California Energy Commission

STAFF REPORT

California Electric Vehicle Infrastructure for Long-Distance Travel

Direct Current Fast Charging Needs to Enable Interregional Long-Distance Travel for Electric Vehicles

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ABSTRACT

This report highlights the methods, inputs, assumptions, and results of the Electric Vehicle Infrastructure for Road Trips (EVI-RoadTrip) model. Key results were previously published in the inaugural Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment, and this report expands upon that report to provide more detailed analysis and discussion.

EVI-RoadTrip simulations project the numbers and locations of direct current fast charging (DCFC) infrastructure needed for long-distance travel of battery-electric vehicles (BEVs) greater than 100 miles within and across California's borders. This work addresses an under-researched, but increasingly important use case for transportation electrification: long-distance travel. A fast-charging network connecting regions within and outside California is critical to accelerating and maximizing the transition to EVs by reducing range anxiety.

The model follows four key steps: trip data generation, energy and charging simulation, station siting and sizing, and grid-hosting capacity analysis. The model simulates interregional and out-of-state road trips by BEVs, estimates energy use and charging demand along the road trip routes, calculates geographic clusters of charging demand, and simulates the existence of charging stations to serve those clusters, locating them in preferred areas with appropriate chargers.

Assuming drivers prioritize charging at their origin or destination, an average of about 1,000 DCFC stations and nearly 2,000 DC fast charging ports are estimated to support the electrified interregional travel of more than 5 million BEVs in 2030. Charging from road trips in this scenario is projected to result in a system peak load of about 60 megawatts around 2 to 3 p.m. However, this report also highlights how these results can significantly vary depending on vehicle population, charging behavior, and other conditions. In particular, it may be possible to meet these charging needs with a smaller number of stations, and the same total number of chargers, as long as charging is available on all interregional travel corridors in the state.

Keywords: Charging, infrastructure, transportation electrification, electric vehicle, road trip

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

Mobile sources in California contribute more than 50 percent of the state's greenhouse gas (GHG) emissions, 80 percent of smog-forming nitrogen oxide pollution, and 95 percent of toxic diesel particulate matter. The associated impacts of these emissions are detrimental to the climate and harmful for the health of California's residents. State policies such as Senate Bill 32 address these negative externalities by requiring statewide GHG emissions to be reduced to 40 percent below the 1990 level by 2030. The electrification of California's transportation system is urgently needed, and the state has continued to pave the way for transportation electrification. Executive Order (EO) B-48-18 established a goal of 250,000 electric vehicle (EV) chargers by 2025 and 5 million zero-emission vehicles (ZEVs) on the road in 2030. Assembly Bill (AB) 2127 (Ting, Chapter 365, Statutes of 2018) tasked the California Energy Commission (CEC) with preparing a statewide assessment of the charging infrastructure needed to achieve these goals and reduce GHG emissions to 40 percent below 1990 levels by 2030. More recently, Governor Gavin Newsom set a goal in EO N-79-20 that 100 percent of in-state sales for new passenger vehicles will be ZEVs by 2035 and expanded the AB 2127 assessment to examine infrastructure requirements to support increased EV adoption.

The CEC collaborated with the National Renewable Energy Laboratory (NREL) to evaluate charging infrastructure needs for light-duty passenger vehicles. This included an updated analysis using the Electric Vehicle Infrastructure Projections (EVI-Pro) 2 model to look at infrastructure requirements for local, short-distance travel, as well as a novel analysis targeting long-distance, interregional travel. To do the latter, NREL and CEC developed a new model, Electric Vehicle Infrastructure for Road Trips (EVI-RoadTrip) to project the direct current fast charging (DCFC) infrastructure needs to enable long-distance trips (LDTs) by battery electric vehicles (BEVs).

LDTs are an historically under-researched area, and while these trips make up a small portion of total travel demand, they represent a significant barrier to widespread EV adoption. Building a properly sized and distributed DCFC network will decrease range anxiety and continued reliance on internal combustion engine vehicles (ICEVs), particularly in single-vehicle households or households looking to transition a second vehicle ICEV to an EV. Thus, this analysis seeks to answer four key questions:

1) How many total charging stations and chargers are needed?
2) Where should charging stations be located?
3) How large should each charging station be (chargers per station)?
4) What is the impact of LDT-related charging load on the electric grid infrastructure?

Key results of this analysis were previously published in the CEC's AB 2127 Commission Report in 2021, and updated results will be published in the second AB 2127 Commission Report in 2023. This report expands on that discussion to detail the methods of EVI-RoadTrip, provide more information on the inputs and assumptions used, and highlight additional results, sensitivity analysis, and key takeaways.

5 Million Battery Electric Vehicles in 2030 Need Nearly 2,000 DCFC Chargers across all long-distance travel corridors in California

The California Air Resources Board's (CARB) Mobile Source Strategy estimates that California needs 8 million light-duty ZEVs (including over 5 million BEVs) in 2030 to meet the goals of EO N-79-20. Those results are being refined as part of CARB's Advanced Clean Cars II regulation. This work investigated three different charging behaviors.

1) **Always Topping Off (ATO)**

   Drivers charge their vehicles to 100 percent state-of-charge (SOC) during every charging session of their trip.

2) **Time Penalty Minimization (TPM)**

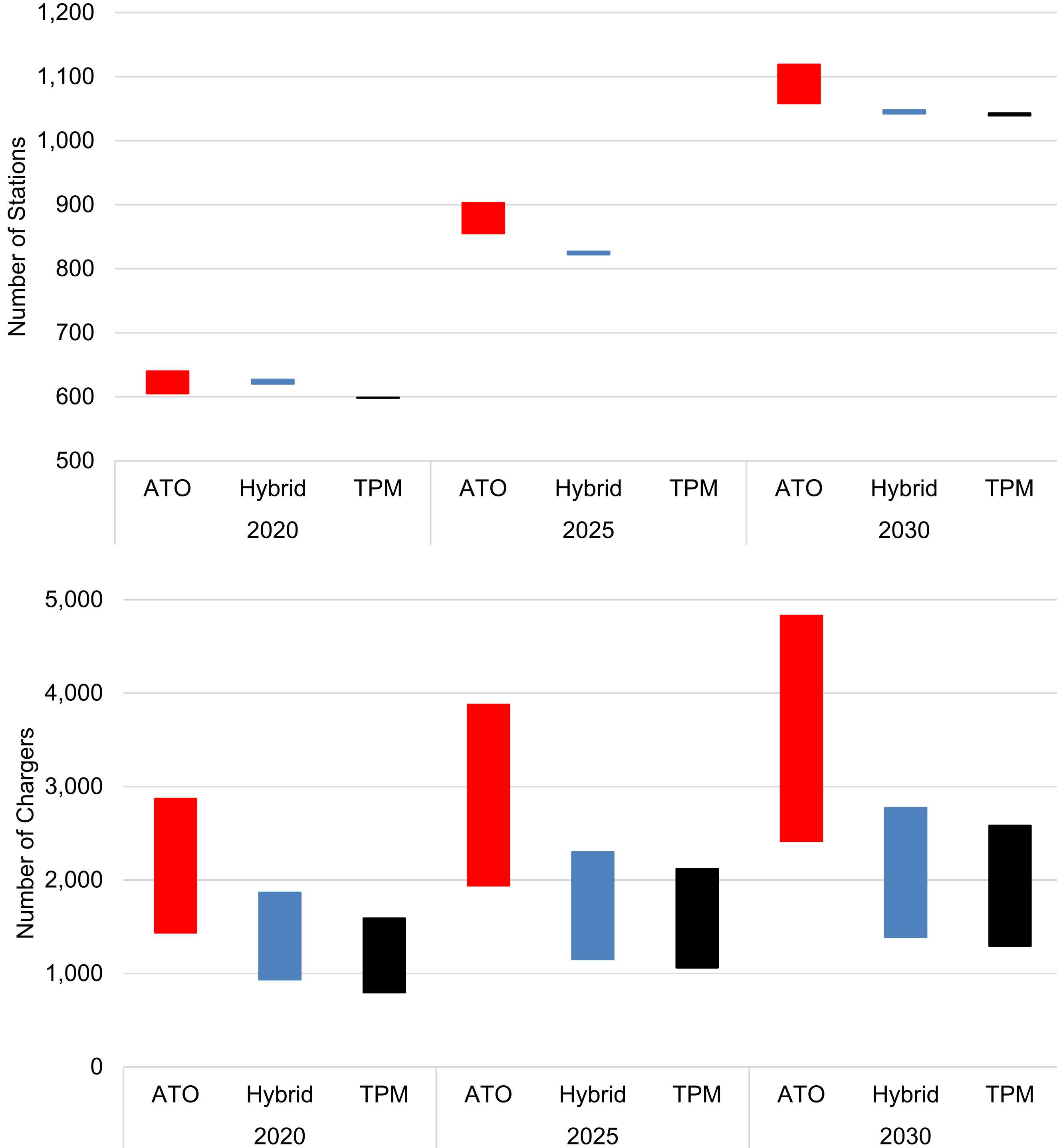
   Drivers stop charging before reaching 100% SOC to minimize charging time, as charging power level (and thus charging speed) drops off significantly at high SOCs.

3) **Hybrid**

   This charging scenario blends ATO and TPM. Drivers adopt the ATO charging behavior except for the last charging event in their trip, where they follow the TPM behavior.

Figure ES-1 shows that under the ideal TPM charging behavior, approximately 1,000 DCFC stations and nearly 2,000 DC fast chargers will support more than 5 million BEVs in 2030. Due to the high cost of establishing DCFC stations, it may be more economical to support BEV long-distance travel with a smaller number of stations with more chargers at each station. However, charging behavior can have a large impact on the network size. In the ATO scenario, the DCFC network increases by 46 percent and 87 percent for stations and chargers, respectively. This is due to increased overlap from longer charging events, which requires more infrastructure to avoid congestion and queuing.

Figure ES-1: DCFC Infrastructure Requirements for Stations (top) and Chargers (bottom) by Simulation Year and Charging Behavior – High BEV Adoption Scenario

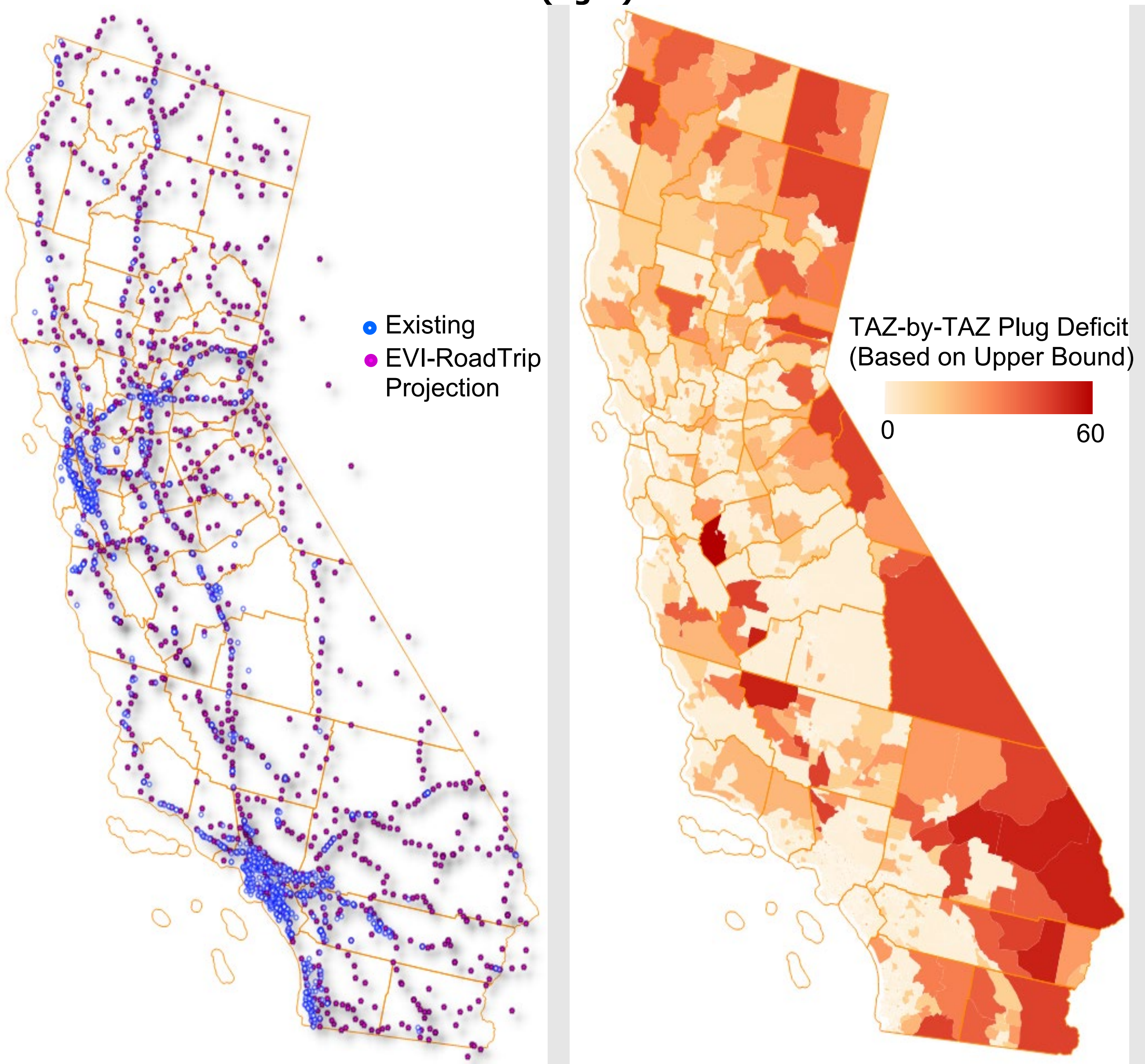


The number of DCFC stations and chargers is expected to increase over time to meet growing BEV travel and charging demand. By 2030, California is projected to need anywhere from 1,039 to 1,119 DCFC stations composed of 1,292 to 4,830 chargers, depending on charging behavior. Under the ideal TPM charging behavior, the infrastructure requirements include an average of about 1,041 stations consisting of nearly 2,000 chargers. Source: CEC and NREL

DCFC Stations along Corridors and Rural Areas Should Be Prioritized to Enable Electrified Long-Distance Travel

The projected DCFC station locations in 2030 present a notable contrast to the existing DCFC infrastructure published by the Alternative Fuels Data Center (AFDC). On the left side of Figure ES-2, the EVI-RoadTrip results for the year 2030 show that future stations will need to cover California's road network more thoroughly to enable long-distance travel for EVs; specific station locations should be interpreted loosely. The right side of Figure ES-2 shows the charger count deficit for each traffic analysis zone (TAZ) in the state, illustrating that the largest gaps in infrastructure primarily occur in rural and less-traveled areas that have not been targeted in the market to date. Many other regions, however, have minimal or no charger deficit for long-distance travel demand due in part to stations sited for local demand. That said, existing station factors, such as power level, embedded charger technology, and other specifics, today may not be suitable for future charger needs and it will be critical to consider the charging network evolution and to future-proof equipment.

