratory’s VISION model, as described in the methodology section.

To derive past vehicle counts by census tracts, publicly available data provided by the Washington State Department of Licensing (DOL) were used that contained vehicle registration transactions tagged with the respective vehicle's census tract. Each vehicle's identification number (VIN) was truncated to include only the first 10 out of 17 digits, so that specific vehicles could not be identified from the data. While they were in similar formats, the data sets from the DOL were split between registration transaction records for all light-duty vehicles (2) and for electric vehicles only (5).[1] For each point in time (month) and for each census tract, a light-duty vehicle count was derived by summing up all new vehicle sales ("Original Registration"[2]) and all vehicle registration renewals ("Registration Renewal") over the past one year (365 days)[3]. These vehicle counts represented the currently registered number of light-duty vehicles for a specific point in time (month) and census tract. Similarly, by summing only over the past one month, a count of new vehicle sales, used vehicle sales, and registration renewals could be derived by counting the "Original Registrations," "Registrations at Time of Transfer," and "Registration Renewals." This process scanned over 39 million past vehicle registration transaction records. Vehicle counts for each month before 2018 were derived from population data for each census tract from 2011 to 2017. The monthly 2018 vehicle counts were scaled according to the relative difference between each census tract's population in the years from 2011 to 2017 and in 2018. This was necessary because registration data for all vehicles were only available from 2018 on. However, registration data for EVs were available for all months back to 2011.

By using the respective counts for all light-duty vehicles and for EVs only, EV shares could be derived as the quotient of EV count and all light-duty vehicle count: EV share of registered vehicles (EV stock share), EV share of new vehicle sales (EV sales share), EV share of used vehicle sales, and EV share of vehicle registration renewals. Since

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[1] Vehicle registration records are publicly available from January 2020 to September 2022. The UW research team worked with the DOL to provide vehicle registration data dating back further than the publicly available dataset. The DOL provided the equivalent vehicle registration data going back to January 2017 so that light-duty vehicle counts could be derived from January 2018 to September 2022.

[2] This and the following expressions in quotation marks denote the transaction type data tags used by the DOL to denote new vehicle registrations, used vehicle registrations, and registration renewals. For more information on this labeling, see https://data.wa.gov/Transportation/Vehicle-Registration-Transactions-by-Department-of/brw6-jymh under "About this Dataset".

[3] Vehicle registration data for one full year before the point in time of interest were required because passenger vehicle registration renewals are required once per year in Washington.

there were 141 months between January 2011 and September 2022 and 1,458 census tracts in Washington[4], 205,578 data points resulted for each of these variables.

Gas Prices

Historic average Washington gas prices for each month since 2011 were taken from the U.S. Energy Information Administration (*6*). The "Washington All Grades Conventional Retail Gasoline Prices" were used in dollars per gallon, representing monthly average gasoline prices in Washington.

EV Charging Stations

Information on the location, type, and quantity of public electric vehicle charging stations was taken from the National Renewable Energy Lab's (NREL) Alternative Fuel Data Center (AFDC) (7). The dataset is a record of all public EV charging stations across the United States. Using the stations' geographic location (latitude, longitude), the respective census tract was derived in which the charging station was situated. With these data, along with station opening dates, the number of all Level 2 and DC fast charging stations was derived for each census tract and month since 2011.

EV Product Variety

The number of EV models available to consumers was estimated by counting the number of unique make/model combinations in Washington at every point in time since 2011. This was done by using the same EV registration transactions dataset used to derive EV counts (see above). The data contained entries of each vehicle's make and model, which were used to identify the unique make/model combinations (such as Tesla Model 3 or Volkswagen ID.4).

Socioeconomic Data

Socio-economic data by census tract were taken from the U.S. Census Bureau's American Community Survey (ACS) five-year estimates for each year from 2011 to 2020 (*8*). These data are released annually for each census tract. At the time of this project, 2021 ACS data had not yet been released; hence, 2020 data were assumed for 2020, 2021, and 2022. These data contain counts of the number of people in each census tract that share certain social, racial, economic, or other properties. Using these counts, the following quantities could be derived from the ACS data: median household income, fraction of

[4] As defined in the 2010 U.S. Census Bureau census tract designations.

residents who were white, share of people with a Bachelor's degree or higher, and share of people living in single-family homes.

Census Tracts

Information on the shape and number of census tracts across Washington was taken from the U.S. Census Bureau. The Bureau changed its census tract designations in 2020, resulting in slightly different numbers of census tracts in Washington because of mergers and splits of neighboring census tracts. The vehicle registration data used to derive census tract-level EV shares were given in the 2020 census tract designation, while all socioeconomic data (from the ACS) before 2020 were given in the 2010 census tract designation. A relationship file was used to convert the vehicle counts and derived EV shares into the 2010 census tract designations.[5]

In addition, GIS shapefiles of Washington census tracts as provided by the U.S. Census Bureau[6] were used to display results on a map.

METHODS

The chosen method projected past EV adoption trends in the different census tracts into the future, with the assumption that both EV sales share and EV stock share (as defined in the previous section) follow an S-shaped technology adoption curve over time, as has been observed with the diffusion of most new technology, including in the automotive sector (*9*, *10*).

The monthly, census tract-level EV shares (stock share and sales share) were first analyzed in regard to geographic and temporal trends. The research team used multiple methods of data visualization to illustrate the strong geographic heterogeneity across Washington in terms of EV adoption levels. The team also produced a set of descriptive statistics, which also included the time trend of the number of EV models (battery-electric

[5] Because Washington grew in the decade from 2010 to 2020, most census tract changes were cases in which a census tract from the 2010 designation was split into two (or more) new census tracts in the 2020 designation. Because of this, the research team decided to express the vehicle counts and EV shares in the 2010 census tract designation. For this, 2020 census tracts were assigned to the 2010 census tract that their area predominantly composed, using the respective census tract relationship file available at https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.html.

[6] The shapefiles are available under https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

vehicle (BEV) and plug-in hybrid electric vehicle (PHEV)) available to Washington consumers.

General Note on Forecasting

Niels Bohr, 1922 Nobel laureate in physics and father of the atomic model, is claimed to have said: "Prediction is hard, especially about the future."[7] This phrase is a reminder that any forecast of uncertain processes, including the mass market adoption of new technologies such as electric vehicles, poses challenges. As a general rule, it is hard to rely on out-of-sample predictions, which in this case means using the past to project the future. This holds true especially regarding predictions on data points that are farther away from the sample data used to calibrate the forecasting model (here: later years in the forecast).

In regard to EV adoption, changes in consumer purchasing behavior, gas prices, product availability, or major policy interventions (and more) could alter EV adoption rates. The forecasts produced by the UW research team relied on the past trends and geographic heterogeneity in EV adoption across the state to develop plausible future adoption scenarios by census tract. Even if they do not turn out to be precisely correct, they may nonetheless be useful in helping charging networks, state and local governments, and utilities evaluate the relative demand for future charging among different locales. As plausible estimates of future EV adoption, these forecasts can serve as one input in developing plans to ensure that local areas will have sufficient capacity from the electric grid and charging stations to meet the projected growth over the next decade.

Forecasting Model

To produce monthly, census tract-level forecasts of EV adoption in Washington, a logistic regression model with a logit-transformed dependent variable representing EV market penetration was used. The dependent variable was the electric vehicle share of either new light-duty vehicle sales (sales share) or the light-duty vehicle stock (stock share). Choosing these two alternative approaches was mainly motivated by the following:

1. Charging infrastructure needs are determined by the number of EVs on the road (stock share).

[7] https://quoteinvestigator.com/2013/10/20/no-predict/

2. State goals are defined in terms of the EV sales share (e.g., 100 percent sales share by 2030 or 2035).

The logistic regression model deployed in this project was expressed with the following equation:

$$\log\left(\frac{p_{it}}{1-p_{it}}\right) = y_0 + \beta_i + \gamma_t + \epsilon_{it}$$

Here, the indices *I* and *t* represent the respective census tract and point in time (month), respectively. Then *p* denotes the EV stock share or sales share (derived from the DOL vehicle registration data as described in the previous section). The transformation using the logarithm of the so-called odds $p_{it}/(1-p_{it})$ ensures that the dependent variable p_{it} will always assume values between 0 and 1 and will move from 0 to 1 as the right hand side of the equation increases. There, y_0 is a constant. The β_I represents census tract-specific fixed effects, quantifying each census tract's propensity for EV adoption. Accordingly, the Υ_t represents time fixed effects, quantifying the general statewide trend toward increasing EV adoption over time. These three quantities[8] are parameters whose values are estimated through the model fitting process. The ε_{it} respresents the residuals of the model (i.e., the difference between predicted and observed value).

In addition, model runs were conducted that included some or all of the following independent variables:

- Public charging station availability
- Race (share of white/non-white people)
- Education (share of people with a college degree)
- Housing type (share of people living in single-family units)
- Median household income
- Gas prices
- EV product variety (number of available EV models).

[8] More precisely, it is 1 + 1458 + 141 = 1600 parameters, reflecting the number of different census tracts *i* and time steps *t* in the data used to fit the model.

In these models, each of the included variables had a model parameter assigned to it whose value was derived as part of the fitting process. The model equation then took the form

$$\log\left(\frac{p_{it}}{1-p_{it}}\right) = y_0 + \beta_i + \gamma_t + \sum_v \alpha^v x_{it}^v + \epsilon_{it} \qquad \text{(Equation 1)}$$

where α^v is the model parameter for variable v (one of the ones listed above), and x^v_{it} is the variable's numeric value in census tract i and in time step t.

The census tract-level fixed effects (β_i) were intended to capture the heterogeneity in terms of EV adoption levels observed between census tracts. These effects were assumed to remain constant over time, corresponding to a continuation of the trend that some areas of the state adopt EVs sooner and faster than others. The time fixed effects (Υ_t) were intended to capture the general statewide rise in EV share over time. These effects were quantified for each step in time in the model fitting process and then were extrapolated into the future based on the observed past trend. This part of the model reflected the assumption of a continuation of past trends in EV adoption. The model used to forecast EV adoption in the state, at this point, was thus not sensitive to specific EV-related policy changes imposed on the federal, state, or local levels, including sales incentives or the installation of public or at-home charging infrastructure.

This forecasting approach yielded two separate forecasts:

1. One forecast of the EV stock share based on the EV stock share as the dependent variable (p_{it})
2. One forecast of the EV sales share based on the EV sales share as the dependent variable (p_{it}).