Figure ES-2: Comparison between Existing DCFC Infrastructure and EVI-RoadTrip Projections in 2030 – Station Locations (left) and Charger Count Deficits by TAZ (right)

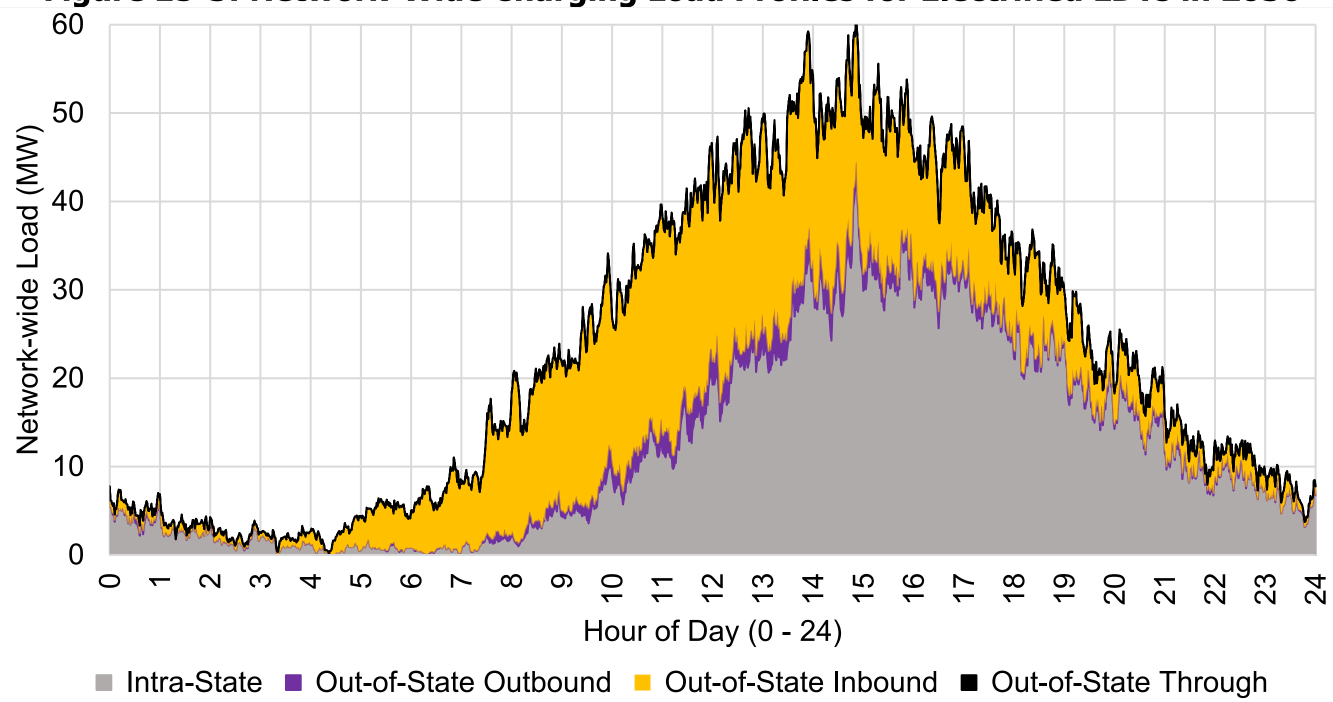


On the left, EVI-RoadTrip results for the TPM charging behavior in 2030 show that DCFC stations will need to cover California's road network more thoroughly than existing stations do today. On the right, a TAZ-by-TAZ analysis shows that the largest projected gaps in charger counts are concentrated in more rural areas of the state that have not been targeted as much in the market. However, many areas have minimal or no charger deficit, especially in urban areas and along major corridors. That said, these results do not consider the power level and embedded technology of existing chargers compared to projected chargers in the future. Source: CEC and NREL

Charging Demand from LDTs May be Minor in Comparison to Local Travel, but Still Require Local Distribution Grid Upgrades

Due to their relatively small share of total travel demand, expected charging load from LDTs will not be as significant as charging load from local passenger vehicle travel. As Figure ES-3 shows, under the TPM charging behavior, the estimated peak load in 2030 is 60 MW around 2 to 3 p.m., which aligns with solar production. A significant portion of this load is attributed to vehicles visitors entering California from neighboring states and Mexico or residents returning to California, highlighting the importance of taking a holistic approach to charging infrastructure needs and continuing coordination across jurisdictions.

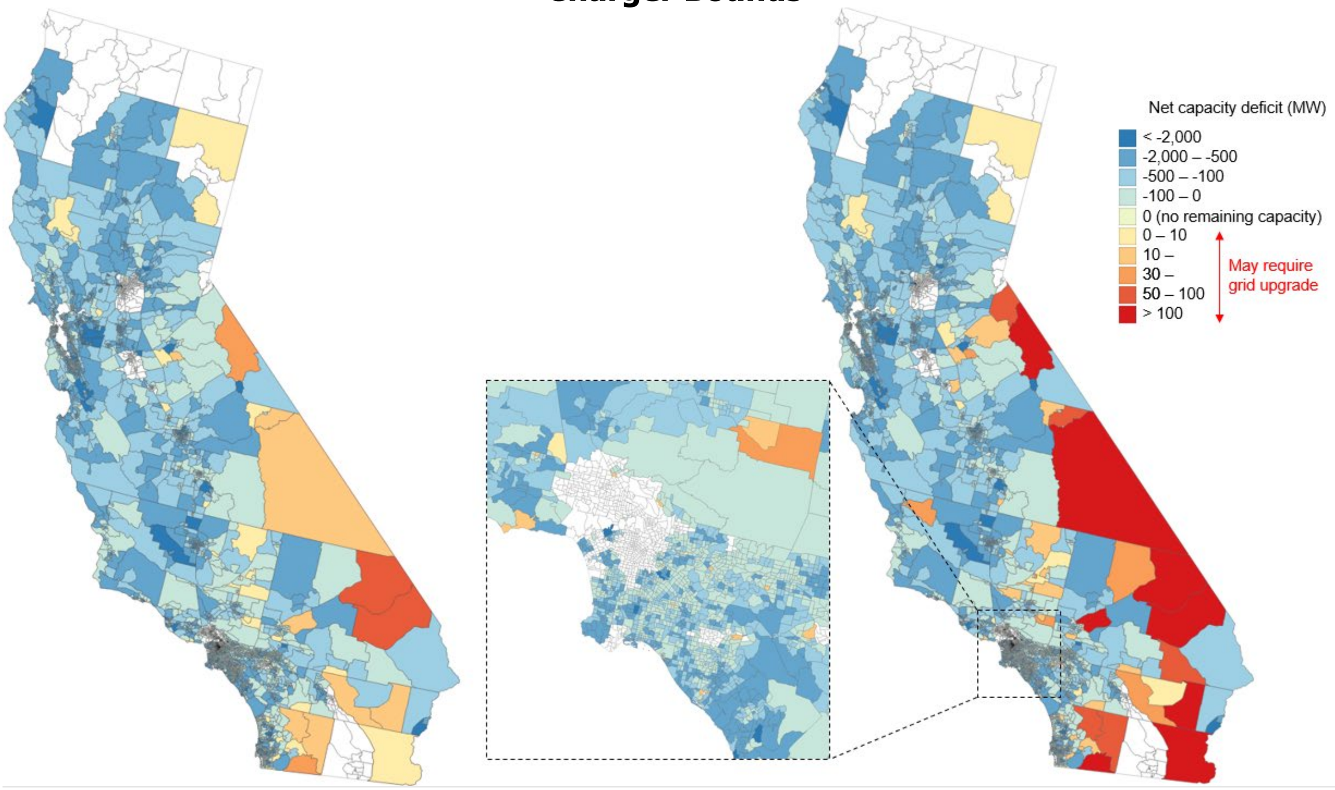
Figure ES-3: Network-Wide Charging Load Profiles for Electrified LDTs in 2030



The projected 2030 load profile in the TPM charging behavior scenario shows that charging from LDTs is not expected to make a significant impact on the grid, with a peak load of 60 MW around 2 to 3 p.m., which aligns with solar production. This charging load is dominated by intra-state and out-of-state inbound trips. Source: CEC and NREL

This analysis also made use of the CEC's Electric Vehicle Supply Equipment Deployment and Grid Evaluation (EDGE) model to conduct a proof-of-concept study on grid hosting capacity for LDT charging load. Figure ES-4 shows the net capacity deficits in MW at the TAZ resolution for lower and upper bounds on chargers. Negative values indicate the existing grid hosting capacity would be capable of supporting increasing charging demand from electrified LDTs. The results show that while most of the state is in a good position to accommodate this specific charging load, more rural or suburban areas along popular interstate highways (especially along the eastern and southern state borders) may require local distribution grid upgrades. The ability for the grid to accommodate fast charging for local travel and for medium and heavy duty truck travel is not assessed in this proof of concept. Furthermore, it is critical to continue coordination with the utilities to refine EDGE, as there are notable data quality and availability issues, such as blank regions on the map that currently have no grid data available.

Figure ES-4: Net Capacity Deficit by TAZ in 2030 for Lower (left) and Upper (right) Charger Bounds



Integrating the EVI-RoadTrip load results with the CEC's EDGE model allows net grid capacity deficits by TAZ to be evaluated for lower (left) and upper (right) bounds on chargers. Positive values indicate a capacity deficit. The results suggest that most LDT charging load could be accommodated by the current grid infrastructure, though more rural regions on the eastern and southern borders of the state may require grid upgrades. Source: CEC and NREL

Conclusions and Future Work

This novel model and analysis address an under-researched, but increasingly important use case for transportation electrification: personal on-road LDTs. To accelerate and maximize the transition to EVs, a DCFC network connecting regions within and outside California is critical to reduce range anxiety and use of ICEVs.

While LDTs represent a small fraction of total travel, they will demand a disproportionate amount of the DCFC infrastructure. An estimated 1,041 stations with nearly 2,000 chargers will be needed to support the long-distance trips of more than 5 million BEVs. The size of this network could change depending on a number of factors, including BEV adoption trajectories, charging behavior, vehicle technologies, market preferences and evolution, and environmental conditions. Additionally, significant local demand reflected in the EVI-Pro 2 modeling will have to be incorporated to properly size stations, especially where stations serving LDT pass through urban areas.

Future analysis will continue as part of the recurring AB 2127 assessments. Model methods and results will be updated to reflect market evolution and policy goals. Integrating EVI-RoadTrip with EVI-Pro 2 will be key to providing a harmonized analysis.

CHAPTER 1: Introduction

Policy Context

Mobile sources in California contribute more than 50 percent of the state's greenhouse gas (GHG) emissions, 80 percent of smog-forming nitrogen oxide pollution, and 95 percent of toxic diesel particulate matter.[1] The associated impacts of these emissions are detrimental to the climate and harmful for the health of California's residents. State policies such as Senate Bill 32[2] address these negative externalities by requiring statewide greenhouse gas emissions to be reduced to 40 percent below the 1990 level by 2030.

In order to achieve these goals, it is critical to convert California's vehicle fleet from conventional internal combustion engine vehicles (ICEVs) to zero emission vehicles (ZEVs). The State of California has continued to pave the way for transportation electrification. Assembly Bill (AB) 118[3] established the Clean Transportation Program and directed the California Energy Commission (CEC) to accelerate the development and deployment of innovative technologies that transform California's fuel and vehicle types to help attain the state's climate change policies with funding of approximately $100 million per year. AB 8[4] extended the Clean Transportation Program through January 1, 2024.

Executive Order (EO) B-16-2012[5] set the initial benchmarks for ZEV adoption in California of 1 million ZEVs by 2020 and 1.5 million ZEVs by 2025. EO B-48-2018[6] established an additional target for 5 million ZEVs by 2030. The EO set an infrastructure goal of 250,000 electric vehicle (EV) charging stations in California, including 10,000 direct current fast charging (DCFC) stations by 2025. The goal also includes 200 hydrogen refueling stations. These policies have been instrumental in promoting ZEV adoption and deploying needed charging infrastructure,

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1 California Energy Commission staff. 2019. 2019 Integrated Energy Policy Report. California Energy Commission. Publication Number: CEC-100-2019-001-CM. Available at https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2019-integrated-energy-policy-report.

2 Senate Bill 32 (Pavley), Statutes of 2006, Chapter 249. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201520160SB32.

3 Assembly Bill 118 (Nunez), Statutes of 2007, Chapter 750. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=200720080AB118.

4 Assembly Bill 8 (Perea), Statutes of 2013, Chapter 401. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201320140AB8.

5 Governor Edmund G. Brown, Jr. Executive Order B-16-2012. Issued March 23, 2012. https://www.ca.gov/archive/gov39/2012/03/23/news17472/index.html

6 Governor Edmund G. Brown, Jr. Executive Order B-48-18. Issued January 26, 2018. https://www.ca.gov/archive/gov39/2018/01/26/governor-brown-takes-action-to-increase-zero-emission-vehicles-fund-new-climate-investments/index.html.

with over 1,111,000 ZEVs registered by the end of 2022 and over 87,000 public and shared private chargers as of January 2023 in the state.[7] Of these chargers, over 9,200 are DCFCs.[8] Most recently, Governor Gavin Newsom issued EO N-79-20,[9] which calls for all in-state sales of new passenger cars and trucks to be zero-emission by 2035 and sets other goals for medium- and heavy-duty and off-road vehicles.

PEVs have been the most popular type of ZEV adopted by consumers. With the increasing adoption of PEVs, infrastructure planning for a widespread and diverse network of public chargers is critical to maximize the fraction of vehicle miles traveled that are powered by electricity (eVMT), alleviate range anxiety, and facilitate the further adoption of PEVs. To address this, AB 2127[10] tasked the CEC to prepare and biennially update a statewide assessment of the EV charging infrastructure needed to support the levels of adoption required for the state to meet its goals of putting at least 5 million ZEVs on California roads by 2030 and reducing GHG emissions to 40 percent below 1990 levels by 2030. EO N-79-20, directed the CEC to update this analysis to support the new 2035 sales targets.

Charging Infrastructure for Electrified Long-Distance Trips

To evaluate the charging infrastructure needed to support the targeted adoption of PEVs, the CEC previously developed the Electric Vehicle Infrastructure Projection (EVI-Pro) tool, in collaboration with the National Renewable Energy Laboratory (NREL). EVI-Pro projects the number, location, and type of chargers required to meet the needs of light-duty PEV drivers. The original EVI-Pro analysis[11] provided results that informed the EO B-48-2018 target of 250,000 electric vehicle chargers by 2025, including 10,000 DC fast chargers.

One of the limitations of the existing EVI-Pro model is that the analysis focuses on local, intraregional travel and charging demand. However, it is important to expand beyond this scope and also assess the potential of electrifying interregional long-distance trips (LDTs).[12] As

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7 CEC. 2021. *California Energy Commission Zero Emission Vehicle and Infrastructure Statistics*. Data last updated April 28, 2023. Retrieved June 14, 2023 from https://www.energy.ca.gov/zevstats.

8 Ibid.

9 Governor Gavin Newsom. Executive Order N-79-20. Issued September 23, 2020. https://www.gov.ca.gov/wp-content/uploads/2020/09/9.23.20-EO-N-79-20-text.pdf.

10 Assembly Bill 2127 (Ting), Statutes of 2018, Chapter 365. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180AB2127.

11 Bedir, Abdulkadir, Noel Crisostomo, Jennifer Allen, Eric Wood, and Clément Rames. 2018. *California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025*. California Energy Commission. Publication Number: CEC-600-2018-001.

12 In this analysis, long distance trips (LDTs) are defined as 100 or more miles one-way from origin to destination. However, this definition is only applied to intra-state LDTs that begin and end in California. For out-of-state or external LDTs, as discussed in Chapter 3, we only know the travel volume and distance for the portion of the trip within California. Due to this lack of knowledge of exact travel distance beyond the state boundary for out-of-state LDTs, we consider trips that include at least 50 miles within California.

technology improvements continue to introduce PEVs with larger batteries and longer ranges, and PEV adoption expands beyond early adopters into the mainstream market, LDTs must be supported with appropriate and adequate charging stations. This will help reduce range anxiety, one of the most commonly cited concerns of drivers, encourage the growth of multi-PEV households, and connect California not only regionally, but also across its borders to neighboring states.

An appropriate charging infrastructure network to support LDT electrification requires determining how many charging stations are needed, where they are needed, how large each charging station should be (in terms of both the number of chargers and power capacity), and the impact of LDT-related charging load on the electric grid. There are no publicly available models, tools, or studies that can provide comprehensive and current answers to those four key questions. Thus, the CEC collaborated with NREL to develop a new model, Electric Vehicle Infrastructure for Road Trips (EVI-RoadTrip) to determine the state-wide charging infrastructure required for electrified LDTs in California, the associated substation-level grid impacts, and policy implications of the results.

This analysis leverages state-wide LDT activity data from the California Department of Transportation's (Caltrans) California Statewide Travel Demand Model (CSTDM)[13] to characterize LDTs in California. This is the most comprehensive and detailed LDT activity data source currently available to CEC staff. This analysis accounts for both intrastate and interstate trips with one-way travel distances greater than 100 miles.

The basic spatial resolution of LDT activity characterization in this analysis is the Traffic Analysis Zone (TAZ), which is inherited from the CSTDM. Based on detailed bottom-up simulations of trip and charging events across California, the charging infrastructure network for electrified LDTs is evaluated for four years – 2020, 2025, 2030, and 2035. Although both plug-in hybrid electric vehicles (PHEVs) and BEVs could be used for electrified LDTs, PHEVs predominantly operate in conventional gasoline vehicle mode, rather than electric drive mode, for these types of trips. Consequently, the scope of this analysis is limited to BEVs and DC fast charging, which is typically the most suitable charging technology for LDTs. More details on the methods and data are discussed in Chapter 3, with the results and conclusions presented in Chapter 4 and 5, respectively.

The goal of this analysis is to answer Five key questions related to DCFC infrastructure needs to enable electrified LDTs:

1) How many total charging stations and chargers are needed by year?
2) What power level will be needed and when?
3) Where should charging stations be located?
4) How large should each charging station be (chargers per station)?

13 Caltrans (California Department of Transportation). (2020). Transportation Demand Modeling and Simulation. https://dot.ca.gov/programs/transportation-planning/multi-modal-system-planning/statewide-modeling/transportation-demand-modeling-simulation.

5) What is the impact of LDT-related charging load on the electric grid infrastructure?

Key results of this analysis were previously published in the CEC's AB 2127 Commission Report.[14] This report expands on that discussion to detail the methods of EVI-RoadTrip, provide more information on the inputs and assumptions used, and show additional results, sensitivity analysis, and key takeaways. In particular, it updates key assumptions and results about the lower and upper bounds of chargers needed.

14 Alexander, Matt, Noel Crisostomo, Wendell Krell, Jeffrey Lu, and Raja Ramesh. July 2021. *Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment: Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030 – Commission Report*. California Energy Commission. Publication Number: CEC-600-2021-001-CMR.

CHAPTER 2:
Literature Review

LDTs are expected to rely on DC fast charging, because charging speed is typically the primary concern. However, designing an effectively sized and distributed DCFC infrastructure network requires numerous considerations, including travel pattern and volume, growth of EV adoption, types of EVs and their attributes (for example, range), DCFC technology (for example, maximum charging power), EV drivers' charging behavior, and electrical grid conditions that may not have available capacity to host high-power charging.

Personal On-Road Long-Distance Travel

LDTs greater than 100 miles account for less than 1 percent of all personal vehicle trips. As a result, personal LDTs make a relatively small impact on overall energy consumption and emissions compared to short-distance travel, and have historically been under-researched in the transportation research community.[15,16,17] For example, the 1995 American Travel Survey (ATS)[18] and 2001 National Household Travel Survey (NHTS)[19] are the only national surveys conducted to collect data for LDT activities in the U.S. Given the lack of LDT-specific surveys available, there is only one national travel demand modeling analysis[20] that provides a county-by-county origin-destination (O-D) matrix, which is built upon the 1995 ATS and 2001 NHTS.

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15 FHWA (Federal Highway Administration). (2008). Our Nation's Highways. FHWA-PL-08-021. Retrieved from: https://www.fhwa.dot.gov/policyinformation/pubs/pl08021/.

16 Bose, J., Giesbrecht, L., Sharp, J., Memmott, J., Khan, M., and Roberto, E. (2004). A Picture of Long-Distance Travel Behavior of Americans Through Analysis of the 2001 National Household Travel Survey. Transportation Research Board, 2004. Retrieved from: http://onlinepubs.trb.org/onlinepubs/archive/conferences/nhts/Sharp.pdf.

17 Aultman-Hall, L. (2018). Incorporating Long-Distance Travel into Transportation Planning in the United States. Retrieved from: https://escholarship.org/uc/item/0ft8b3b5.

18 Ibid.

19 Hu, P. S. and Reuscher, T. R. (2004). 2001 National Household Travel Survey. Summary of Travel Trends. Federal Highway Administration. U.S. Department of Transportation. Retrieved from: https://nhts.ornl.gov/2001/pub/STT.pdf.

20 Ibid.

However, there have been more state-level efforts to collect LDT data, mainly to develop and calibrate state-wide travel demand models and forecasts.[21,22] An example is the 2010–2012 California Household Travel Survey (CHTS)[23], which included add-on questions specifically about LDTs.

Apart from the lack of detailed data for LDTs, there are more fundamental challenges for research on LDTs, such as a lack of a universal definition for LDTs. In some cases, trips greater than 100 miles are considered LDTs (as in the 1995 ATS[24]). Others use different distance thresholds, such as 50 miles in the 2010–2012 CHTS and 2001 NHTS.

Even though LDTs have a relatively minor impact on the overall travel volume and lack appropriate activity data and clear definitions, LDTs are an essential part of the overall transportation system and its economic and environmental sustainability.[25] Thus, more research is needed to gain a deeper understanding of the nature and impact of LDTs in a wide range of spatial and temporal scales.

Research on LDTs is also relevant for vehicle electrification and corresponding charging infrastructure. Single-vehicle households will purchase a vehicle to serve a variety of use cases, not just short-distance travel. Therefore, lowering the barriers for electrified LDTs through means such as providing appropriate charging infrastructure and alleviating range anxiety is critical to promote EVs among mainstream consumers. Evaluating the expected impacts of electrified LDTs also allows relevant stakeholders like electric utilities to take those impacts into account for their asset management and planning processes.

The Design (Siting and Sizing) of DCFC Station Network for LDTs

Studies have tackled the challenge of designing a DCFC station network for electrified LDTs. When designing a network of DCFC stations, objectives include determining the location and

21 Horowitz, A. J., & Farmer, D. D. (1999). Statewide Travel Forecasting Practice: A Critical Review. *Transportation Research Record*, 1685(1), 13–20. https://doi.org/10.3141/1685-03.

22 NAS (National Academies of Sciences). (2012). Long-Distance and Rural Travel Transferable Parameters for Statewide Travel Forecasting Models. Washington, DC: The National Academies Press. https://doi.org/10.17226/22661.

23 Kunzmann, M. and Masterman, V. (2013). 20102012 California Household Travel Survey Final Report. California Department of Transportation. June 14, 2013. Retrieved from: https://www.nrel.gov/transportation/secure-transportation-data/assets/pdfs/calif_household_travel_survey.pdf.

24 Hwang, H -L, and Rollow, J. (2000). Data Processing Procedures and Methodology for Estimating Trip Distances for the 1995 American Travel Survey (ATS). Retrieved from: https://www.osti.gov/servlets/purl/763239-wnN0lB/native/.

25 Aultman-Hall, L. (2018). Incorporating Long-Distance Travel into Transportation Planning in the United States. Retrieved from: https://escholarship.org/uc/item/0ft8b3b5.

size of DCFC stations. This "location problem"[26] has been a classic topic in the field of operations research, computer science, and other areas.

Historically, the traditional location model framework to address this problem has been divided into three categories – node-based p-median (node-based), path or flow-based, and a hybrid of the two. The p-median approach determines the locations of facilities so that total weighted distance, maximum distance, and/or access costs between the nodes of demands (for example, consumers) and facilities (for example, grocery stores) can be minimized, or covered demands (by the facilities) can be maximized.[27] One of the limitations of the node-based approach is that the location of facilities is determined only based on the set of nodes of demands or facilities, so internal and external flows between or through the nodes are not accounted for. In contrast, the path or flow-based facility location approach incorporates flow into the location determination process by maximizing the number of flows (for example, trips) served by facilities. The two approaches require different forms of input data. For example, population or other demand metric and road network information could be used for the node-based approach, while traffic count and Origin-Destination data[28] could be used for the path/flow-based method.[29,30] Facility location problems need to consider both nodes and flow. The hybrid approach could be used for both node-based and flow data.

From the standpoint of DCFC station siting for LDTs, a flow-based or hybrid method would be more useful than the node-based p-median approach, since it is important to account for vehicle activities along and around the corridors through which long-distance travelers move. However, Wood et al. argue that the node-based approach can also be useful for the DCFC station siting for LDTs.[31] Another study shows that the best approach could depend on the geography for which the DCFC station network needs to be designed, as the flow or path-

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26 Daskin, M. S. (1995). Network and Discrete Location: Models, Algorithms, and Applications. John Wiley & Sons, Inc. ISBN 0-471-01897-X.

27 Church, R. L. and Revelle, C. S. (1976). Theoretical and Computational Links between the p-Median, Location Set-covering, and the Maximal Covering Location Problem. Geographical Analysis, Vol. VIII. 406-415.

28 Origin-Destination data refers to travel surveys or other data formats recording the start and end points of trips that has been aggregated to show the number trips traveling from one location to another.

29 Upchurch, C. and Kuby, M. (2010). Comparing the p-median and flow-refueling models for locating alternative-fuel stations. Journal of Transport Geography 18 (2010) 750–758. https://doi.org/10.1016/j.jtrangeo.2010.06.015.

30 Ghamami, M., Zockaie, A., and Nie, Y. (2016). A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel. Transportation Research Part C 68 (2016) 389–402. http://dx.doi.org/10.1016/j.trc.2016.04.016.