The two approaches yielded census tract-level results for each month from the present through 2035. The results can be examined at the census tract level or aggregated to statewide EV shares by using the total light-duty vehicle count in each census tract. More specifically, the statewide EV sales or stock share $p_{WA,t}$ can be derived from the census tract-level results by using

$$p_{WA,t} = \frac{\sum_i p_{it} \cdot n_{it}}{\sum_i n_{it}},$$

where n_{it} is either the number of all light-duty vehicles or the number of new vehicle sales in census tract i at time step t.

Vehicle Stock Turnover Model

The Argonne National Laboratory (ANL) developed a model, called VISION, to estimate energy use and carbon emission impacts of the adoption of various advanced vehicle technologies (*11*). The model can be used to simulate the turnover of a vehicle fleet (or stock) given certain market shares of different vehicle technologies over time. To accomplish this, VISION keeps track of different vehicle vintages and retirement cycles based on data for the average lifetimes of light-duty passenger vehicles and the typical dynamics of the used vehicle market.

Using VISION in its current 2022 version, the statewide EV adoption forecast results obtained from the model developed in this project could be converted into the following alternative quantities:

1. The statewide EV stock shares over time could be converted into statewide EV sales shares that would be required to yield the forecasted stock shares.
2. The statewide EV sales shares over time could be converted into statewide EV stock shares that would result from the forecasted sales shares.

Because VISION is spreadsheet-based and non-programmable, fleet turnover dynamics were not simulated for all 1,458 census tracts of the state but only for the statewide results and for specifically selected census tracts.

RESULTS

Characterization of the EV Fleet Across Washington: Past and Present

Washington state is one of the leading states in the U.S. in terms of electric vehicle adoption (*12*). Given the DOL vehicle registration data used in this work, in the first nine months of 2022, the EV share of new light-duty vehicle sales was 6.7 percent. EVs also made up about 1.8 percent of Washington's 2022 light-duty vehicle stock, as shown in Table 6. About 76 percent of the electric vehicles in Washington were all-electric models (BEVs), with the rest being plug-in hybrids (PHEVs). As of September 2022, all but two Washington census tracts had at least one electric vehicle registered in its light-duty vehicle stock, representing 99.94 percent of Washington's population. While 90 percent of all census tracts had at most 174 registered EVs, the leading tract had 722 EVs registered (in the City of Issaquah). The highest EV share in the light-duty vehicle stock in one census tract was 12.5 percent (520 of 4,159 light-duty vehicles, in Belltown in the City of Seattle).

Table 6. Statewide means and median of census tracts in terms of EV share in Washington's light-duty vehicle stock.

Vehicle Type	Statewide Mean	Median of Census Tracts
Electric Vehicle	1.79%	1.12%
Battery Electric Vehicle	1.36%	0.78%
Plug-In Hybrid Electric Vehicle	0.43%	0.34%

The statewide distribution of EV stock share by census tract is shown in figures 3, 4, and 5. Figure 3 shows a map of the EV stock share in Washington's census tracts in 2015 and 2022. As one can see in these maps, the EV share in the light-duty vehicle stock substantially increased in the seven years from 2015 to 2022. In 2015, the vast majority of tracts had less than 0.5 percent of EVs registered in their vehicle stock. Only some tracts in the Puget Sound region, most of them in King County, had EV shares of more than 0.5 percent, with only a handful exceeding 1.79 percent (the 2022 statewide mean EV stock share). By 2022, EV shares had increased in all census tracts, with 18 percent (or 259) of all census tracts exceeding an EV stock share of 3 percent; 61 tracts had an EV share of 6 percent or more. These leading tracts were geographically concentrated around Lake Washington and Lake Sammamish in the cities of Seattle, Sammamish, Issaquah, Bellevue, and Mercer Island (in no particular order). Generally, most of the high-adopting tracts were located in the west and northwest of the state, with notable exceptions around Vancouver, the Tri-Cities, and Spokane.

Figure 4 shows the distribution of the EV stock share across Washington's census tracts. The chart shows that most census tracts had EV shares of less than 2 percent. The median tract had 1.12 percent EVs in its light-duty vehicle stock. About one third of all census tracts (486) had an EV stock share that was above Washington's statewide mean of 1.79 percent.

Figure 5 displays the per-county number of EVs by plotting the number of all light-duty vehicles (of any powertrain) against the share of EVs in the county vehicle stock. Each bar represents one Washington county, and the area of each bar corresponds to the number of EVs in each respective county. The top eight counties in terms of EV stock share are color coded. King County was the leading county in the state both in terms of EV share

(3.6 percent) and in the total number of EVs (about 56,000). King County thus represented more than 53 percent of all EVs in Washington (in comparison to only 26 percent of all light-duty vehicles). This highlights the strong propensity for EV adoption in King County, which was substantially above most of the other counties. In addition, all top eight counties in terms of EV share were located in the west of the state. San Juan County had the second highest EV share (at 3.3 percent) but represented only a small total number of EVs (as it is a small county with comparatively few registered vehicles).

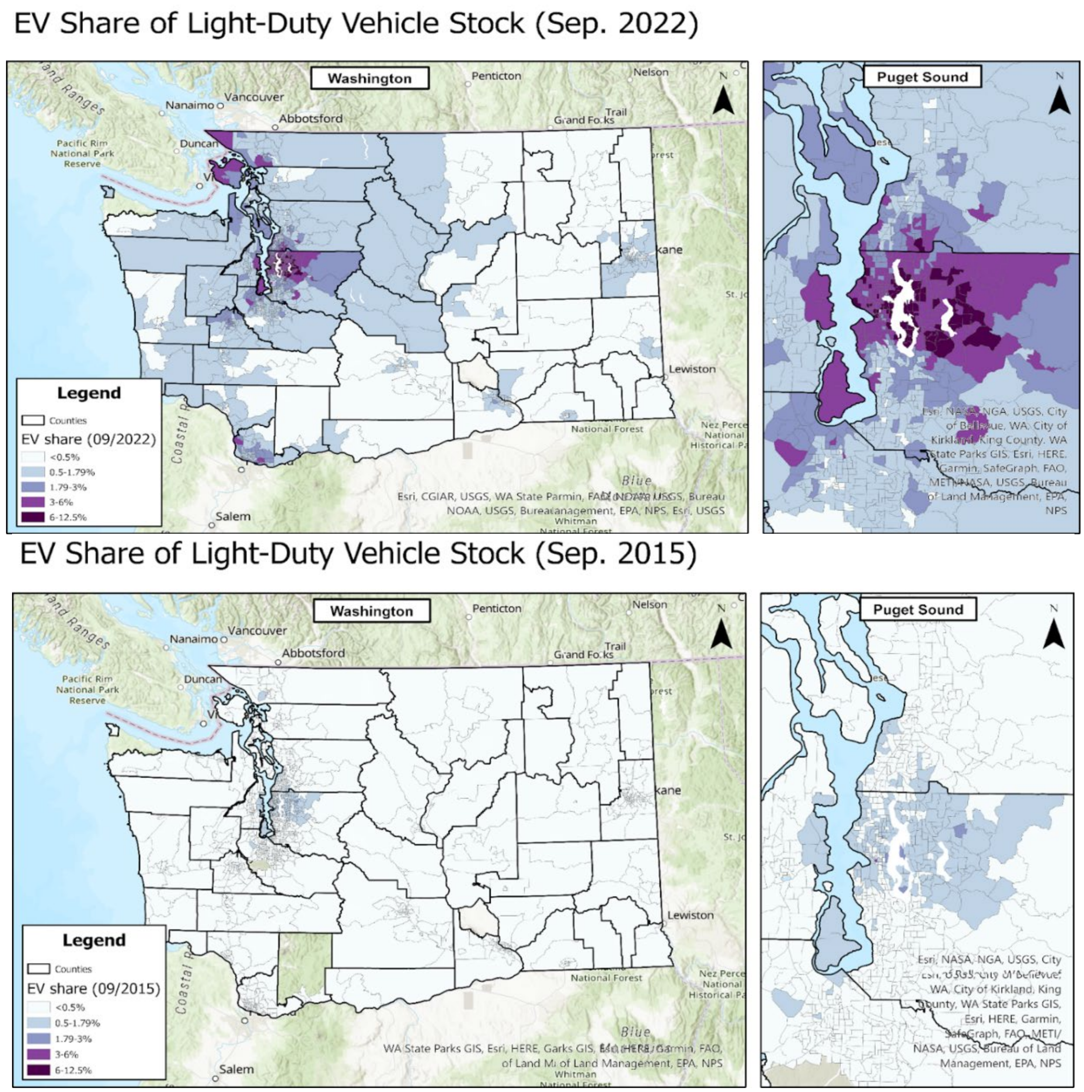

Figure 3: Census tract-level map of the EV share in the light-duty vehicle stock in 2015 and 2022

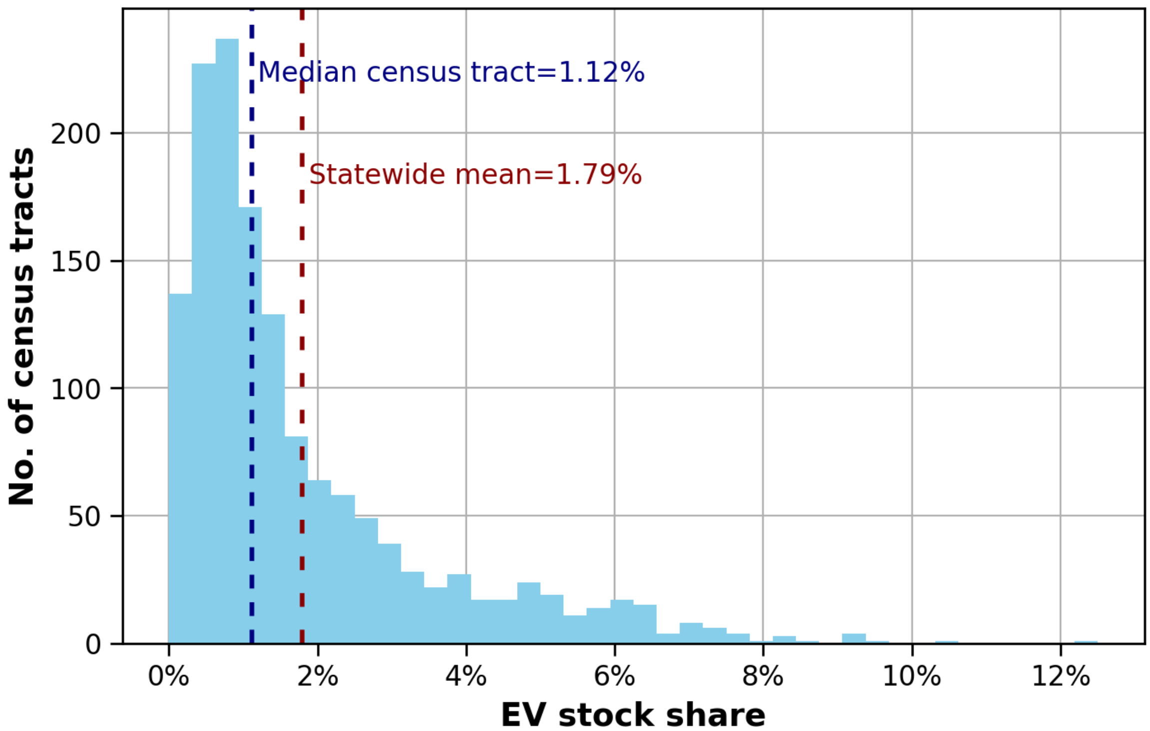

Figure 4: Distribution of EV share in the light-duty vehicle stock in Washington by census tract (as of September 2022).