31 Motoaki, Y. (2019). Location-Allocation of Electric Vehicle Fast Chargers—Research and Practice. World Electr. Veh. J. 2019, 10(1), 12. https://doi.org/10.3390/wevj10010012.

based approach seems to produce more reasonable results than the p-median counterpart for larger geographical scales (for example, state vs. city).[32]

DCFC station network studies have focused on various levels of geography. Some have investigated the DCFC needs along segments of highways,[33,34] while others have tackled this at a larger geographical scale like the state level.[35,36,37,38]

At the multi-state regional scale, M.J. Bradley and Associates (MJB&A) developed the Electric Vehicle Infrastructure Location Identification Tools, which identify suitable locations for public DCFC infrastructure along 14,000 miles of corridors from North Carolina to Maine.[39] Notably, the MJB&A tools utilize a multi-criteria weighting approach incorporating factors like annual average daily traffic, peak traffic volume, population density, and commercial centers. This approach is unlike most of the other DCFC infrastructure network design studies that employ the traditional location model framework mentioned previously.

Some studies have conducted national-scale analyses of the DCFC infrastructure requirements for electrified LDTs. Wood et al. assessed DCFC station network for LDTs for the contiguous U.S., based on a 70-mile station-to-station distance interval along the interstate highways.[40] The adoption of the 70-mile interval between the nodes may be categorized as a network

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32 Upchurch, C. and Kuby, M. (2010). Comparing the p-median and flow-refueling models for locating alternative-fuel stations. Journal of Transport Geography 18 (2010) 750–758. https://doi.org/10.1016/j.jtrangeo.2010.06.015.

33 Nie, Y. and Ghamami, M. (2013). A corridor-centric approach to planning electric vehicle charging infrastructure. Transportation Research Part B 57 (2013) 172–190. http://dx.doi.org/10.1016/j.trb.2013.08.010.

34 Ghamami, M., Zockaie, A., and Nie, Y. (2016). A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel. Transportation Research Part C 68 (2016) 389–402. http://dx.doi.org/10.1016/j.trc.2016.04.016.

35 Li, S. and Huang, Y. (2015). Development of Electric Vehicle Charging Corridor for South Carolina. International Journal of Transportation Science and Technology. Volume 4, Issue 4, 2015, Pages 395-411. https://doi.org/10.1016/S2046-0430(16)30170-8.

36 Li, S., Huang, Y., and Mason, S. (2016). A multi-period optimization model for the deployment of public electric vehicle charging stations on network. Transportation Research Part C 65 (2016) 128–143. http://dx.doi.org/10.1016/j.trc.2016.01.008.

37 Zhang, L., Shaffer, B., Brown, T., and Samuelsen, G. S. (2015). The optimization of DC fast charging deployment in California. Applied Energy 157 (2015) 111–122. http://dx.doi.org/10.1016/j.apenergy.2015.07.057.

38 Xie, F., Liu, C., Li, S., Lin, Z., and Huang, Y. (2018). Long-term strategic planning of inter-city fast charging infrastructure for battery electric vehicles. Transportation Research Part E 109 (2018) 261–276. https://doi.org/10.1016/j.tre.2017.11.014.

39 MJB&A. (2021). Electric Vehicle Infrastructure Planning Tools. Available at: https://www.mjbradley.com/mjb_form/EV-tools.

40 Wood, E., Rames, C., Muratori, M., Raghavan, S., and Melaina, M. (2018). National Plug-In Electric Vehicle Infrastructure Analysis. National Renewable Energy Laboratory.

location model. In contrast, discrete location models allow stations to be located with varying distances between nodes. He et al. also evaluated the DCFC infrastructure requirements for LDTs in the contiguous U.S. by utilizing the framework of a flow-refueling location model based on a network of nodes along the major U.S. highways, with about 60-miles between nodes.[41]

Regardless of the station siting method used for various geographical scales, previous studies shed light on important factors that influence the results for DCFC infrastructure networks for LDTs. From the demand-side perspective of DCFC stations, travel volume and BEV types and their ranges are among the most important parameters identified in the existing studies. A higher LDT volume correlates to a larger number of required DCFC stations. Larger battery sizes (and thus longer ranges) result in decreasing the DCFC station network size, as less frequent charging during LDTs is required. BEV range is determined not only by battery size, but also vehicular energy consumption rate. As with assumptions related to battery size, the methods of estimating vehicle energy consumption vary from one study to another. Some rely on detailed vehicle dynamic simulation, while others adopt a fixed energy consumption rate.

From the supply-side perspective, DCFC power is an influential factor. DCFC power (or speed) can be particularly important when evaluating the waiting time or queuing of BEVs in DCFC stations. Once it is assumed that BEVs can wait in the queue for charging, the required size of DCFC stations can decrease, compared to the case in which all BEVs are assumed to charge as soon as they arrive at the stations.

Charging behavior and its impact has not been thoroughly examined in the existing body of literature on DCFC station network design for LDTs. Depending on the state of charge (SOC) at which drivers decide to plug or unplug their BEVs, the overall charging station network requirement and station utilization rate can change significantly.

When sizing DCFC stations, most transportation infrastructure planning studies adopted a demand-centric approach – estimating the size of stations primarily based on projected charging demands (for example, total peak charging load). However, the size of a charging station can also vary with supply-side variables such as the cost associated with the station (capital, operating, maintenance costs) or financial incentives. This may become more important, especially when determining the size of individual stations, than estimating the overall fleet- or area-wide charging network requirement. Individual stations' sizing can be impacted by numerous other factors contributing to the overall decision-making process, including on-site renewable electricity generation, energy storage, system architecture (for example, vehicle-to-grid), and control or operation strategy of charging events or activities (for example, smart charging). The size of a station can also be a function of the location, meaning that the size and location of a station are sometimes interdependent.

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41 He, Y., Kockelman, K. M., and Perrine, K. A. (2019). Optimal locations of U.S. fast charging stations for long-distance trip completion by battery electric vehicles. Journal of Cleaner Production 214 (2019) 452–461. https://doi.org/10.1016/j.jclepro.2018.12.188.

Although there is no known standardized method that outlines how the optimal or maximum size of a station should be determined—including both the maximum power rating and the maximum number of chargers per station, increasing power and increasing numbers of chargers per station can be observed empirically. This may be due to economies of scale that can be achieved by grouping chargers together, possibly lowering the cost of installation and maintenance on a per-charger basis. The pressure for economies of scale is counterbalanced by the need to distribute station over the network so customers can conveniently find a charging station. The number of chargers per station in this report are illustrative and aggregation of demand between adjacent stations may be possible to decrease costs without negatively affecting the consumer experience.

Grid Impact of DCFC for Electrified LDTs

DC fast charging can impact the electric grid in numerous ways, such as by creating imbalances between power supply and demand, voltage deviation, power quality degradation, and reduced lifetime of distribution and transmission components.[42]

Assessing potential grid impacts of DC fast charging on the electric grid requires a holistic analysis accounting for the dynamics and operation of the grid, charging stations, and EVs. One of the foremost challenges and knowledge gaps is the extent to which the existing distribution capacity is capable of managing the high-power demand from DC fast charging. Planners must identify how much additional capacity is needed at which locations by what time. To date, not much information or analysis on this topic is available in the literature. Metcalf et al. (2016) evaluated potentially ideal locations of DCFC stations accounting for the available distribution capacity of existing service transformers in Pacific Gas & Electric Company (PG&E) territory.[43] Other than being used as a constraint for station site selection or identification, information related to net capacity additions required for the development of DCFC station networks to enable electrified LDTs is missing in the existing literature.

Knowledge Gap

As illustrated in Table 1, numerous approaches are applicable to the design of DCFC infrastructure networks for electrified LDTs on various geographical scales. The existing analyses tend to focus on methodological aspects (for example, optimization technique) of the DCFC infrastructure design. The methodological focus is valuable, particularly for operations

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42 Ashique, R. H., Salam, Z., Aziz, M., Bhatti, A. (2017). Integrated photovoltaic-grid dc fast charging system for electric vehicle: A review of the architecture and control. Renewable and Sustainable Energy Reviews. Vol. 69, 1243 - 1257. https://doi.org/10.1016/j.rser.2016.11.245.

43 Metcalf, M., Mohamed, S., McKenzie, L., Donadee, J., Cutter, E., Horvat, A., Jenks, R., Jariwala, A., Wiseman, M., Kollamthodi, S., Norris, J., Bubna, P., Nicholas, M., Tal, G., and Ji, W. (2016). Electric Program Investment Charge (EPIC). EPIC 1.25 – Develop a Tool to Map the Preferred Locations for DC Fast Charging, Based on Traffic Patterns and PG&E's Distribution System, to Address EV Drivers' Needs While Reducing the Impact on PG&E's Distribution Grid. Available at: https://www.pge.com/pge_global/common/pdfs/about-pge/environment/what-we-are-doing/electric-program-investment-charge/EPIC-1.25.pdf.

research. However, this emphasis on optimization methods may come at the expense of not fully accounting for critical variables influencing the DCFC network design.

EVI-RoadTrip analysis presented in this paper takes a slightly different approach, putting less focus on network design methodology. This uses a simplistic heuristic approach and builds upon the list of factors that existing studies have identified as critical for DCFC infrastructure design. This work accounts for a wider range of BEV types and DCFC power levels. Researchers examined the impact of varying charging behavior, which was not explored in the existing analyses of DCFC network design for electrified LDTs. Leveraging detailed driving and charging simulations, this analysis also attempts to determine the latitude-longitude locations of DCFC stations using prioritized land use types for potential station sites.

Table 1: Key Relevant Previous Studies – Scope and Approach

	Geography	Siting method	BEV type/range	Vehicle energy consumption	DCFC power	Waiting or queuing	Grid impact
Upchurch and Kurby (2010)	Orlando (metro area); Florida (state)	p-median; and flow-based	BEV100	N/A	N/A	N/A	N/A
Nie and Ghamami (2013)	Chicago–Madison corridor	Flow-based	BEV50 to BEV200	Fixed (0.4 kWh/mile)	20 to 300 kW	Considered	N/A
Zhang et al. (2015)	California	Set-covering	BEV60, BEV100, and BEV200	N/A	N/A	Considered	N/A
Ghamami et al. (2016)	Chicago–Madison–Minneapolis corridor	Flow-based	BEV100 to BEV250	Fixed (0.4 kWh/mile)	50 kW	Considered	N/A
Metcalf et al. (2016)	PG&E's territory	Flow-based	BEV100 and BEV200	Fixed	65 kW	N/A	Distribution capacity
Li et al. (2016)	South Carolina	Flow-based	BEV100 and BEV150	N/A	N/A	N/A	N/A
Wood et al. (2018)	Contiguous U.S.	Flow-based	BEV100 and BEV250	Reduced form of vehicle dynamic simulation model	50 to 150 kW	N/A	N/A
Xie et al. (2018)	California	Flow-based	BEV75 to BEV300	N/A	N/A	Considered	N/A
He et al. (2019)	Contiguous U.S.	Flow-based	BEV60 to BEV250	N/A	150 kW	N/A	N/A
Jie et al. (2019)	California	Flow-based	BEV80 to BEV300	N/A	N/A	N/A	N/A

CHAPTER 3: EVI-RoadTrip Methods

EVI-RoadTrip

This analysis uses EVI-RoadTrip, a new charging infrastructure analysis model developed collaboratively by the CEC and NREL, to evaluate the DCFC infrastructure needs to support electrified LDTs for passenger vehicles within and across California's borders. In contrast to the existing EVI-Pro model, which focuses on destination charging for short-distance travels, EVI-RoadTrip evaluates waypoint charging demands along the routes between origins and destinations for LDTs. This analysis assumes charging activity before and after LDTs, whether at origins or destinations, which is accounted for in EVI-Pro and thus not considered in EVI-RoadTrip.

EVI-RoadTrip takes a bottom-up approach consisting of four sequential steps: 1) trip data generation; 2) energy and charging simulation; 3) station design (siting and sizing); and 4) hosting capacity analysis. This analysis covers the state of California and includes results on five-year intervals from 2020 to 2035.

The following sections describe the data and methods in detail for each of the four steps.

Step 1 – Trip Data Generation

Travel Volume and Routing between Origins and Destinations

As charging demands inherently depend on vehicle movement and corresponding energy consumption, vehicle activity is one of the primary inputs for EVI-RoadTrip. This analysis uses the O-D matrix from the CSTDM Version 3[44] to understand the volume and spatial distribution of LDTs in California.