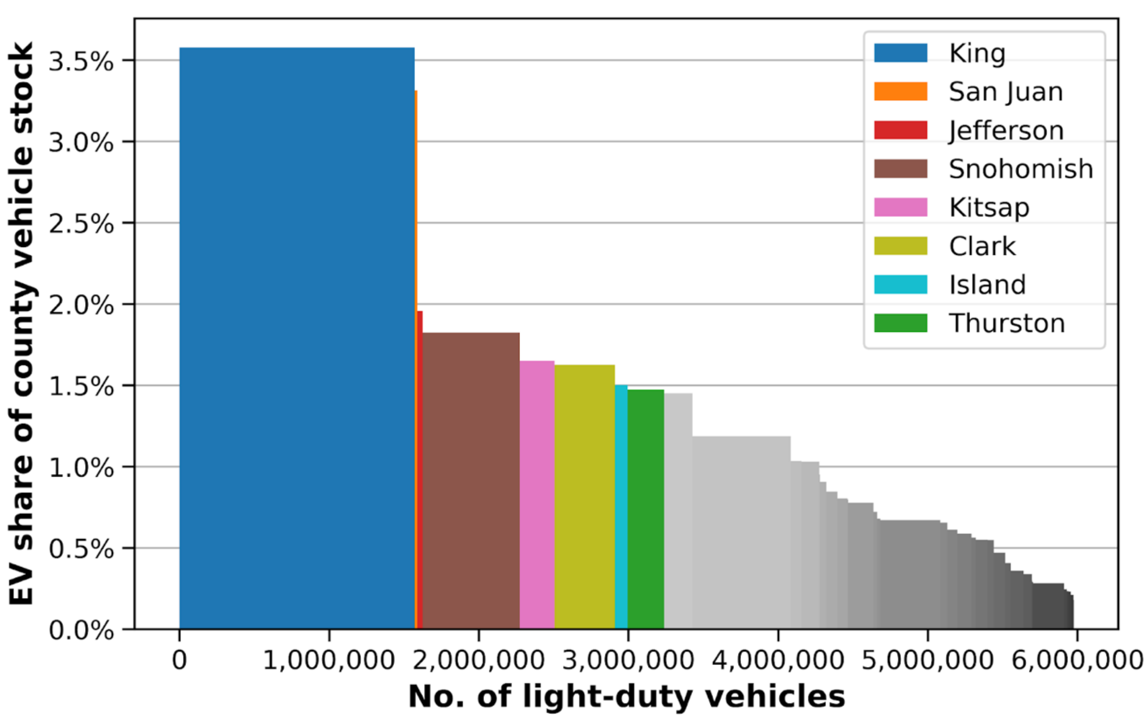

Figure 5: EV share and number of light-duty vehicles in Washington counties (as of September 2022).

The tables and figures above illustrate the strong geographic heterogeneity in EV adoption across Washington state, as well as an overall increasing time trend in the number of registered EVs. Most of Washington's EVs have been registered in a relatively small number of counties or census tracts. These two observations also indicate that using a model with census tract fixed effects (to represent the geographic heterogeneity) and time fixed effects (to represent the statewide trend toward increasing EV adoption) is sensible.

Over time, more and more EV product variety has given consumers more choice among different EV makes and models, as shown in Figure 6. As of 2022, there were more than 120 unique make-model combinations among the EVs registered in Washington, 60 of which were battery-electric models.

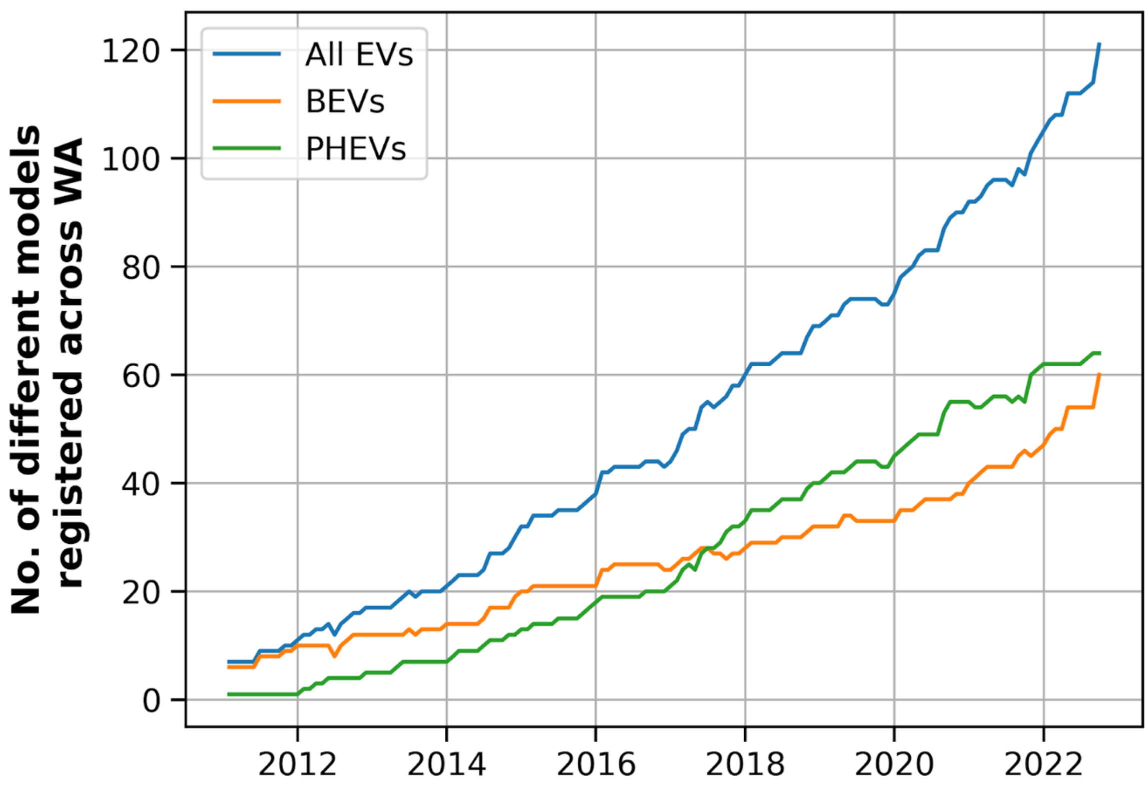

Figure 6: Number of different EV models registered across Washington over time.

Among these models, the Tesla Model 3 comprised more than 25 percent of all registered BEVs in Washington, as can be seen in Figure 7 (left). The top four BEV models (Tesla Model 3, Tesla Model Y, Nissan Leaf, and Tesla Model S) made up 69 percent of the BEVs registered in Washington, representing a very high market concentration. The 50 BEV models with the lowest market share represented only 12.5 percent of Washington's

BEV stock. Similarly, the right hand side of Figure 7 shows the market share of the different PHEVs' in Washington's PHEV stock. With the market concentration being slightly lower than that for BEVs, the top two PHEV models (Chevrolet Bolt and Toyota Prius Prime) comprised about 30 percent of all PHEVs in Washington.

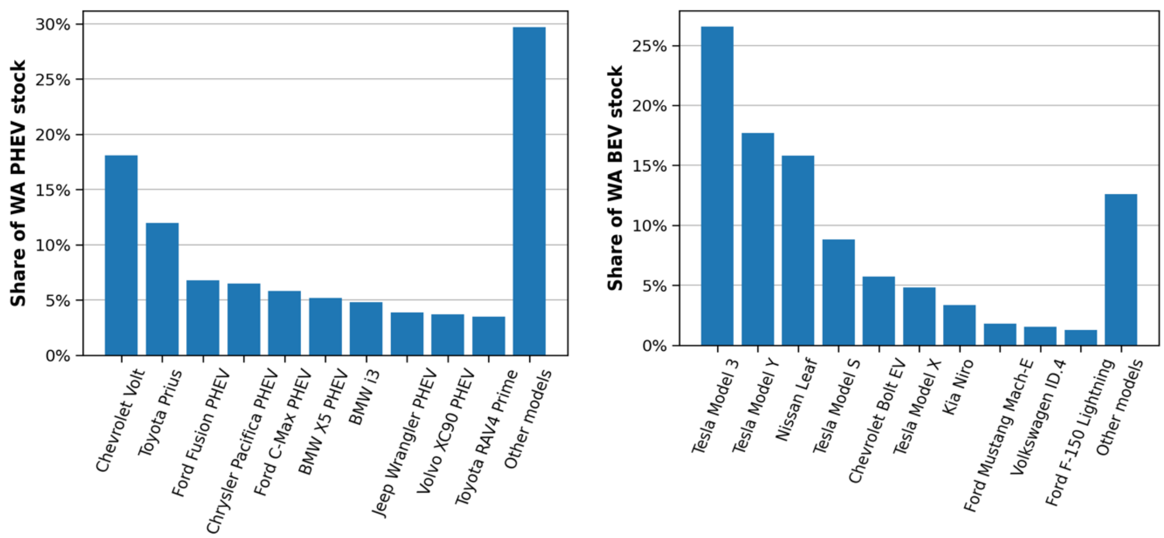

Figure 7: Distribution of unique EV models among Evs registered in Washington (as of September 2022). Left: BEVs. Right: PHEVs

<u>Regression Model Specifications and Their Predictive Power and Limitations</u>

As part of this work, different model specifications were tested to understand their respective ability to predict past EV adoption patterns across the state. Table 7 shows the results of this process. The table lists different model specifications (that are defined by the different sets of predictors or independent variables included in the model formulation, see Equation 1). The coefficient of determination (or R^2) describes the proportion of the variation present in the dependent variable (e.g., EV stock share) that is explained by the chosen set of predictors. The share of residuals within a certain range shows what share of the data points could be explained by the model with a certain maximum deviation from the input data. Higher shares in either of these indicators mean a greater predictive power by the chosen model. As one can see from the table, all models achieved comparable results in terms of their ability to predict a large majority of the EV stock share data points across Washington since 2011. In model configurations with more independent variables (in addition to or instead of the time and census tract fixed effects), more than 60 percent of the EV stock shares across all census tracts in all months since 2011 could be predicted with a deviation of less than 0.1 percentage point, and more than 95 percent of the data points could be predicted with a deviation of less than 1 percentage point. Different subsets of predictors appeared significant in different model configurations to predict EV adoption in Washington. The sign of each predictor (i.e., whether or not a certain variable was positively linked with higher EV adoption) varied depending on the chosen subset of the predictors, since many were cross-correlated (such as the percentage of people with a Bachelor's degree and the median household income in a given census tract).

Table 7: Explained variation in the data in different model configurations (different sets of predictors) for the model with the EV stock share as the dependent variable. The asterisks (*) denote significant variables.

Predictors	**Coefficient of determination (R^2)**	**Share of residuals within +/- 0.001=0.1%**	**Share of residuals within +/- 0.01=1%**
Time fixed effects Census tract fixed effects	0.8253	53.5%	88.4%
Time fixed effects Census tract fixed effects No. of charging stations Pct. Of white people (*) Pct. With Bachelor degree Pct. In single-family units (*) Median household income (*)	0.8264	61.0%	95.0%
Time fixed effects Census tract fixed effects No. of charging stations (*)	0.8253	60.8%	94.3%
Time fixed effects Census tract fixed effects No. of charging stations Median household income (*)	0.8263	61.0%	94.9%
No. of charging stations Gas price (*) EV product variety (*) Pct. Of white people (*) Pct. With Bachelor degree (*) Pct. In single-family units (*) Median household income (*)	0.8263	61.0%	94.9%

A reasonably high predictive power can be achieved in the model that includes only the time and census tract fixed effects (first row in Table 7). This model does not rely on data or forecasts of any of the other independent variables (such as socioeconomics or charging station availability) to make predictions on either historic or future EV adoption. This observation suggests that it is a sensible approach to select the model with only the time and census tract fixed effects for the purposes of EV adoption forecasting. In other words, most of the variation that *can* be explained is explained by the heterogeneity of the state (census tract effects) and an overall time trend of rising EV adoption (time effects). This choice is furthermore supported by the fact that identifying causality between any of the independent variables and the dependent variable (i.e., the EV stock share or sales share) is difficult. This is because there is not a clear directionality between certain quantities, such as EV adoption and charging station availability.[9] Assuming a certain directionality in these correlations might not always hold true. In addition, not all of the independent variables, in particular not the socioeconomic data, represent policy levers that can be manipulated through federal, state, or local policies to increase EV adoption.[10]

EV Adoption Forecasts

This section presents and discusses some of the results obtained from the EV adoption forecasts produced in this project. Census tract-level forecasts until 2035 were produced in terms of the EV share of new light-duty vehicle sales (sales share) and the EV share of all registered light-duty vehicles (stock share). These forecasts were obtained from using either the EV sales share or the EV stock share as the dependent variable in the forecasting model and then converting the forecast results into the respective other variable using ANL's VISION model, as described in the methodology section.

Figure 8 shows the results aggregated to show the statewide EV sales shares (left) and stock shares (right) over time in comparison to the statewide target of 100 percent EV sales share by 2030 (light blue) and the requirement of 100 percent ZEV sales share by 2035 (dark blue). The forecasts obtained from using the EV stock share as the dependent

[9] Access to EV charging stations may increase the likelihood for adopting EVs, but there is also an observed trend that public charging infrastructure is typically built in areas with higher EV adoption because station operators expect higher utilization and revenue in such areas.

[10] For example, while higher incomes are typically linked with higher EV adoption rates, increasing the median household income in all areas of the state is, while a desirable outcome, not a direct incentive for EV purchases, especially among groups with historically below-average EV adoption.

variable are shown in red, and those from using the EV sales share are in orange. Past EV adoption is shown with the black data points to the left of the vertical line that marks today. As one can see, neither of the two forecasts produced in this work projected that Washington will hit either the goal of 100 percent EV sales share by 2030 or the mandate of 100 percent ZEVs by 2035, based on past trends. The forecast obtained from using the EV sales shares as the dependent variable projected a higher EV adoption than the other one, with the 2035 sales share reaching 34 percent by the end of 2030 and 67 percent by the end of 2035. The S-shaped EV adoption pathway in this forecast resulted in an EV stock share of 25 percent by the end of 2035.

One additional relevant takeaway from the vehicle stock turnover modeling using ANL's VISION model is that, even in the scenario of 100 percent EV sales share by 2030, the EV stock share did not exceed 60 percent by 2035, as it would take time for the whole vehicle fleet to gradually be replaced with electric vehicles.

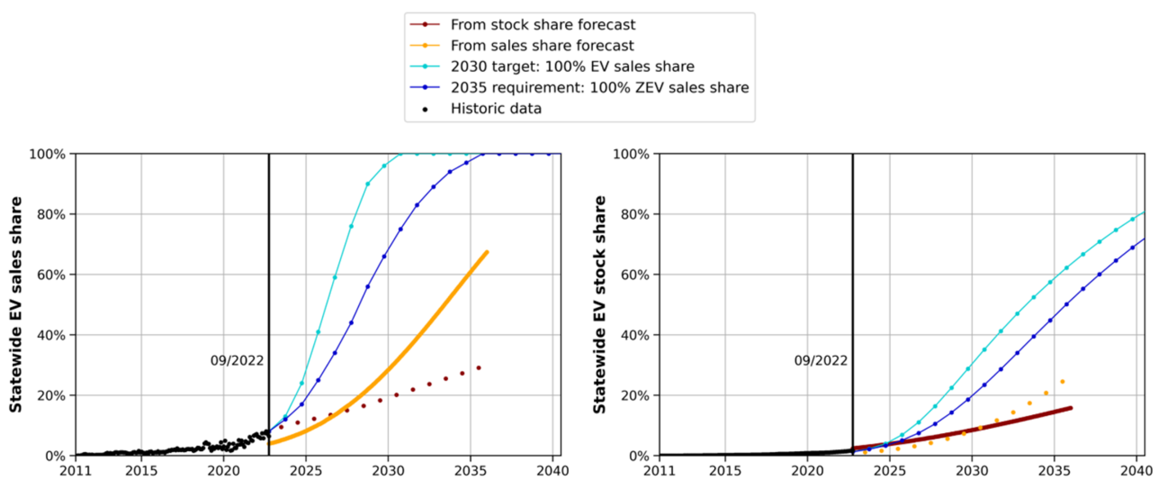

Figure 8: EV adoption forecast results in terms of statewide EV sales shares (left) and stock shares (right).

Figure 9 shows the results from the forecast using the stock share as the dependent variable (red lines in Figure 8) on a map with the census tract-level EV stock share in 2035. In comparison to the maps shown in Figure 3 for 2015 and 2022, the EV share in the light-duty vehicle stock was forecasted to increase substantially. The map in Figure 9 is characterized by an overall larger number of areas across the state, with EV stock shares exceeding 6 percent. Yet, as the figure also reveals, an even stronger geographic heterogeneity would result if past trends of EV adoption across Washington were used to project the future: Some census tracts were characterized by fast EV adoption pathways, with EV stock shares reaching more than 50 percent and up to 73 percent in the fastest-adopting census tract. On the other hand, other tracts would still have EV shares of less than 0.5 percent in their vehicle stock (white tracts in Figure 9), implying an even greater discrepancy between the highest- and lowest-adopting census tracts across Washington. These highly lagging census tracts could be specifically targeted by policies and state grants to accelerate local EV adoption.

The map also reveals that the west and northwest regions of the state would be likely to remain leading in Washington's EV adoption pattern if past trends prevailed. Especially areas in and around the Puget Sound were among the highest adopting tracts projected in this forecast.

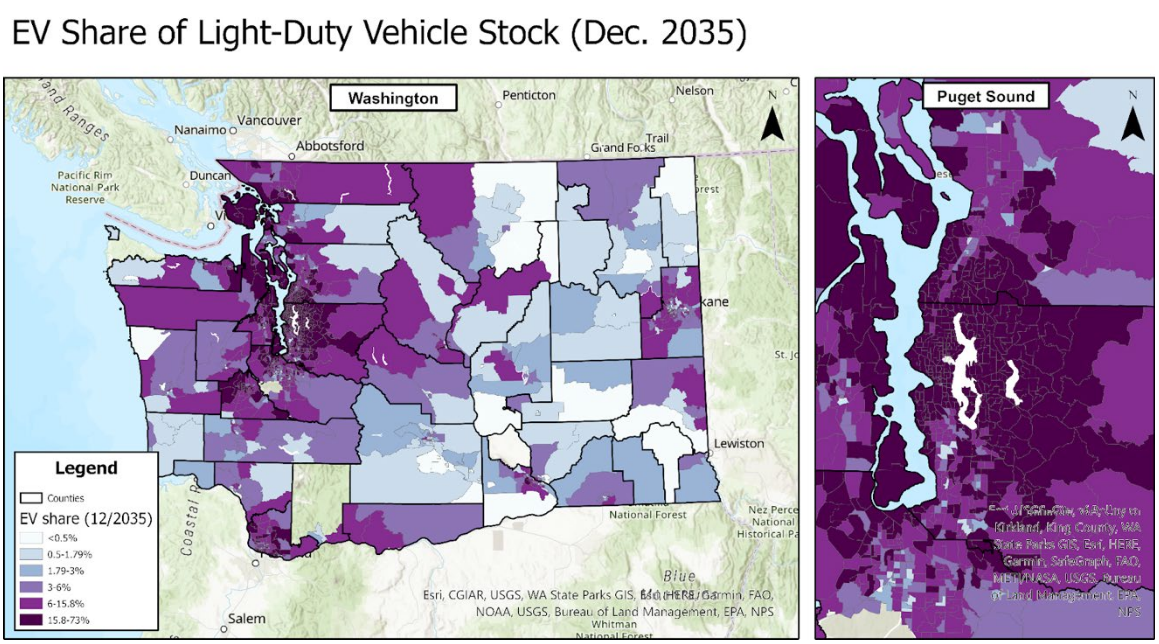

Figure 9: Census tract-level map of the EV share in the light-duty vehicle stock in Washington in 2035 based on the forecast using the EV stock share as the dependent variable.