The CSTDM estimates trips for every resident of California for a typical spring or fall weekday and is built upon a microsimulation activity-based choice demand model, accounting for a complete series or chain of trips made by a person over the course of the day. The travel behavior is calibrated based on the CHTS as well as the Census Bureau's Journey to Work Survey, among others. The CSTDM divides the state into approximately 5,500 TAZs (Figure 1), assigns each person or household to a home TAZ, and forecasts travel activities of all residents and households within and between TAZs based on the person-by-person microsimulation. The CSTDM is validated against observed data, on various geographical and temporal scales,

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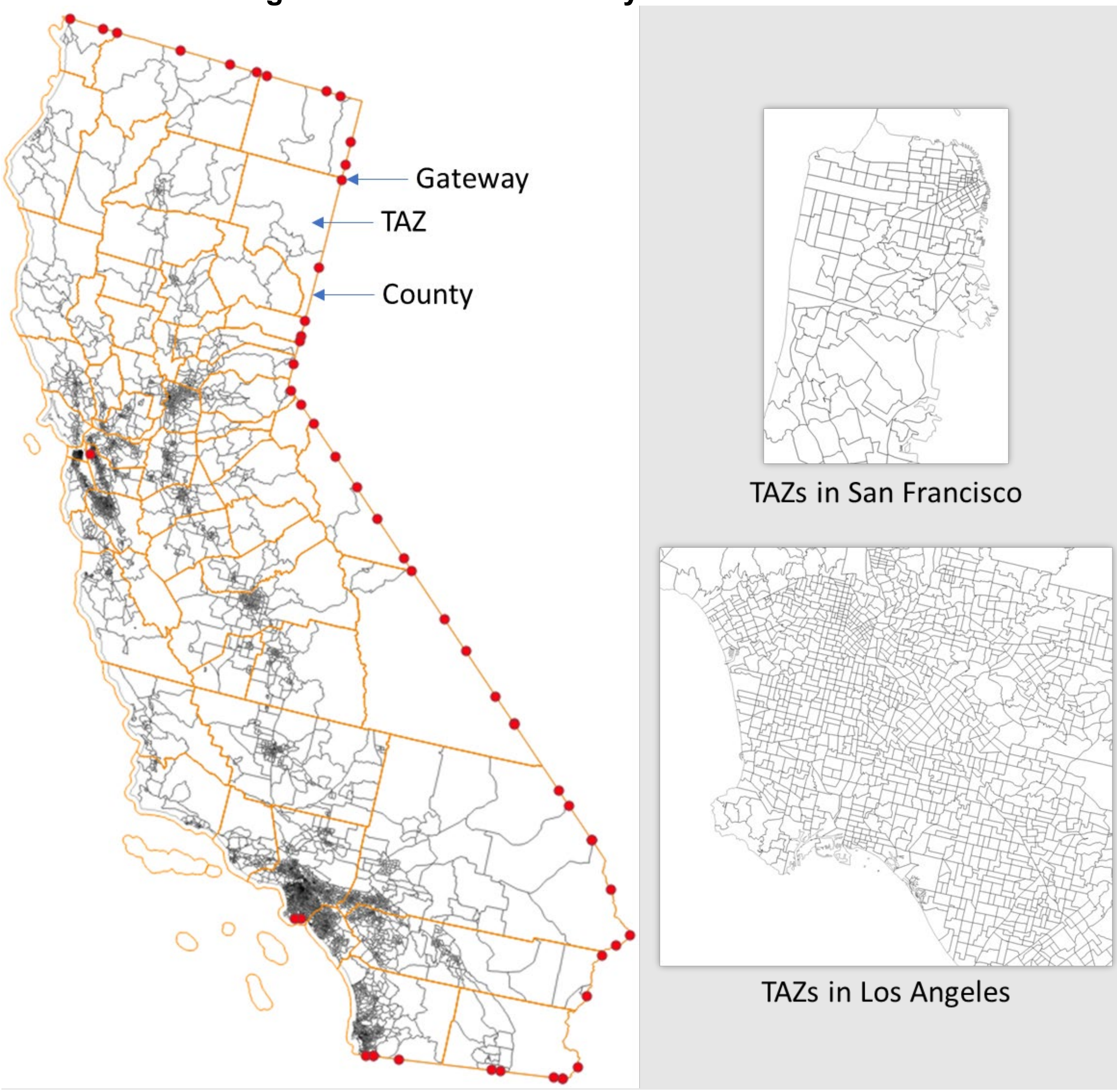
44 Caltrans (California Department of Transportation). (2020). Transportation Demand Modeling and Simulation: https://dot.ca.gov/programs/transportation-planning/multi-modal-system-planning/statewide-modeling/transportation-demand-modeling-simulation.

and in terms of travel times, congested speeds, vehicle miles traveled, vehicle flows, transit ridership, modal split, and more.

Figure 1: TAZs and Gateways in the CSTDM[45]



The CSTDM developed by Caltrans contains nearly 5,500 TAZs, which are sized to contain roughly equal portions of the population. In addition, the CSTDM contains 53 gateways (50 points in the road network and three ports) along the state boundary to track travel across the California border. Source: Caltrans

To characterize state-wide LDT activity, we rely on the O-D matrix from the CSTDM that provides estimates of travel volume within and between TAZs for current and future years.

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45 Caltrans (California Department of Transportation). (2020). Transportation Demand Modeling and Simulation: https://dot.ca.gov/programs/transportation-planning/multi-modal-system-planning/statewide-modeling/transportation-demand-modeling-simulation.

TAZs in the CSTDM are defined only within the boundary of California. Thus, to account for out-of-state travel, the CSTDM incorporates 53 gateways (50 points in the road network and three ports) where vehicles cross the California border.

The adoption of gateways in the CSTDM allows the estimation of LDT activity to and from out-of-state locations. This is particularly important for California's travel demand characterization, as more than half of California's state-wide LDT activity is composed of out-of-state travel.[46,47] However, travel volume information is available only up to and from gateways along the state boundary, so exact locations of out-of-state origins and destinations are unknown.

To achieve a detailed spatial analysis, the latitude-longitude GPS coordinates of trip origins and destinations from the 2012 CHTS[48] are used to generate LDTs (Figure 2). In addition, 30 meter by 30 meter land use data (residential, commercial, and recreational sites) is used from the national land use data (NLUD) set to determine where to site DCFC stations.[49] The NLUD-based coordinates data set shown in Figure 2 is much larger than CHTS and helps address sample size deficiencies in the CHTS-based coordinates. With this data, the model randomly samples the coordinates as many times as needed to match the travel volume for each TAZ.

Using the set of sampled coordinates as geospatial reference points for origins or destinations, EVI-RoadTrip generates routes between origins and destinations by running trip simulations with the Open Source Routing Machine (OSRM).[50] The output of OSRM contains detailed information of waypoints between origins and destinations, including total trip duration, vehicle coordinates, and trip distance. A time interval of one minute was selected to balance computational efficiency with spatial/temporal resolution. This interval allows, for example, the location of a vehicle driving 60 miles per hour to be observed every mile.

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46 Caltrans (California Department of Transportation). (2020). Transportation Demand Modeling and Simulation: https://dot.ca.gov/programs/transportation-planning/multi-modal-system-planning/statewide-modeling/transportation-demand-modeling-simulation.

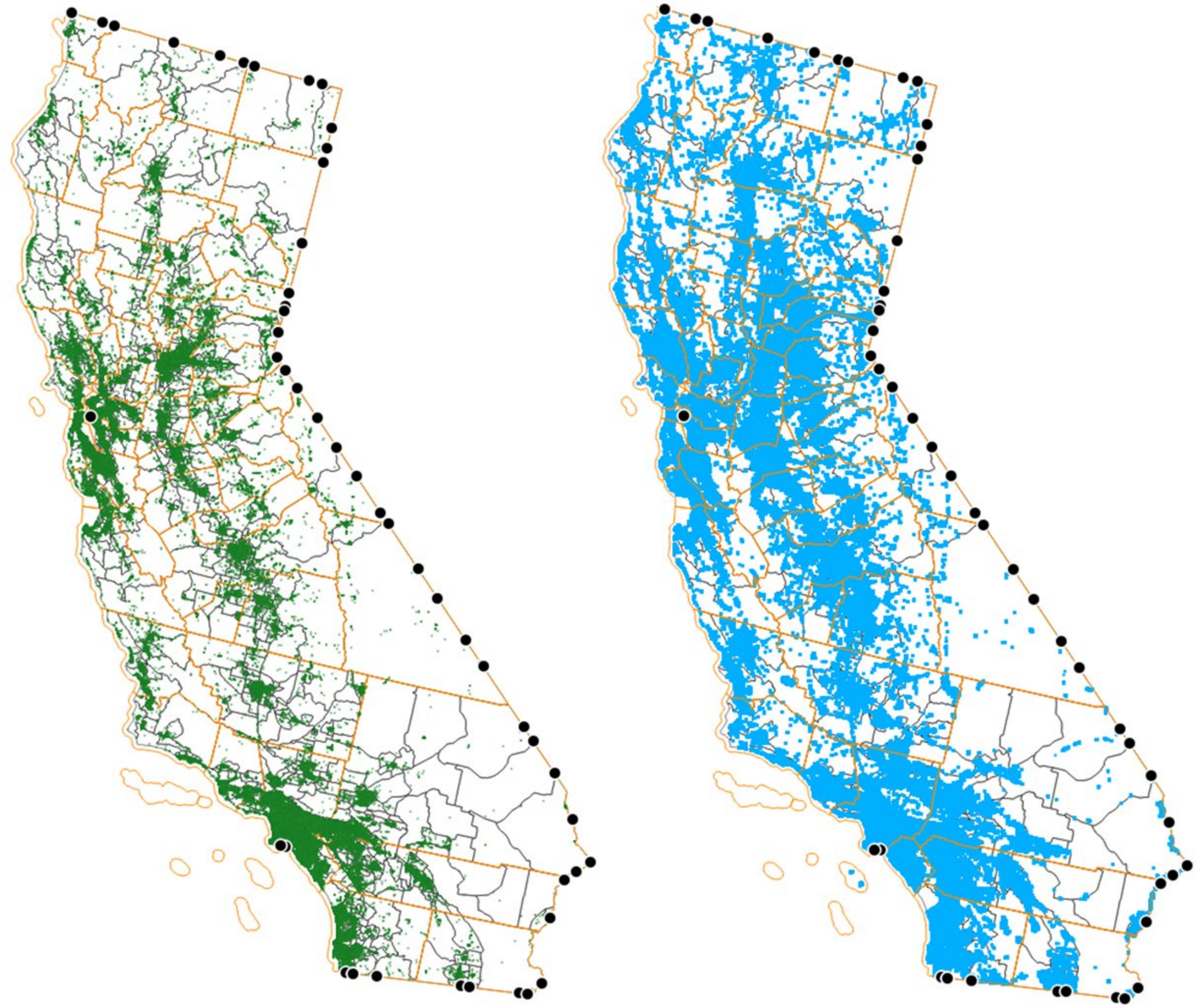
47 U.S. Department of Transportation, Bureau of Transportation Statistics, Transportation Statistics Annual Report 2017 (Washington, DC: 2017).

48 Kunzmann, M. and Masterman, V. (2013). 20102012 California Household Travel Survey Final Report. California Department of Transportation. June 14, 2013. Retrieved from: https://www.nrel.gov/transportation/secure-transportation-data/assets/pdfs/calif_household_travel_survey.pdf.

49 Theobald DM (2014) Development and Applications of a Comprehensive Land Use Classification and Map for the US. PLoS ONE 9(4): e94628. doi:10.1371/journal.pone.0094628.

50 Open Source Routing Machine (OSRM): http://project-osrm.org/

Figure 2: Coordinates from 2012 CHTS[51] (left) and NLUD[52] (right)



The left map shows the CHTS trip origin and destination coordinates while the right map shows the larger NLUD coordinate dataset, which is used to identify potential charging station locations. Source: CHTS and NLUD

51 Kunzmann, M. and Masterman, V. (2013). 20102012 California Household Travel Survey Final Report. California Department of Transportation. June 14, 2013. Retrieved from: https://www.nrel.gov/transportation/secure-transportation-data/assets/pdfs/calif_household_travel_survey.pdf.

52 Theobald DM (2014) Development and Applications of a Comprehensive Land Use Classification and Map for the US. PLoS ONE 9(4): e94628. doi:10.1371/journal.pone.0094628.

Vehicle Electrification Rate

The volume and spatial distribution of LDTs in the CSTDM are for all on-road light-duty personal vehicles, without consideration of vehicle technologies and powertrains. As summarized in Table 2, the CSTDM estimates that approximately 0.6 million LDTs occur throughout California in a typical fall or spring weekday. This total LDT volume is for ICEVs and EVs. Therefore, this raw travel volume is scaled down so the total daily volume of electrified LDTs with BEVs in EVI-RoadTrip matches projected activity of electrified LDTs.

Table 2: Daily Volume of LDTs (Electrified and Non-Electrified) in the CSTDM

Year	Intra-State	Out-of-State	Total
2020	215,150	344,100	559,250
2025	211,700	362,300	574,000
2030	210,800	372,900	583,700

Source: Adapted from the TAZ-by-TAZ travel volume data in the CSTDM.53 Values are rounded to the nearest 50.

Researchers used LDT electrification rates as scaling factors for California (intra-state), non-California (domestic out-of-state), and Mexico (international out-of-state) to scale down the original LDT volume estimates from the CSTDM for electrified LDTs. Table 3 shows the various vehicle projections used to determine the number of California-based electrified LDTs (those made by BEVs registered in California). The Low case uses the CEC's 2020 Integrated Energy Policy Report (IEPR) low forecast, which results in a BEV fleet share of about five percent by 2030.[54] The Mid case uses the CEC's 2020 IEPR aggressive forecast, resulting in a BEV fleet share of about 10 percent by 2030. This forecast serves as a proxy for the five million ZEVs by 2030 goal called for in EO B-48-18 and AB 2127. The High case uses the California Air Resources Board (CARB) *Revised Draft 2020 Mobile Source Strategy* planning scenario.[55] While the CEC IEPR forecasts are based on consumer choice modeling, CARB's *Revised Draft 2020 Mobile Source Strategy* is a policy achievement scenario that identifies the level of ZEV adoption needed to meet climate, air quality, and transportation electrification goals. The ZEV adoption trajectory in this scenario achieves the EO N-79-20 target of 100 percent light-duty

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53 Caltrans (California Department of Transportation). (2020). Transportation Demand Modeling and Simulation: https://dot.ca.gov/programs/transportation-planning/multi-modal-system-planning/statewide-modeling/transportation-demand-modeling-simulation.

54 Gee, Quentin, Stephanie Bailey, Jane Berner, Michael Comiter, Jim McKinney, and Tim Olson. 2021. Final 2020 Integrated Energy Policy Report Update. California Energy Commission. Publication Number: CEC-100-2020-001-V1-CMF.

55 California Air Resources Board staff. 2021. *Revised Draft 2020 Mobile Source Strategy*. California Air Resources Board.

ZEV sales by 2035 and results in almost eight million ZEVs by 2030, with BEVs making up 17 percent of the total fleet in 2030.

This analysis also used Low, Mid, and High BEV adoption scenarios for LDTs based outside California. The U.S. Energy Information Administration (EIA) predicts that 2.5 percent of on-road light-duty vehicles will be BEVs by 2030 in its baseline scenario,[56] which is used for the Mid non-California BEV adoption rate in the U.S. For the Low and High scenarios, the EIA's lowest (1.8 percent by 2030) and highest (3.9 percent by 2030) electrification projections are used. Researchers used the BEV adoption rate in Mexico estimated by the International Energy Agency[57] for international out-of-state travels originated from or returning to Mexico. Electrification rates are summarized in Table 3.