Figure 10 shows the results from the forecast using the EV sales share as the dependent variable (in orange) for the 95th percentile census tract[11] (tract number 53033028600, in West Seattle). The 95th percentile represents a tract with very high EV adoption. As can be seen from this graph, the state's leading census tract might be able to

[11] 95th percentile in terms of forecasted EV sales share at the end of 2035.

get close to the 2035 EV sales share requirement of 100 percent, even if past trends of EV adoption prevailed. This tract would reach a 90 percent EV sales share by the end of 2035 in this particular forecast. The EV stock share in that census tract would closely follow the stock share that would result from reaching the 2035 ZEV sales requirement (in dark blue), with an EV stock share exceeding 40 percent by 2035.

The results showed that, while the state average might not be on track to achieve or get close to either of the two EV adoption targets, Washington's leading census tracts might very well be. That being said, based on historic trends, a considerable geographic heterogeneity in EV adoption could remain across the state. Targeted policies for low-adoption areas, particularly in rural Washington in the east and south, could help mitigate the gap between the leading and lagging census tracts. Especially those tracts and areas projected to continue having a very low EV share in 2035 (e.g., the white tracts in Figure 9) could be the focus of such policies, including on the county and municipal levels.

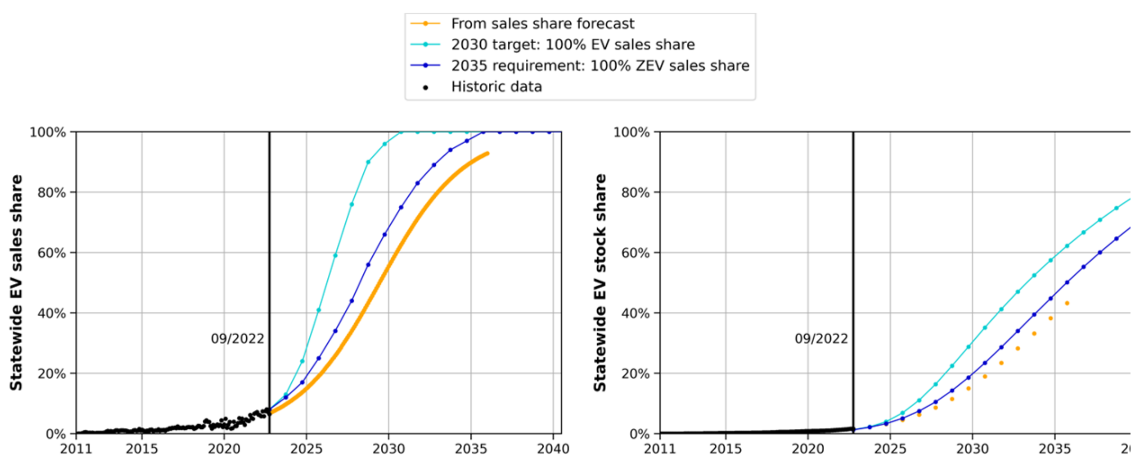

Figure 10: EV adoption forecast results in terms of statewide EV sales shares (left) and stock shares (right) in the 95th percentile census tract (i.e., a high-adopting census tract, located in West Seattle).

IMPLICATIONS FOR SUPPORTING EV ADOPTION ACROSS WASHINGTON

These forecasts imply that the product, price, and policy trends of the last 10 years won't result in EV adoption rates that are rapid enough to achieve the state's official policy goals. While new vehicle models, falling prices, and new federal and state policies may alter the underlying trends, our modeling built in some of that already by describing the adoption process with an S-shaped adoption curve. Actual EV adoption rates will be influenced by future policy measures, gas prices, vehicle supply chain constraints, availability of charging infrastructure, and other factors that could yield higher or lower adoption rates than presented in our forecasts.

Nonetheless, the outcomes of this analysis suggest that binding ZEV requirements for new vehicles will be necessary to achieve 100 percent by 2030 or 2035. To get the EV market share beyond the early adopters, people who have historically not considered buying an electric vehicle will need to be convinced. For this, ensuring that new EV buyers have a good experience with their vehicles is key to increasing adoption as the market grows beyond early adopters.

CHAPTER 3
EVALUATING FUTURE DEMAND FROM LIGHT-DUTY ELECTRIC VEHICLES AT DC FAST CHARGE STATIONS ON WASHINGTON STATE HIGHWAYS

BACKGROUND

In recent years, federal and state policymakers have allocated public funds to WSDOT to make grants to accelerate the construction of DC fast charge stations. WSDOT staff need to make decisions about the locations and plug configurations of charging stations that will receive grant funds. Our research discussed in this chapter evaluated where stations are needed and how different station configurations affect charging times and the potential waiting time for a free plug to start charging.

WSDOT has multiple objectives in deciding which stations to fund; our analysis focused on four in particular:

1. WSDOT wants to ensure adequate electric power supply along state highways to meet future charging demand.
2. WSDOT wants coverage across the state highway system. We used the standard of having a charging station every 50 miles or less for any trip along the shortest route between two ZIP codes in the state.
3. WSDOT wants low to no wait times at stations in the early years. The state anticipates rapid growth in EVs over the next decade so stations should have excess capacity in early years to accommodate growth and provide the best possible charging experience for recent adopters.
4. WSDOT wants to avoid large amounts of unused charging capacity. While WSDOT anticipates building in excess capacity to accommodate growth, investing public funds in too much excess capacity could undermine the coverage goal of the first objective and invite criticism for being wasteful.

Station sizing and other design parameters should be informed by station performance under realistic current and future scenarios. To quantify system-level performance, we identified highway segments that are infeasible to travel for the typical EV (see section on Task 1). As part of Task 3, we developed a map identifying the long distance power demand throughout the highway network. Together, these identified the aggregate quantity and power of stations required to support long distance within-state EV travel across any highway corridor.

To quantify station-level performance, we developed a queueing simulation model. This quantified performance more precisely by modeling the interaction between simulated EV drivers and a theoretical charging station with customizable parameters (e.g., plug count, power). Several scenarios were tested to demonstrate the model and estimate station performance under current and future conditions.

MAP OF WASHINGTON STATE HIGHWAY POWER DEMAND

The aggregate power demand for a highway segment can inform high-level decisions on corridor prioritization and station sizing. To this end, we developed a map of theoretical power demand by long distance EVs on the Washington state highway network. Long distance trip counts between ZIP codes were estimated by using a gravity model (13). The resulting trips were assigned to the state highway network on the basis of the shortest path between ZIP codes.

An EV traveling a roadway segment at a fixed speed consumes a certain amount of energy (kWh) per mile, depending on the energy efficiency of the vehicle. This power demand can be expressed in kW by assuming a fixed speed (mph). This power represents the energy consumed on the segment per unit of time per vehicle.

The equation below shows the calculation of power demand in kW from a given MPGe value.

$$\frac{gallon\text{-}eq}{mi} * \frac{kWh}{gallon\text{-}eq} = \frac{kWh}{mi} * \frac{mi}{h} = kW$$

We assume a fixed speed of 60 mph. A lower speed would decrease power demand. The equation below shows the calculation of a fixed power demand for each EV traveling the network.

$$\frac{1}{95} * \frac{33.7}{1} = 0.35 * \frac{60}{1} = 21\ kW\ (energy\ per\ second\ per\ vehicle)$$

This metric slightly overestimates power demand, as all EVs will begin with some initial state of charge that does not necessarily need to be met by direct current fast charging (DCFC) stations on each road segment. Regardless, we multiply this instantaneous power demand by the long distance average annual daily traffic (AADT) for each segment and the current state BEV share (0.94 percent) in 2022. This produces a map of average power demand for each corridor in the state (Figure 11) in 2022.

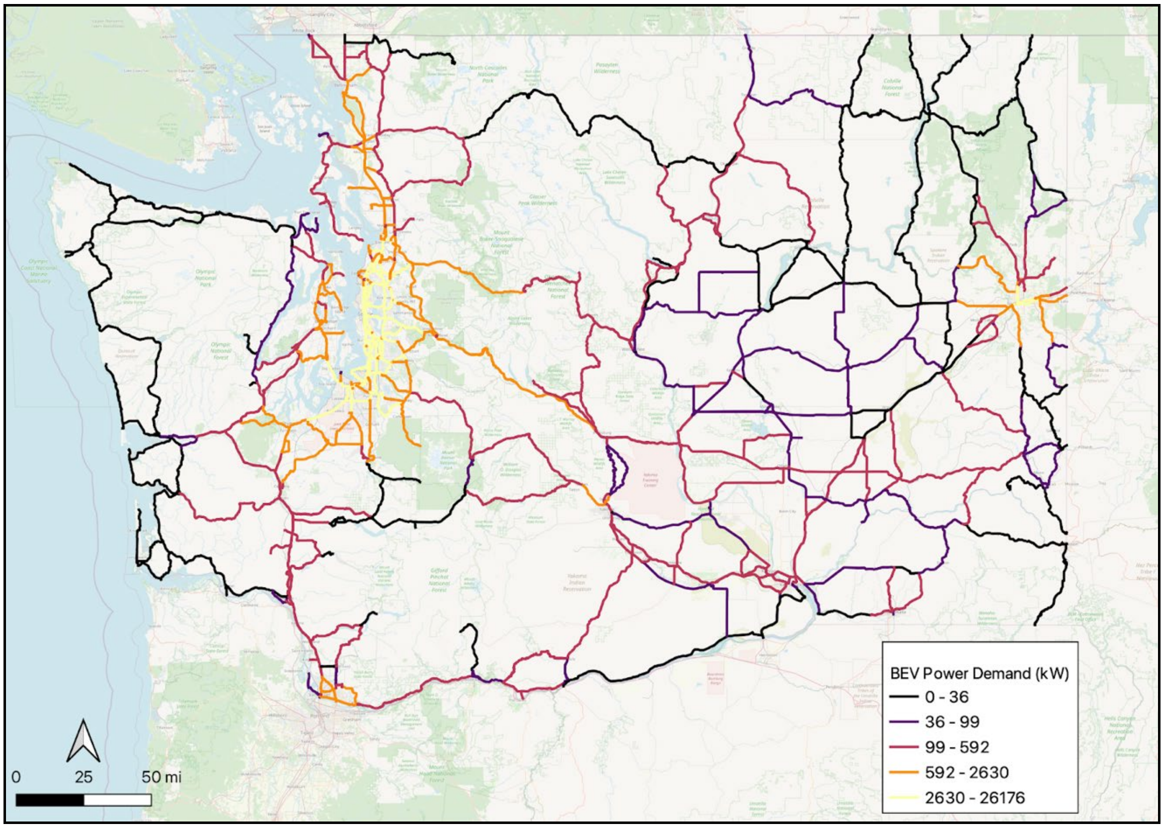

Figure 11: BEV power demand for highway corridors in Washington state. Demand is heavily concentrated in the Puget Sound region, as well as near Spokane.

DCFC STATION SIMULATION

We developed a microsimulation model using the GAMA simulation environment to model vehicle arrivals, charging sessions, and departures for a single DCFC station (14). This analysis was meant to reveal the impacts of station design on individual drivers, as well as daily trends in power draw and queueing delay. Table 8 shows the default parameters for the queueing simulation.

Table 8: Default parameters for DCFC queueing simulation

Parameter Label	Default Value	Description
AADT (veh/day)	3,000	The total count of daily long distance trips that traverse our theoretical highway segment.
EV Proportion of Fleet (%)	0.94	The percentage of the fleet that is a BEV.
Station Spacing (mi)	50	The distance between consecutive charging stations on our theoretical highway segment.
Range Anxiety Buffer (mi)	10	The minimum range an EV driver will allow their vehicle to reach, when accounting for current charge and distance to the next station.
Test Cycle Adjustment Factor (%)	15	The percentage difference between fueleconomy.gov stated and real-world MPGe.
Plugs and Powers (kW)	150, 150 150, 150	The quantity of plugs available, and their charging capacity.
SOC to Leave Station (%)	80	The state of charge that EV drivers will obtain before departing the station.
Min Vehicle Efficiency (mi/kWh)	1.87	The lowest vehicle efficiency sampled uniformly for arriving vehicles.
Max Vehicle Efficiency (mi/kWh)	3.32	The highest vehicle efficiency sampled uniformly for arriving vehicles.
Vehicle Ranges (mi)	303, 275 259, 212 320, 396	EV ranges based on design vehicle data from fueleconomy.gov. They are sampled uniformly for arriving vehicles.
Vehicle Max Desired Power (kW)	150, 135 55, 150 150, 250	The maximum power that an EV driver will seek when choosing an available plug.
Min C-Rate Slope	-0.75	The minimum decrease in power acceptance per increase in battery SOC. Sampled uniformly for arriving vehicles.
Max C-Rate Slope	-2.50	The maximum decrease in power acceptance per increase in battery SOC. Sampled uniformly for arriving vehicles.

These default parameters represented current-day conditions for a highway segment with relatively high long distance AADT. In the GAMA software, we ran simulations of vehicles arriving and charging to show real-time power consumption, queue length, vehicle delay, and state of charge (SOC). Figure 12 shows the input parameters and graphical user interface (GUI) of the simulation during operation.

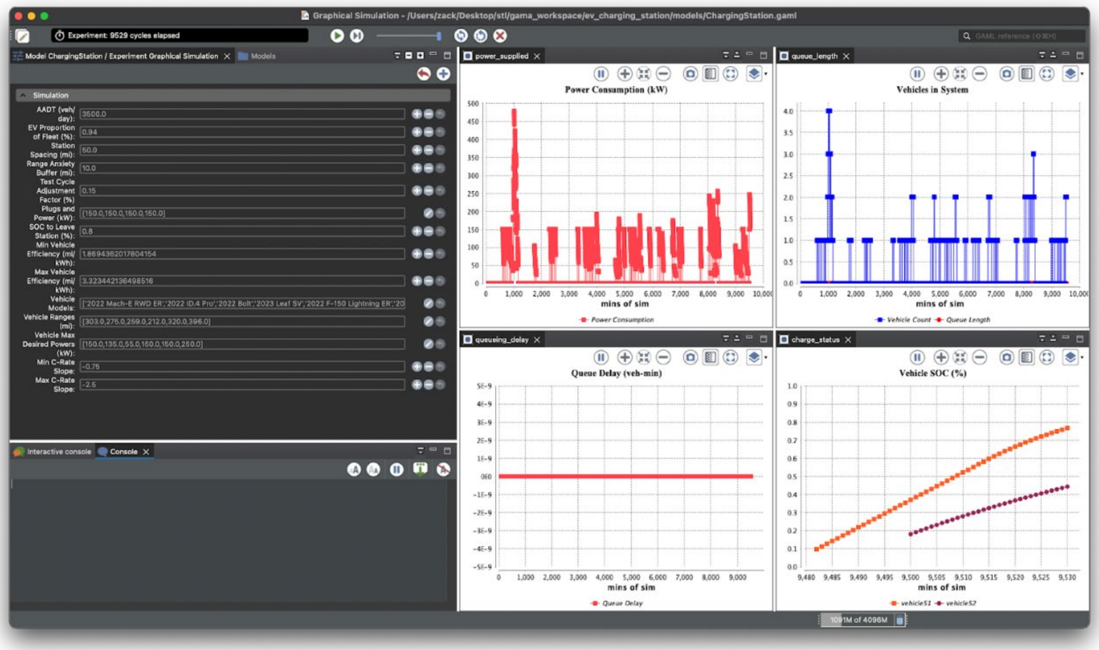

Figure 12: Input parameters and displays for the GAMA simulation. Two vehicles are currently in the system charging and will depart at 80 percent SOC. Each simulation step corresponds to 1 minute of simulated time. With currently low (~1 percent) fleet share, there are rarely delays even at stations with high numbers of long distance AADT.

There were several key assumptions built into the simulation that dictated how often vehicles would arrive, the quantity and speed at which they consumed energy while charging, and how the queue operated. First, the design vehicles used in the simulation were assumed to arrive according to a Poisson process (random, independent arrivals), which could be characterized with a single parameter λ, or average arrival rate, which had units of arrivals/time. Each class of design vehicle has a different range, which means that each class would stop at a different proportion of the stations (e.g., a vehicle with 200-mile range would stop once every four stations if stations were spaced every 50 miles). Therefore we modeled a separate arrival rate for each class of design vehicle.

The overall arrival rate begins with the total long distance AADT, multiplied by the EV fleet share and a K-factor. The K-factor changes throughout the day, and describes the proportion of the daily traffic that arrives in a given minute. This gives the total number of long distance EVs arriving in a given minute.

$$\lambda_{all} = AADT * \% BEVs * KFactor$$

Next, the arriving EVs are split up according to the proportion of the fleet belonging to each design vehicle class. These weights must add up to 100 percent and str specified as parameters for the simulation. The default value is an even split across all design vehicles.

$$\lambda_{design\ vehicle\ i} = \lambda_{all} * Weight_i * Stopping_i$$

Last, we calculate the proportion of vehicles from each design class that stop at a given station. The basic formula is spacing (S) / vehicle range (R). However, there are other simulation parameters that influence the "usable" range for a given design vehicle. The departure SOC (σ) multiplied by the total range determines the maximum range. A vehicle will not pass a charging station if it knowingly cannot reach the next one; therefore, the minimum range of an arriving vehicle is the anxiety buffer (B), and the maximum is S + B (technically (S - 1) + B since a vehicle with exactly enough range to reach the next station would carry on, but we assume S for simplicity). The expected value of an arriving vehicle's range is then B + (S / 2), giving the formula for the proportion of stopping vehicles from a given design class.

$$Stopping_{design\ vehicle\ i} = \frac{S}{\sigma R_i - (B + \frac{S}{2})}$$

At each time step of the simulation a vehicle from each design class is generated with probability λi.

Note that the arrival rate is independent of all vehicle design parameters other than the maximum range. The vehicle efficiency and C-rate instead determine the quantity of energy that must be provided during charging and how quickly the vehicle can accept that energy. The choice of available plugs may also be a limiting factor. The efficiency and C-rate are sampled uniformly between their minimum and maximum input parameters, and the battery size (in kWh) for an individual vehicle is calculated upon its arrival based on its range and sampled efficiency.

Drivers do not queue for specific plugs, and they do not change plugs mid-charge if a more powerful plug becomes available. Rather they queue for the station and choose the lowest power plug available that still meets their maximum desired charge rate. Therefore, as fewer plugs are available, there is some efficiency loss because vehicles are not paired to their ideal charging powers, instead taking the first plug that becomes available. The following is pseudo-code for driver plug choice and the station's first-in-first-out (FIFO) queue.

```
DriverChoosePlug:
    desired_power_met = false
    best_plug = -1
    best_plug_power = 0
    loop over available plugs:
        if best_plug_power >= desired_power:
            desired_power_met = true
        if desired_power_met and plug_power < best_plug_power and plug_power >
desired_plug_power:
            best_plug = plug
            best_plug_power = plug_power
        else if plug_power > best_plug_power:
            best_plug = plug
            best_plug_power = plug_power
    return best_plug

StationServeQueue:
    loop over vehicle in queue:
        chosen_plug = DriverChoosePlug
        if best_plug > 0:
            vehicle_incoming_charge = plug_power[chosen_plug]
            plug_availability[chosen_plug] = false
```

For the default parameters related to EV vehicle design, we collected data from six leading EVs in 2021 (15). These default parameters could be changed to test different fleet compositions in the simulation model. We gathered range and MPGe data for each vehicle from FuelEconomy.gov, which were then used to derive battery capacity. Charging power curves were collected from EV Insider (16-21). We used battery capacity and the power curves to establish C-rate curves, which showed the ratio of accepted charge power for different battery SOC. Figure 13 shows the different C-rate curves for each design vehicle.