Table 3: LDT Electrification Rates

Year	BEV Adoption Scenario	California (Intra-State)	Non-California (Domestic Out-of-State)	Mexico (International Out-of-State)
2020	Initial condition	2%	0.5%	0.002%
2025	Low	3.4%	1%	0.01%
2025	Mid	5.8%	1.4%	0.02%
2025	High	6.7%	2.2%	0.03%
2030	Low	4.8%	1.8%	0.02%
2030	Mid	9.7%	2.5%	0.06%
2030	High	17%	3.9%	0.08%

Source: CEC, NREL, CARB, EIA, IEA

Researchers assumed that 50 percent of the total LDT travel volume crossing California's borders is a return trip for a vehicle coming back to its California home. For example, if 100 personal light-duty vehicles left California, 50 of those vehicles are assumed to be registered in and originated from California, while the other 50 vehicles are assumed to be registered in and heading back to their origins in non-California home states. For each of those two categories, the appropriate electrification rates corresponding to each vehicle's home state or country are applied.

56 Energy Information Administration (EIA). 2020. Annual Energy Outlook 2020. Available at: https://www.eia.gov/outlooks/aeo/.

57 International Energy Agency (IEA). 2019. Global EV Outlook 2019. Available at: https://www.iea.org/reports/global-ev-outlook-2019.

Table 4 shows electrified vehicle activity for different years under the High BEV adoption scenario, broken down by travel type. Researchers estimated that 8,000 LDTs are electrified per day in 2020, but the travel volume will increase to over 70,000 by 2030. Intra-state and out-of-state have almost the same share of overall LDTs on a given day, illustrating the importance of accounting for out-of-state LDTs. Due to the assumption that 50 percent of out-of-state LDTs are return trips, travel volumes for inbound and outbound out-of-state trips are almost identical. The other two BEV adoption scenarios, Low and Mid, result in electrified LDT volumes of 21,000 and 41,000 per day in 2030, respectively. It is important to note that LDT activity may vary seasonally or by location, but current data limitations do not allow for this variation to be accounted for.

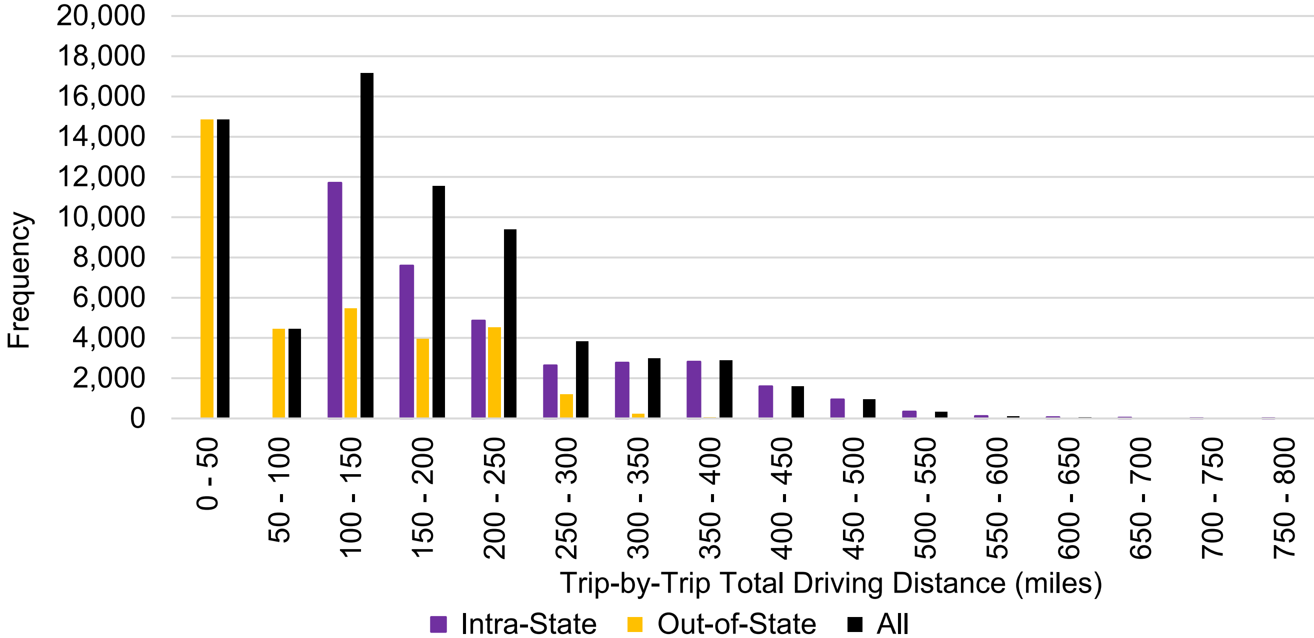
Table 4: Number of Electrified LDTs Per Day – High BEV Adoption Scenario

Year	Intra-State	Inbound (US)	Inbound (Mexico)	Outbound (US)	Outbound (Mexico)	Through	Total
2020	4,230	1,140	730	1,140	730	18	8,000
2025	14,270	4,380	2,640	4,430	2,670	90	28,480
2030	35,500	10,490	6,820	10,460	6,870	170	70,310

Source: CEC and National Renewable Energy Laboratory. Values rounded for simplicity.

As shown in Figure 3, the average distance for intra-state LDTs is about 230 miles, whereas it is roughly 100 miles for out-of-state LDTs. This latter distance is only for the portion of the trip within the boundary of California. Average travel duration of intra-state LDTs is approximately 270 minutes, and 120 minutes for out-of-state LDTs. Accordingly, the average trip speed for LDTs within California's boundaries is 45–50 miles per hour.

Figure 3: Distribution of LDT Distance within the California Boundary – High BEV Adoption in 2030



The average distance for intra-state and out-of-state LDTs is about 230 miles and 100 miles, respectively, in 2030. However, out-of-state LDTs only include the portion of the trip within California. Source: CEC and NREL

Table 5 provides spatial distribution of LDTs, with San Diego and the Greater Los Angeles Area (including Los Angeles, Riverside, San Bernardino, Imperial, and Orange counties) accounting for about 60 percent of total LDTs. Origin-based trips are defined as those that start in the respective county, while destination-based trips end in that county. San Diego's significant contribution of LDTs is attributed to out-of-state LDTs, particularly those going to or coming from Mexico.

Table 5: Electrified LDTs Per Day in California by County (Top 10) in 2030 – High BEV Adoption Scenario

County	Number of Origin-based Trips	Number of Destination-based Trips
San Diego	9,240	9,250
Los Angeles	7,320	7,380
Riverside	3,170	3,050
San Bernardino	2,820	2,800
Imperial	2,000	2,090
Orange	2,000	1,970
Sacramento	1,910	1,880
Santa Clara	1,800	1,700
El Dorado	1,580	1,560
Placer	1,410	1,380

Source: CEC and National Renewable Energy Laboratory

Vehicle Assignment

The next step in trip generation involves assigning the electrified LDTs to BEVs, which are grouped into three broad categories: 1) short-range cars and sedans (SR-Cars); 2) long-range cars and sedans (LR-Cars) and 3) sport utility vehicles (SUVs). Cars and sedans are differentiated by their range, as SR-Cars (e.g., Nissan Leaf) have about 150 miles per full charge in 2020 and LR-Cars (e.g., Tesla Model 3 Long Range or Tesla Model S) have around 350 miles. SUVs, such as the Tesla Model X, are assumed to have approximately 320 miles of range per full charge in 2020.

To account for vehicle technology advancements, model years (MYs) are differentiated by four MY groups – 2015, 2020, 2025, and 2030. MY2015 BEVs include those produced in 2015 or earlier, as well as those manufactured in bridge years such as 2016, 2017, and 2018. Similarly, the MY2020 group is for BEVs produced in 2020 as well as a few pre- and post-2020 years (2017, 2018, 2019, 2021, 2022, and 2023). To avoid double-counting, bridge years are assumed to be split evenly between the earlier and later MY group. This allows a relatively smooth transition of vehicle technology characteristics or attributes between different MY groups.

The electric range is assumed to increase over time, reaching about 200 miles for SR-Cars, 450 miles for LR-Cars, and 400 miles for SUVs by 2030. For the same battery capacity (kilowatt-hours, kWh), electric range can vary significantly depending on driving conditions (e.g., city vs. highway, ambient temperature, elevation gain), manufacturer, trim (e.g., standard vs. performance), MY, and more. The principal assumption used is battery capacity, rather than exact range in miles, shown in Table 6. Electric range, a byproduct of energy consumption, is determined separately for individual trips, vehicle type, and model year, as described in Section 3.3.

Table 6: BEV Battery Capacity (kWh) Assumption

MY Group	SR-Car	LR-Car	SUV
2015* and 2020	40	100	100
2025	45	125	125
2030	45	125	125

*** For simplicity, MY 2020 values are used for MY 2015 due to the small share of pre-2020 MY BEVs in the vehicle population.**

Source: CEC, CARB, and NREL

For some vehicle types, the battery capacity assumption may be high or low, especially for future model years. As the BEV market matures over time, it is possible that cheaper models with smaller battery capacity become more popular, decreasing the overall MY or fleet-wide average battery capacity. One the other hand, it is also possible that BEVs with larger battery capacities (100+ kWh) could dominate the entire market in the future. It is difficult to predict the exact future battery capacity for BEVs, but we consider the three BEV types and their combinations effectively capture the general mix and evolution of different vehicle types and their battery capacities.

Table 7 shows the distribution of vehicle populations for each calendar year, model year, and vehicle type for the projections made by the CEC and used in this report. The distribution of BEV populations shown in Table 7 is applied to BEVs in both the U.S. and Mexico due to limited data availability. In 2020, SR-Cars and LR-Cars make up the majority of BEVs. The dominance of LR-Car continues over time, composing almost 50 percent of the total BEV population by 2030. However, the share of SR-Car diminishes significantly over time as these are replaced by SUVs, which become increasingly popular and represent about a third of the BEV population in 2030. These trends have important implications for the charging network requirements, as will be discussed later. For example, for the same travel distance, SUVs, which have longer ranges may need less frequent charging between origin and destination compared to SR-Cars, resulting in a smaller DCFC network.

Table 7: BEV Population Distribution – High BEV Adoption Scenario

Calendar	Model Year Group	Short Range Car	Long Range Car	SUV
2020	2015	8.5%	5.2%	1.0%
2020	2020	23.4%	53.7%	8.3%
2020	**Total**	**31.9%**	**58.9%**	**9.3%**
2025	2015	1.2%	0.9%	0.1%
2025	2020	4.3%	9.8%	1.6%
2025	2025	13.0%	42.2%	26.9%
2025	**Total**	**18.5%**	**52.9%**	**28.6%**
2030	2015	0.3%	0.2%	0.03%
2030	2020	1.2%	2.8%	0.5%
2030	2025	4.2%	14.3%	9.3%
2030	2030	9.3%	31.5%	26.4%
2030	**Total**	**15.0%**	**48.8%**	**32.3%**

Source: NREL and CEC

Step 2 – Energy and Charging Simulation

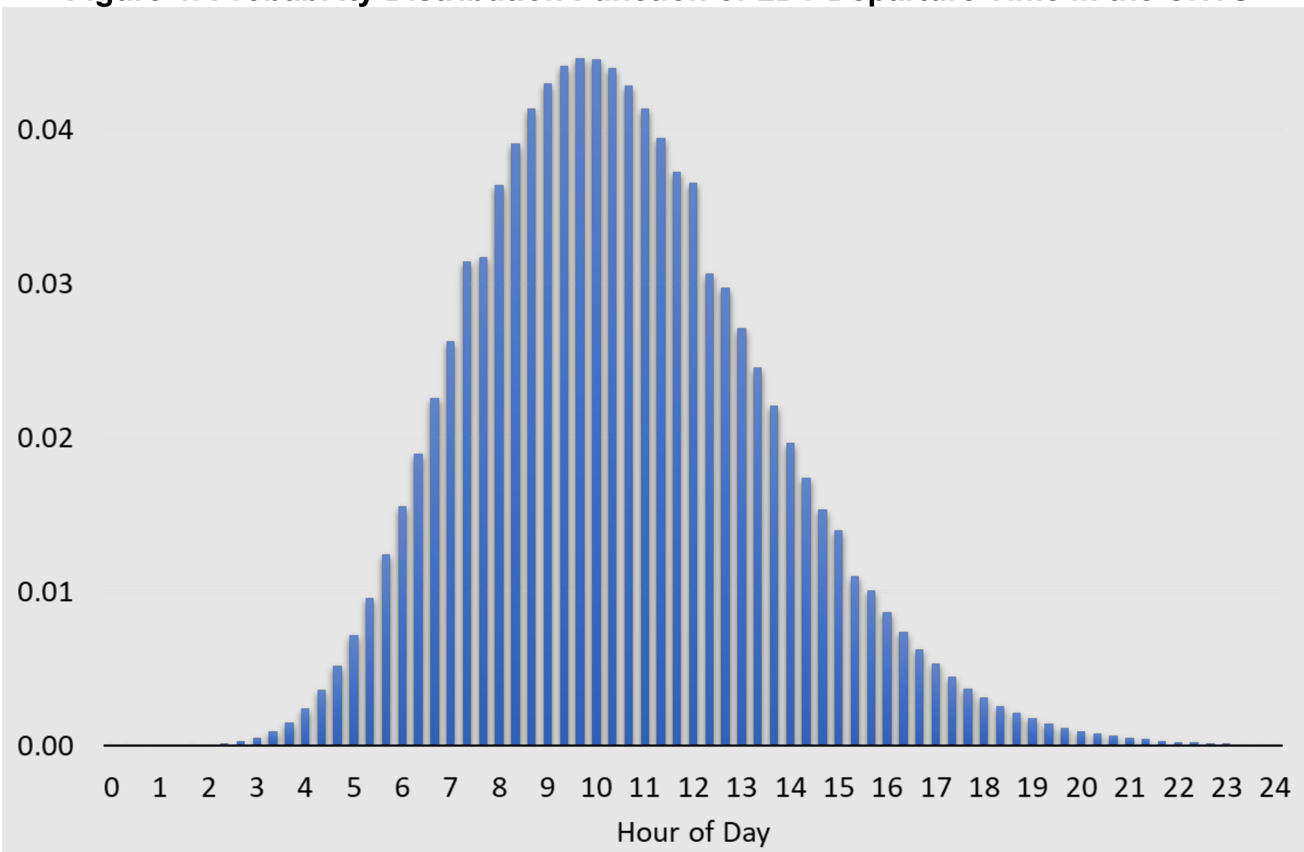
The second step in EVI-RoadTrip assigns departure times, estimates energy consumption along the route, and simulates on-route charging events for each trip generated in Step 1.

Time Reference

The trip data generated in Step 1 does not include any time-related information besides trip duration. As a result, it is necessary to determine when trips start and end before conducting charging simulations. While short-distance trips tend to have a two-peak pattern tied to morning and evening commutes, CHTS data indicates that LDTs have only one peak, centered around 10 a.m. as depicted in Figure 4.

Each trip is assigned either a departure or arrival time depending on the LDT type. Departure time (Figure 4) is used as the time reference for intra-state and outbound (e.g., from California to Nevada) LDTs. However, since the out-of-state component for inbound trips is unknown, these trips are instead assigned an arrival time based on their departure time, travel/driving distance, and time spent for on-route charging (Figure 5) based on the statistics of the intra-state LDTs, assuming that travelers would prefer to arrive at their destinations around the same time as for intra-state LDTs. The distribution of departure times in Figure 5 is included for reference and matches the distribution shown in Figure 4. A uniform distribution of entry time to the state gateways is used for through trips (e.g., Mexico to Canada), which account for a negligible share of the overall travel volume.

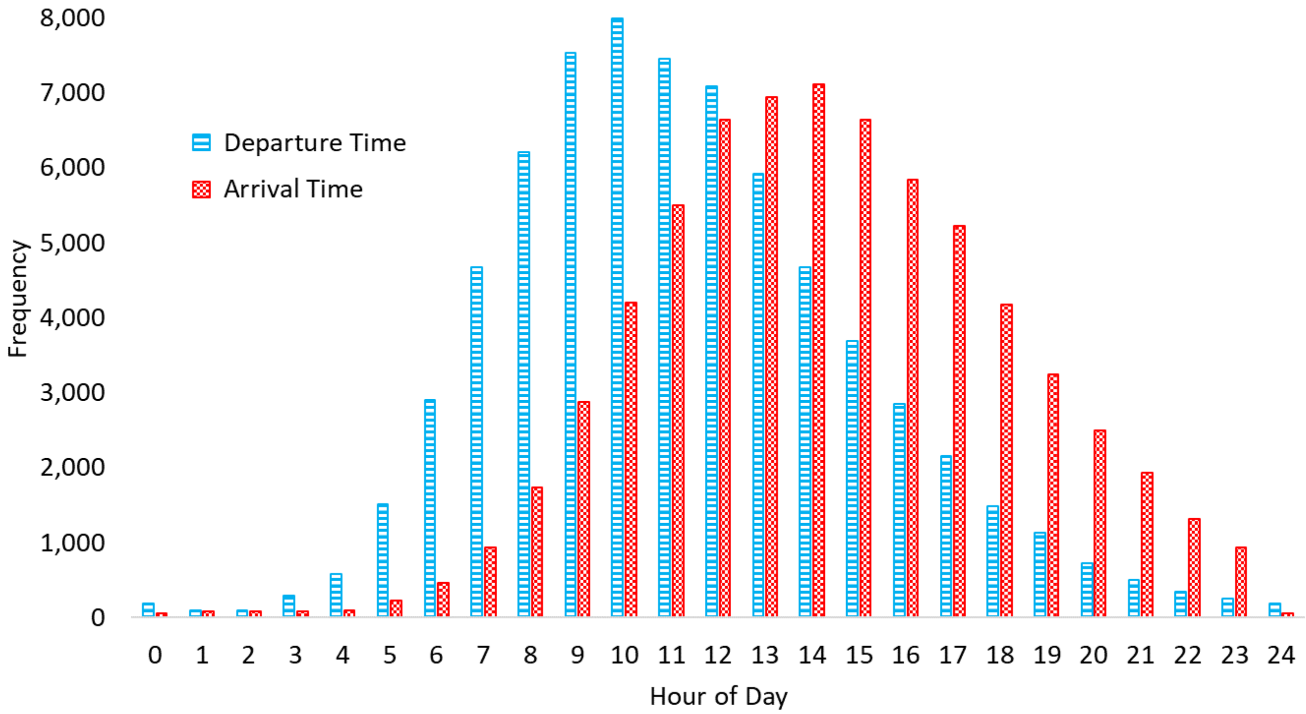
Figure 4: Probability Distribution Function of LDT Departure Time in the CHTS



Data from the CHTS shows a single departure time peak for LDTs around 10 a.m. Source: California Household Travel Survey.[58]

58 Kunzmann, M. and Masterman, V. (2013). 20102012 California Household Travel Survey Final Report. California Department of Transportation. June 14, 2013. Retrieved from: https://www.nrel.gov/transportation/secure-transportation-data/assets/pdfs/calif_household_travel_survey.pdf.

Figure 5: Simulated Departure and Arrival Time Distribution for the High BEV Adoption Scenario in 2030



Simulated departure and arrival times show peaks at 10 a.m. and 2 p.m., respectively. Source: CEC and National Renewable Energy Laboratory

Energy Consumption Estimation

After determining the time reference, EVI-RoadTrip estimates energy consumption for each trip along its route. Since each trip is paired with a different vehicle type and MY, energy efficiency is differentiated by vehicle type and MY accordingly, as shown in Figure 6.

BEV energy consumption rate (ECR, kWh/mile) is estimated based on NREL's vehicle dynamic simulation model, FASTSim.[59] ECR is calculated as a function of average road link speed[60] to reflect varying driving conditions for different trips. For this, NREL's Transportation Secure

59 Brooker, A., Gonder, J., Wang, L., Wood, E. et al., "FASTSim: A Model To Estimate Vehicle Efficiency, Cost, and Performance," SAE Technical Paper 2015-01-0973, 2015, doi:10.4271/2015-01-0973.

60 Average road link speed is different from average trip speed, as the former is for vehicles in motion along the road network (links), whereas the latter is a statistic for the total trip (entire route between origin and destination). Since the focus on this analysis is on waypoint charging, which depends on on-route energy consumption, average link speed was selected as more appropriate than average trip speed.

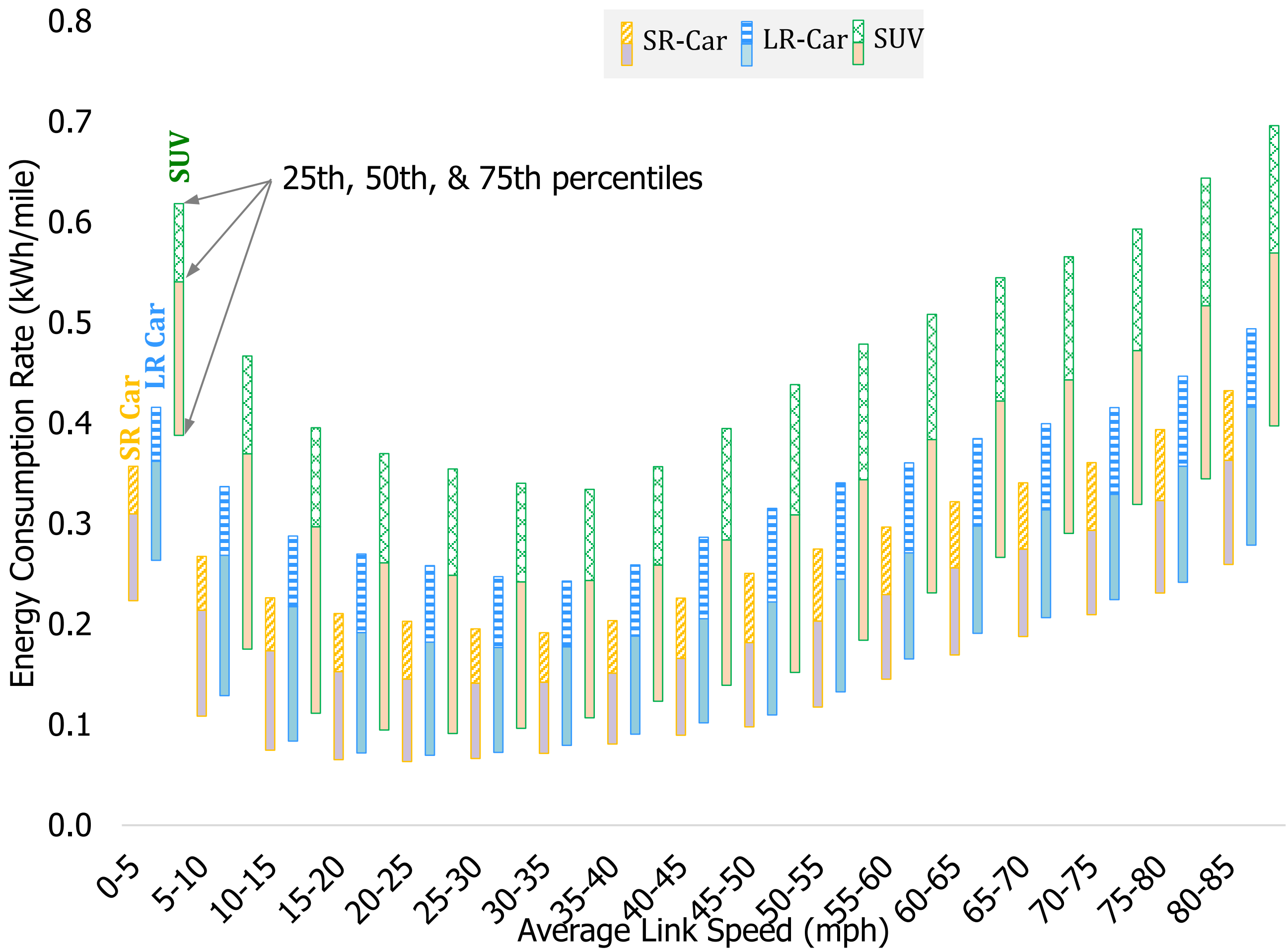
Data Center[61] is used to simulate real-world drive cycles for different BEV types and MYs in FASTSim. Figure 7 shows the statistical distribution for different bins of link average speed.

While vehicle age could affect ECR, for simplicity longitudinal efficiency degradation is assumed to be negligible (e.g., a MY 2020 vehicle does not become less efficient by simulation year 2030). As shown in Figure 6, ECR decreases for newer MYs, as technology improves from factors such as building vehicles that are lighter in weight. Larger and heavier vehicles (e.g., SUVs) consume more energy per mile than smaller and lighter vehicles (e.g., SR-Cars).

ECR values are shown in Figure 6, with the 50th percentile representing typical passenger loading (2 to 3 people), ambient temperature (75 °F), and road grade (flat) conditions. However, the ECR of BEVs can change drastically depending on variations in these conditions. The impact of temperature is addressed as a sensitivity scenario in Section 4.5. The impact of road grade is assumed to be embedded in the uncertainty range (ranging from 25- to 75-th percentiles), inheriting road grade characteristics from the real-world drive cycles.

61 National Renewable Energy Laboratory. Transportation Secure Data Center. Available at: https://www.nrel.gov/transportation/secure-transportation-data/

Figure 6: Energy Consumption Rate (kWh/mile) as a Function of Vehicle Type, Model Year, and Average Road Link Speed



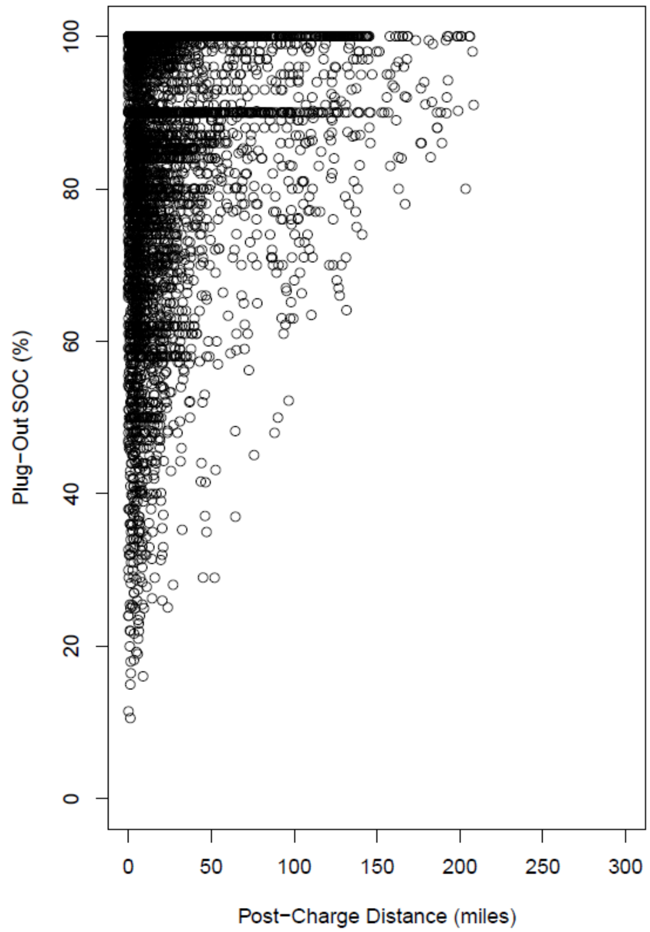
FASTSim results show that energy consumption rate (kWh/mile) is lowest when vehicles are driving between 30 and 35 miles per hour. Vehicle efficiency improves over time, as seen by the trend comparing the solid bars for 2020 and dashed bars for 2030. Short-range cars are most efficient, followed by long-range cars and then SUVs, which are much less efficient. Source: CEC and National Renewable Energy Laboratory

Charging Simulation

Charging events are triggered when the battery SOC falls below a certain threshold. Two layers are used for the minimum SOC threshold. First, it is assumed that drivers and vehicle manufacturers prefer to maintain SOC above five percent, which may translate to different distance values depending on battery capacity and other factors. Second, a five-mile distance buffer is enforced on top of the first layer so that vehicles can comfortably reach a DCFC station from the point that drivers realize they need to charge their vehicles on the road.