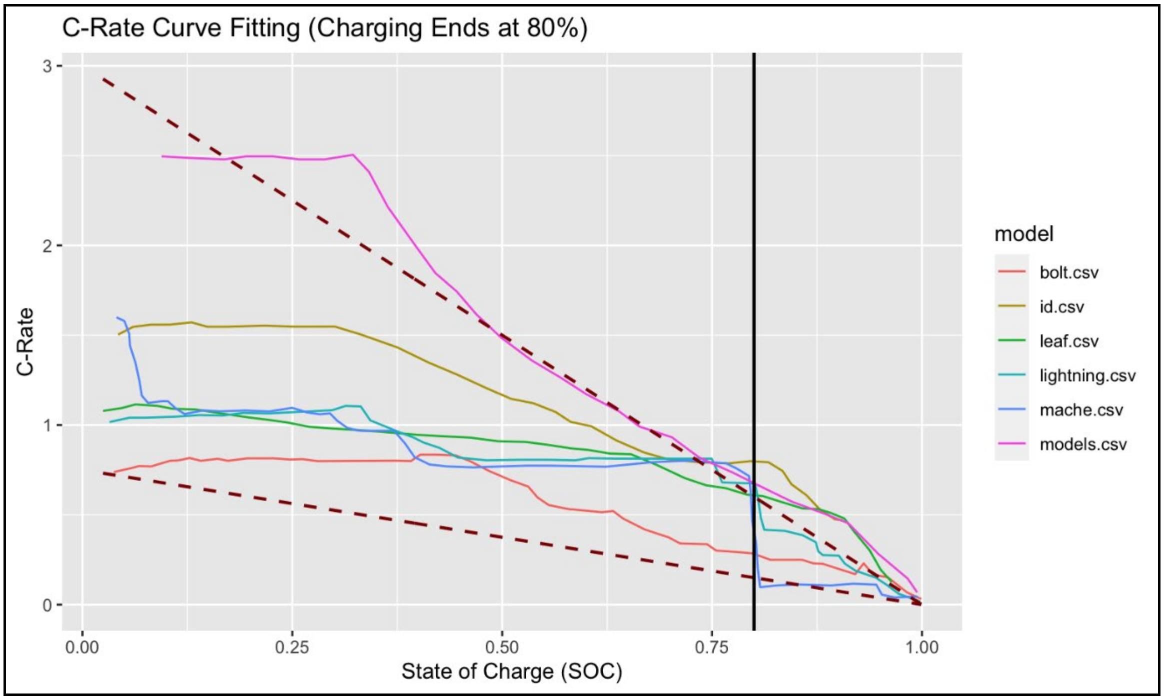

Figure 13: C-rate curves for each design vehicle. The dotted lines show the minimum and maximum C-rate slopes that were sampled for arriving vehicles in the simulation. All curves are assumed to have a 0 C-rate when SOC is 100 percent.

For the K-factor curve, we used WSDOT loop detector data averaged across both directions of travel from loop detectors at five locations on Washington state highways. These were Highway 2 near Sultan, Interstate 5 near Centralia, Interstate 90 near North Bend and Spokane, and Interstate 182 near Kennewick. Figure 14 shows the average K-factor curve used in our simulation.

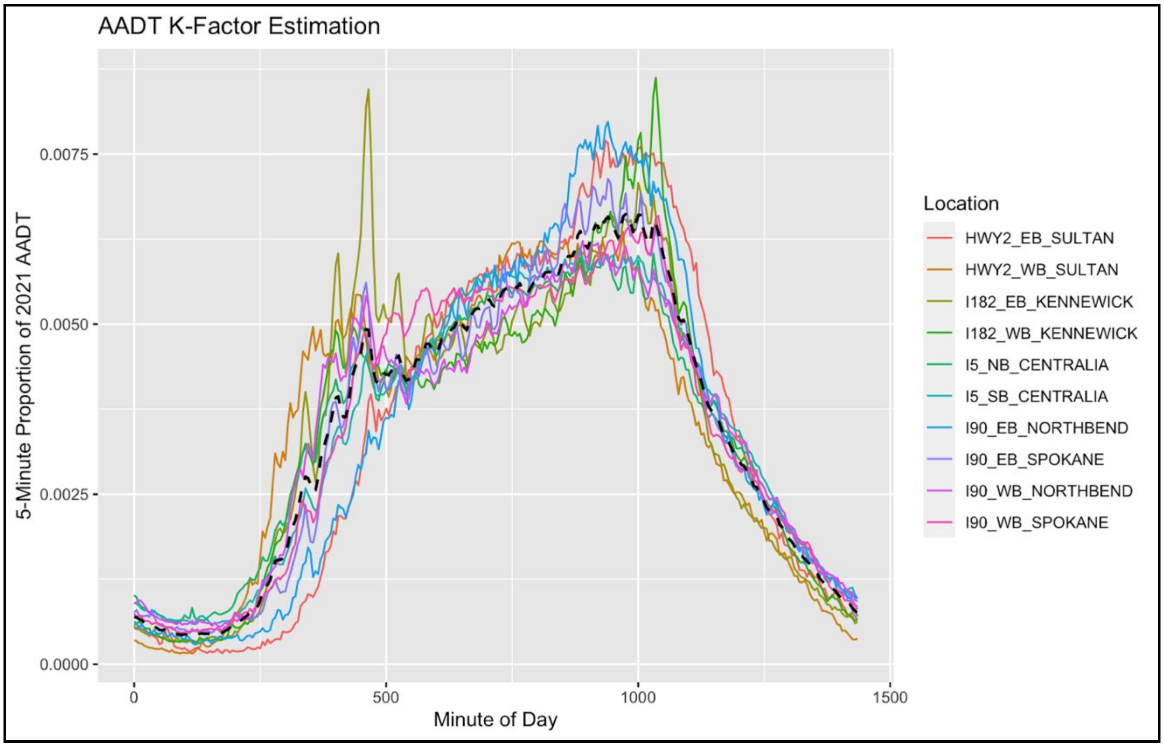

Figure 14: Daily K-factor from WSDOT loop detector data. The dashed black line indicates the average used in our simulations.

SIMULATION RESULTS

We ran each simulation 30 times and averaged the results across all runs. The number of plugs was adjusted in each scenario such that 95 percent of arriving vehicles experienced a delay of 5 minutes or less. We tested six different long distance AADT levels from 30 to 3,000 vehicles per day and six different EV adoption levels from 1 to 100 percent. These created some overlapping scenarios (e.g., 10 percent adoption rate and 300 vehicles per day is equivalent to a 1 percent adoption rate and 3,000 vehicles per day). Figure 15 consolidates these scenarios into their respective EV long distance AADT counts.

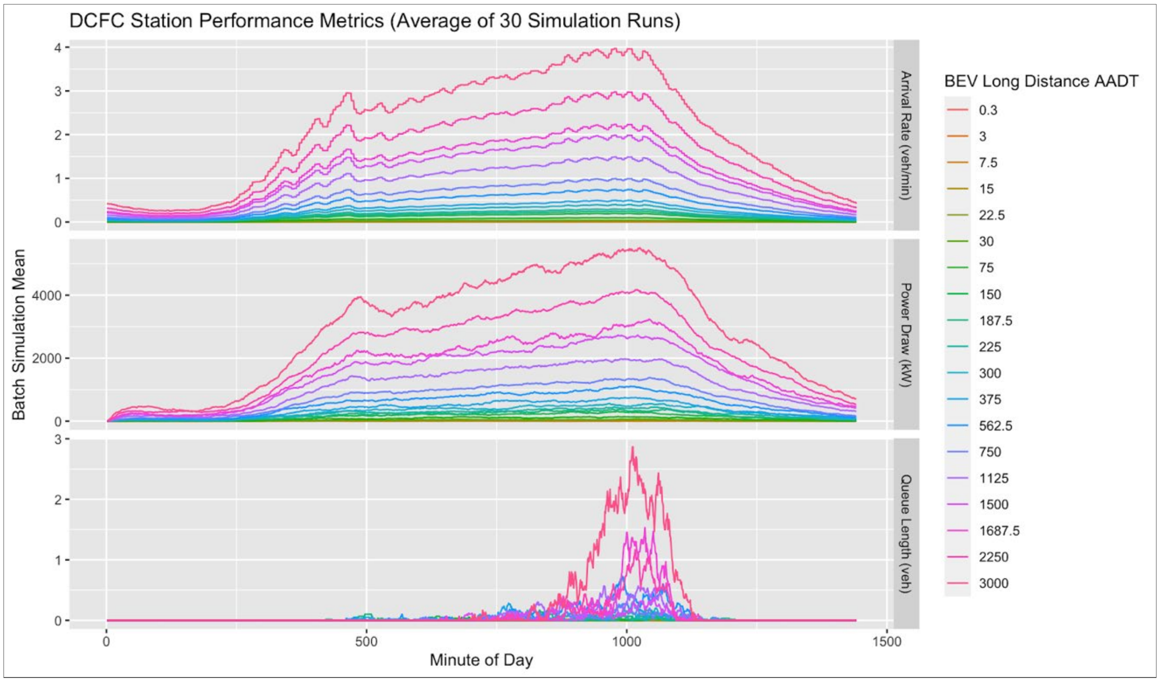

Figure 15: Simulation metrics averaged across 30 runs. Arrival rate and power draw follow similar trends, and queue length grows rapidly during the peak hour. In each scenario, the number of 150-kW plugs has been adjusted such that 95 percent of arriving vehicles wait less than 5 minutes.

Table 9 shows the count of plugs required to meet the performance standard in each scenario, as well as the number of daily charging sessions, peak power (max across all 30 simulations), peak power utilization, total energy provided, and average power utilization. Each combination of long distance AADT and EV share remains split out, which creates some redundancy but also shows the number of plugs required to build out a corridor over time as EV share increases. Green cells show scenarios in which the current 4x150-kW standard meets the performance metric of 5 minutes or less of delay at the 95th percentile.

Peak utilization was near 100 percent station capacity for scenarios in which there were few plugs (and correspondingly low AADT/EV share). This is because it was likely that several low-SOC vehicles would arrive simultaneously and draw maximum power from all available plugs. As the number of plugs increased, this became less likely, and peak utilization fell to 70 to 80 percent of station capacity. On the other hand, average utilization was quite low in low-adoption scenarios but increased rapidly in higher adoption scenarios, even with greater plug counts.

Table 9: Simulation results for levels of long distance AADT, EV market share

Average Annual Daily Traffic	Electric Vehicle Share	1%	10%	25%	50%	75%	100%
30 veh/day	Plugs	1	2	2	2	3	3
	Daily Charging Sessions (veh)	1	1	2	4	6	8
	Peak Power Demand (kW)	150	300	300	300	411	448
	Peak Utilization (%)	1.00	1.00	1.00	1.00	0.91	1.00
	Total Energy Provided (kWh)	14	72	161	382	493	687
	Average Utilization (%)	0.00	0.01	0.02	0.05	0.05	0.06
300 veh/day	Plugs	2	3	4	7	9	10
	Daily Charging Sessions (veh)	1	8	20	40	61	77
	Peak Power Demand (kW)	201	385	599	812	1083	1197
	Peak Utilization (%)	0.67	0.86	1.00	0.77	0.80	0.80
	Total Energy Provided (kWh)	56	696	1783	3494	5383	6895
	Average Utilization (%)	0.01	0.06	0.12	0.14	0.17	0.19
750 veh/day	Plugs	2	4	8	12	16	21
	Daily Charging Sessions (veh)	2	20	50	100	150	194
	Peak Power Demand (kW)	300	515	1068	1471	1810	2235
	Peak Utilization (%)	1.00	0.86	0.89	0.82	0.75	0.71
	Total Energy Provided (kWh)	150	1712	4408	8942	13187	17047
	Average Utilization (%)	0.02	0.12	0.15	0.21	0.23	0.23
1500 veh/day	Plugs	2	7	12	21	29	39
	Daily Charging Sessions (veh)	4	40	99	199	287	391
	Peak Power Demand (kW)	300	863	1421	2276	2847	4058
	Peak Utilization (%)	1.00	0.82	0.79	0.72	0.65	0.69
	Total Energy Provided (kWh)	312	3498	8898	17585	25456	34742
	Average Utilization (%)	0.04	0.14	0.21	0.23	0.24	0.25
2250 veh/day	Plugs	3	9	16	29	42	55
	Daily Charging Sessions (veh)	6	61	147	292	439	575
	Peak Power Demand (kW)	397	1023	2015	3078	4424	5340
	Peak Utilization (%)	0.88	0.76	0.84	0.71	0.70	0.65
	Total Energy Provided (kWh)	561	5385	13073	26094	39093	51152
	Average Utilization (%)	0.05	0.17	0.23	0.25	0.26	0.26
3000 veh/day	Plugs	3	10	21	39	55	70
	Daily Charging Sessions (veh)	8	78	192	389	588	778
	Peak Power Demand (kW)	442	1315	2294	4083	5516	6643
	Peak Utilization (%)	0.98	0.88	0.73	0.70	0.67	0.63
	Total Energy Provided (kWh)	758	6865	17117	34771	52140	69031
	Average Utilization (%)	0.07	0.19	0.23	0.25	0.26	0.27

Given that peak utilization drives required capacity costs, and average utilization drives revenue, stations on long distance corridors might not be profitable for the near future. One way to alleviate this might be load management systems that cap and distribute power to different vehicles depending on their individual C-rates and a load management strategy. This would reduce the maximum capacity that would have to be supplied at the station while still providing full requested power to vehicles when the station was not capacity-constrained. This might also encourage off-peak charging, when drivers would be able to draw maximum power according to their vehicle's capabilities.

IMPLICATIONS FOR POLICY

We found that in future scenarios of EV adoption, for all but the lowest AADT corridors, there will be a need for higher capacity and more than four 150-kW DCFC station plugs. Therefore, it would be beneficial to build capacity for future plug expansion in corridors where demand is expected to be high. However, there will also be locations where the current National Electric Vehicle Infrastructure (NEVI) standard of 4x150-kW chargers will generate significant excess capacity even up to an EV adoption rate of 25 percent. This will create an opportunity to use state dollars more efficiently by providing plug counts greater than the NEVI standard in some areas and fewer in others. We also found that high peak-low average power utilization will create an opportunity to lower overall capacity requirements and to incorporate load management systems to handle power distribution during peak periods. Decreasing overall capacity requirements with this method may speed the journey toward station profitability.

CHAPTER 4
NEXT STEPS

The Washington State Legislature gave WSDOT the task of mapping and forecasting the adoption of zero-emission vehicles and their supporting infrastructure in HB 1287 with a tool that's accessible to the public. This study reviewed the available resources for accomplishing this assignment and developed two key analytic building blocks necessary for a robust and transparent approach to forecasting. This report and the effort to build the ZEV-MFT tool are part of a broader effort by WSDOT, the Department of Commerce, and their sister agencies in state government to accelerate the conversion of the surface transportation fleet to zero-emission vehicles. Those efforts are now supported by the planning of the Electric Vehicle Coordinating Council and their consultants.[12]

As efforts continue to implement HB1287, the UW research team's efforts under this project identified several additional tasks to help achieve the legislation's objectives:

- Use census tract-level EV forecasts as an input to estimate future long-distance EV travel demand on state highway links.
- Use census tract-level EV forecasts to estimate future charging demand for home, office, and public fast chargers.
- Develop methods to regularly update the EV forecasts to match ongoing adoption trends.

The EV charging simulation research also suggested areas of additional inquiry that will help planners and policymakers better prepare for new station deployment:

- Model the effects of differences in battery capacity and C-rate on charging times and optimal station configurations.
- Develop vehicle and charging demand forecasts for medium- and heavy-duty vehicles to supplement the analysis of light-duty vehicles

The forecasting and station modeling results also have implications for current grant-making by WSDOT:

[12] See https://www.commerce.wa.gov/growing-the-economy/energy/clean-transportation/ev-coordinating-council/

- Stations should be planned with the capacity to add more plugs as the size of the EV fleet increases. Sizing utlity connections and conduit to allow the addition of more high capacity plugs may reduce the overall costs of building out charging stations.
- Making grants for rural fast charge stations with fewer that four 150-kW plugs (the federal standard for the NEVI program) with the capacity to add new plugs may allow for the best coverage across state highways with state dollars.
- The adoption of control software that can manage the charging load across all of the plugs at a charging station could significantly lower the electrical capacity requirements and therefore the costs of the utility service to the station.

Our census tract analysis showed rapidly accelerating adoption of EVs in parts of Washington state. Equipping policymakers and planners with better analytic tools could help direct public funds and policies to the areas and topics that will allow the transition to zero-emission vehicles serve all of Washington. The research team at the University of Washington is pleased to have had the opportunity to advance our shared understanding of the shift to zero-emission vehicles and looks forward to supporting WSDOT in the future.

REFERENCES

1. Data.WA.gov. Electric Vehicle Share of New Registrations | Data.WA | State of Washington. https://data.wa.gov/Transportation/Electric-Vehicle-Share-of-New-Registrations/wzin-vviu. Accessed Dec. 22, 2022.

2. Data.WA.gov. Vehicle Registration Transactions by Department of Licensing. https://data.wa.gov/Transportation/Vehicle-Registration-Transactions-by-Department-of/brw6-jymh. Accessed Dec. 28, 2022.

3. WA Sets 2030 Goal to Phase out Gas Cars. *The Seattle Times*. https://www.seattletimes.com/seattle-news/transportation/wa-sets-2030-goal-to-phase-out-gas-cars/. Accessed Dec. 22, 2022.

4. WA Adopts Zero-Emission Standards for Car Sales by 2035. *The Seattle Times*. https://www.seattletimes.com/seattle-news/wa-adopts-zero-emission-standards-for-car-sales-by-2035/. Accessed Dec. 22, 2022.

5. Data.WA.gov. Electric Vehicle Title and Registration Activity. https://data.wa.gov/Transportation/Electric-Vehicle-Title-and-Registration-Activity/rpr4-cgyd. Accessed Dec. 28, 2022.

6. U.S. Energy Information Administration. Washington Gasoline and Diesel Retail Prices. https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_swa_m.htm. Accessed Dec. 28, 2022.

7. NREL. Alternative Fuel Stations API | NREL: Developer Network. https://developer.nrel.gov/docs/transportation/alt-fuel-stations-v1/. Accessed Dec. 28, 2022.

8. U.S. Census Bureau. American Community Survey (ACS). *Census.gov*. https://www.census.gov/programs-surveys/acs. Accessed Dec. 28, 2022.

9. Rogers, E. M. *Diffusion of Innovations, 5th Edition*. Simon and Schuster, 2003.

10. Zoepf, S., and J. B. Heywood. Characterizations of Deployment Rates in Automotive Technology. *SAE International Journal of Passenger Cars - Electronic and Electrical Systems*, Vol. 5, No. 2, 2012, pp. 541–552. https://doi.org/10.4271/2012-01-1057.

11. Argonne National Laboratory. VISION Model. https://www.anl.gov/esia/vision-model. Accessed Dec. 28, 2022.

12. Gerald Tracy. Washington State Continues Pushing toward Frontlines of Electric Vehicle Movement in US. *KOMO*. https://komonews.com/news/local/washington-state-continues-pushing-toward-frontlines-of-electric-vehicle-movement-in-us. Accessed Dec. 30, 2022.

13. Jabbari P, Khaloei M, MacKenzie D. Estimating potential demand for long-distance electric vehicle travel in Washington State. In 2019 [cited 2023 Jun 22]. Available from: https://trid.trb.org/view/1573197

14. GAMA Platform | GAMA Platform [Internet]. [cited 2023 Jun 22]. Available from: https://gama-platform.org/

15. White A. 12 Bestselling Electric Vehicles of 2021 [Internet]. Car and Driver. 2022 [cited 2023 Jun 22]. Available from: https://www.caranddriver.com/features/g36278968/best-selling-evs-of-2021/

16. Kane M. 2021 Tesla Model S Plaid Fast Charging Analysis (3 Cars Compared) [Internet]. InsideEVs. 2021 [cited 2023 Jun 22]. Available from: https://insideevs.com/news/549335/three-tesla-plaid-charging-analysis/

17. Moloughney T. Exclusive: How Fast Does The Ford F-150 Lightning Charge? [Internet]. InsideEVs. 2022 [cited 2023 Jun 22]. Available from: https://insideevs.com/news/585794/ford-f150-lightning-fast-charging/

18. Kane M. Ford Mustang Mach-E First Edition In-Depth DC Fast Charging Analysis [Internet]. InsideEVs. 2021 [cited 2023 Jun 22]. Available from: https://insideevs.com/news/492727/ford-mustang-mache-fast-charging-analysis/

19. Moloughney T. How Long Does It Take To Charge a Chevrolet Bolt EV? [Internet]. InsideEVs. 2022 [cited 2023 Jun 22]. Available from: https://insideevs.com/news/589169/how-long-charge-chevrolet-bolt-ev/

20. Kane M. Nissan LEAF Might Have A Good Fast Charging Curve With Active TMS [Internet]. InsideEVs. 2021 [cited 2023 Jun 22]. Available from: https://insideevs.com/news/495913/nissan-leaf-dc-fast-charging-curve/

21. Kane M. Volkswagen ID.4 (82 kWh) In-Depth DC Fast Charging Analysis [Internet]. InsideEVs. 2021 [cited 2023 Jun 22]. Available from: https://insideevs.com/news/492606/volkswagen-id4-82kwh-dc-fast-charging-analysis/

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