The SOC at time of departure for intra-state and outbound LDTs is determined based on an empirical relationship between travel distance and initial SOC, depicted in Figure 7.[62] This real-world charging data indicates that longer trips begin with a higher SOC.

Figure 7: The Relationship between Plug-Out (Departure) SOC and Travel Distance



This figure shows that drivers tend to start longer trips with a higher SOC. Source: Lincoln Electric System

As discussed previously, the CSTDM only includes information for the portions of trips within California's borders. For inbound or through trips, the origins and routes leading up to the entry points (gateways) along the state boundary are unknown. For those cases, the same initial SOC approach cannot be used. Instead, these trips are simulated in EVI-RoadTrip to

62 Lincoln Electric System. 2020. EV Study on Driving and Charging Behavior. Retrieved from: https://www.les.com/sites/default/files/ev-webinar-072020-study-results.pdf.

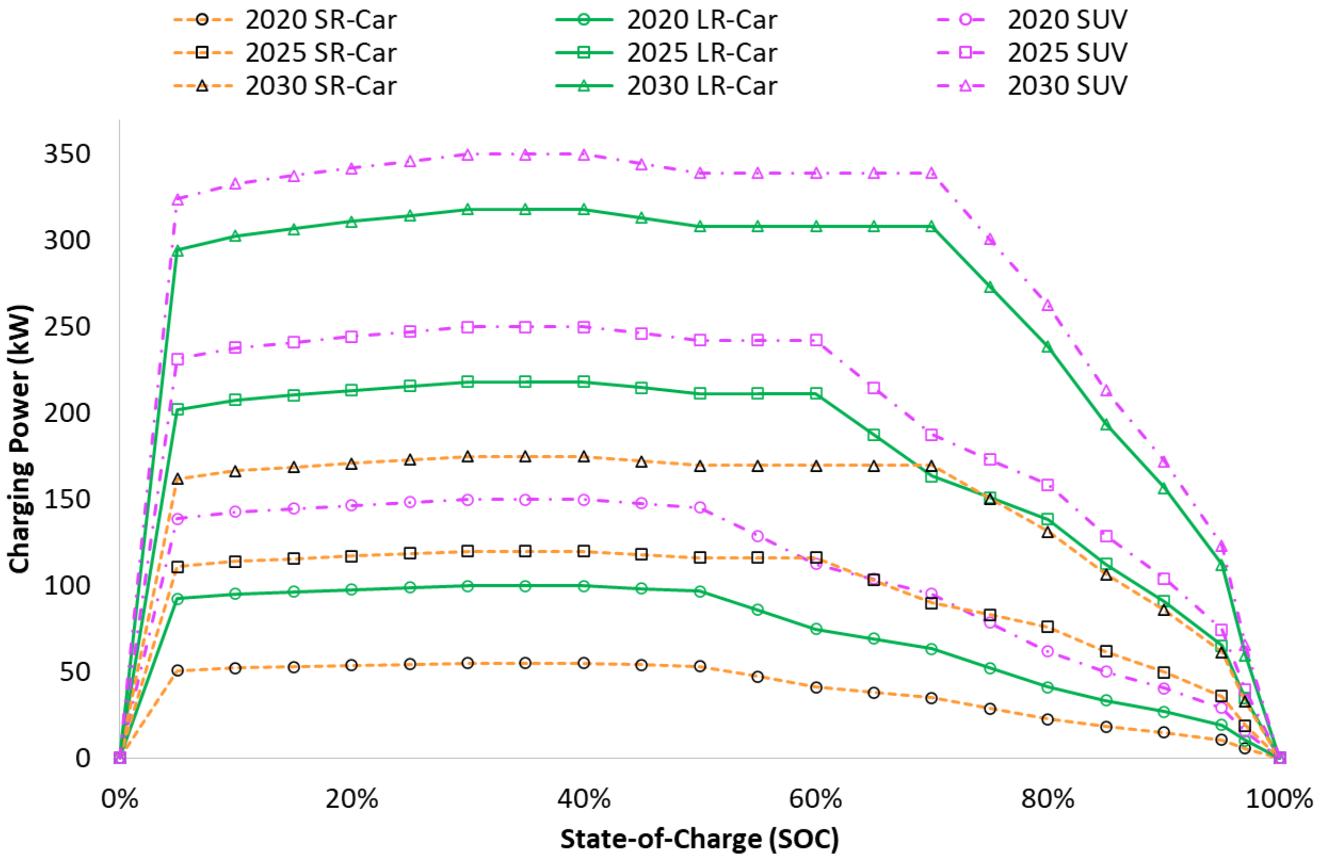
estimate the SOC at the point where vehicles cross the state boundary.[63] This entry SOC statistic is then used for initial SOC values at gateways for inbound and through LDTs.

After the initial SOC is determined, the rest of the SOC evolution along the route depends on the energy consumption described in Section 3.3.2. SOC for each vehicle is traced along the route based on the ECR, and charging is triggered once SOC drops below the thresholds mentioned above. Once charging is triggered, vehicles are assumed to deviate from their original route along the road network and travel to charging stations. At charging stations, two factors, one technological (charging power) and one behavioral (charging behavior), are considered for charging simulations.

Different BEVs can accept different levels of DCFC power at charging stations, which also varies by year as future BEVs become capable of more powerful charging. For this analysis, charge curves were developed with industry stakeholder input to capture the vehicle charging power (kW) as a function of battery SOC. As seen in Figure 8, charging power (kW) varies with the level of SOC, BEV type, and model year. One of the most significant effects of the relationship between SOC and charging power is charging speed. For the same initial and final SOC, a higher charging power will result in a shorter charging session.

63 FHWA (Federal Highway Administration). (2013). Traffic Analysis Framework Part IIA - Establishing Multimodal Interregional Passenger Travel Origin Destination Data. Program Support for Highway Policy Analysis. Retrieved from: https://www.fhwa.dot.gov/policyinformation/analysisframework/docs/taf_final_report.pdf.

Figure 8: DC Fast Charging Power (kW) as a Function of Battery SOC (%)



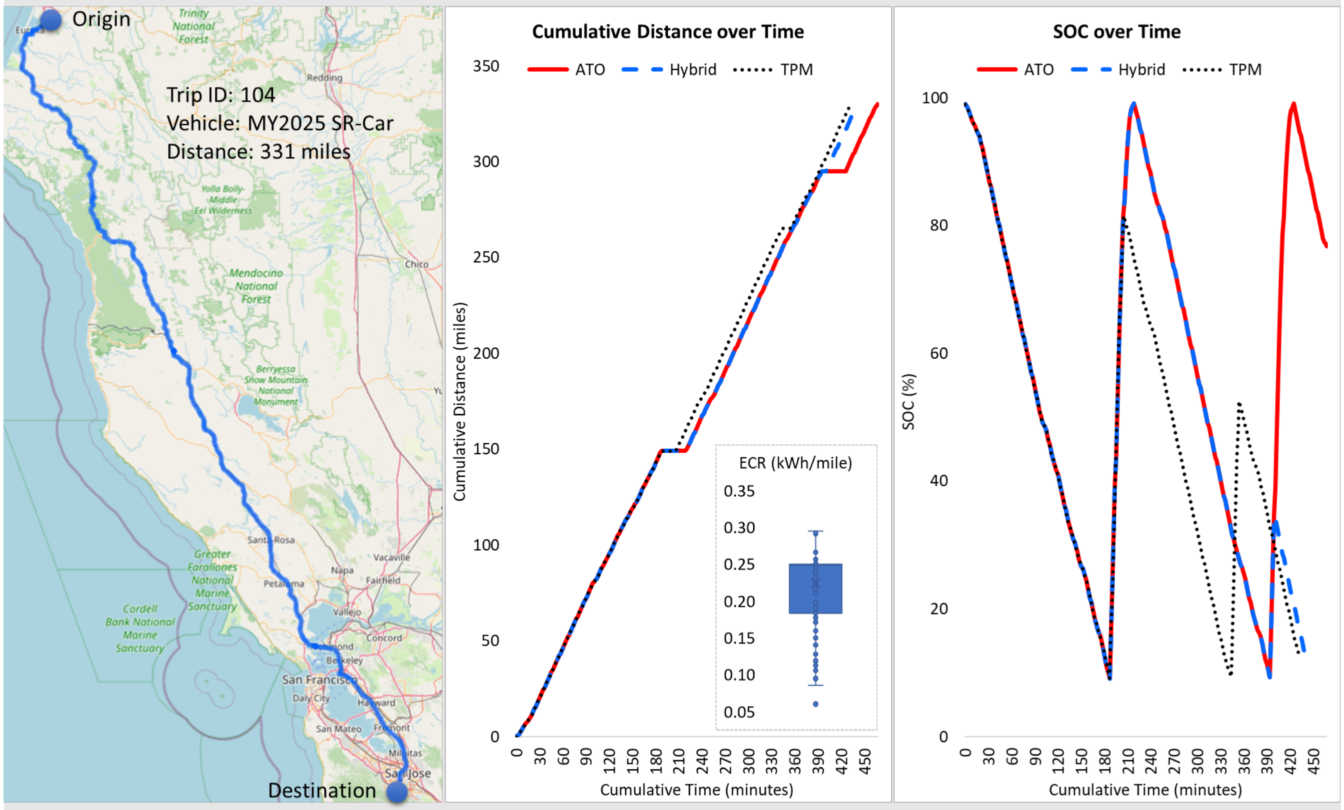
Charge curves illustrate how the vehicle charging power (kW) changes as a function of battery state-of-charge (SOC). These DCFC charge curves were developed for three classes of vehicles on five-year intervals for model years. In general, charging power drops significantly around 80 to 85 percent SOC. Source: CEC and National Renewable Energy Laboratory

In addition to charging technology and power level, charging behavior also plays an important role in charger utilization and charging speed. For example, some BEV drivers may choose to charge their vehicles up to 100 percent SOC, similar to the topping-off behavior that is common with ICE vehicles at gasoline stations. This behavioral scenario is referred to as Always Topping Off (ATO), and results in the longest charging time, as higher SOC (e.g., 80 percent SOC or above) typically entails a lower charging power and thus much longer time for a marginal increase in SOC. Some drivers may opt to minimize their charging time, which we refer to as Time Penalty Minimization (TPM). Finally, it is also possible that drivers could use a combination of the ATO and TPM behaviors. We refer to this hypothetical scenario as the Hybrid behavior, where drivers adopt the ATO charging behavior for all charge events except the last one on their trip, when they then use the TPM charging behavior.

Figure 9 illustrates the difference between the three different charging behaviors for the same trip from Eureka to San Jose. The total travel distance is 331 miles, and it takes 470 minutes to complete the trip for ATO, 445 minutes for Hybrid, and 435 minutes for TPM. Assuming a MY2025 SR-Car with 45 kWh battery, all three charging behaviors require two charging events between origin and destination. As can be seen in the SOC evolution chart, for the first charging event, TPM charges only up to 80 percent, whereas ATO and Hybrid charge up to

100 percent. For the second charging event, both Hybrid and TPM charge only up to the level that is required to make it to the destination, while ATO charges up to 100 percent.

Figure 9: Example of O-D Pair, Route, Energy Use, and Charging



This figure illustrates the energy use and charging under three different charging behaviors for the same trip from Eureka to San Jose. The Time Penalty Minimization behavior, where drivers minimize time spent charging, results in a total trip duration of 7 hours and 15 minutes, arriving at the destination with about 15 percent SOC remaining. The Always Topping Off behavior, where drivers always charge to 100 percent SOC, results in a total trip duration of 7 hours and 50 minutes, arriving at the destination with about 75 percent SOC remaining. In between these two scenarios is the Hybrid charging behavior, where drivers charge to 100 percent SOC for all charging events except the last one on their trip, at which point they only charge as much as is needed to reach the final destination. In this case, the total trip duration is 7 hours and 25 minutes, reaching the final destination with about 15 percent SOC remaining. Source: CEC and National Renewable Energy Laboratory

Step 3 – Station Design (Siting and Sizing)

Once all electrified LDTs and their charging events are simulated, the next step is to design the charging station network capable of accommodating those individual charging demands. This includes determining both the location and size (number of chargers) of each DCFC station.

Station Siting

Based on the spatial distribution of charging demands along the road network determined in the previous step, points of demand are then clustered together. When doing so, it is assumed that a station can cover a five-mile radius range, absorbing charging demands within five miles of the station. The five-mile range is based on the estimated average distance between highway exits and is also inherited from the five-mile distance buffer assumption used in the charging simulations above.

A modified k-means clustering method is used to group charging events, starting with larger clusters and breaking these down until the average size of clusters (virtual bubbles around stations) becomes five miles. This clustering method generates centroids, which are used to select the locations of stations. However, there are no locational constraints on these centroids during clustering. For example, cluster centroids could wind up in a lake in an extreme case. To keep the centroids along the road network, the point of charging demand closest to the modeled centroid for each cluster is used.

Once the location of charging demand that can represent each cluster is identified, two land use data sets are used to determine a reasonable location for a DCFC station: 1) national land use data (NLUD)[64] and 2) OpenStreetMap's retail gas station location data[65] shown in Figure 10.

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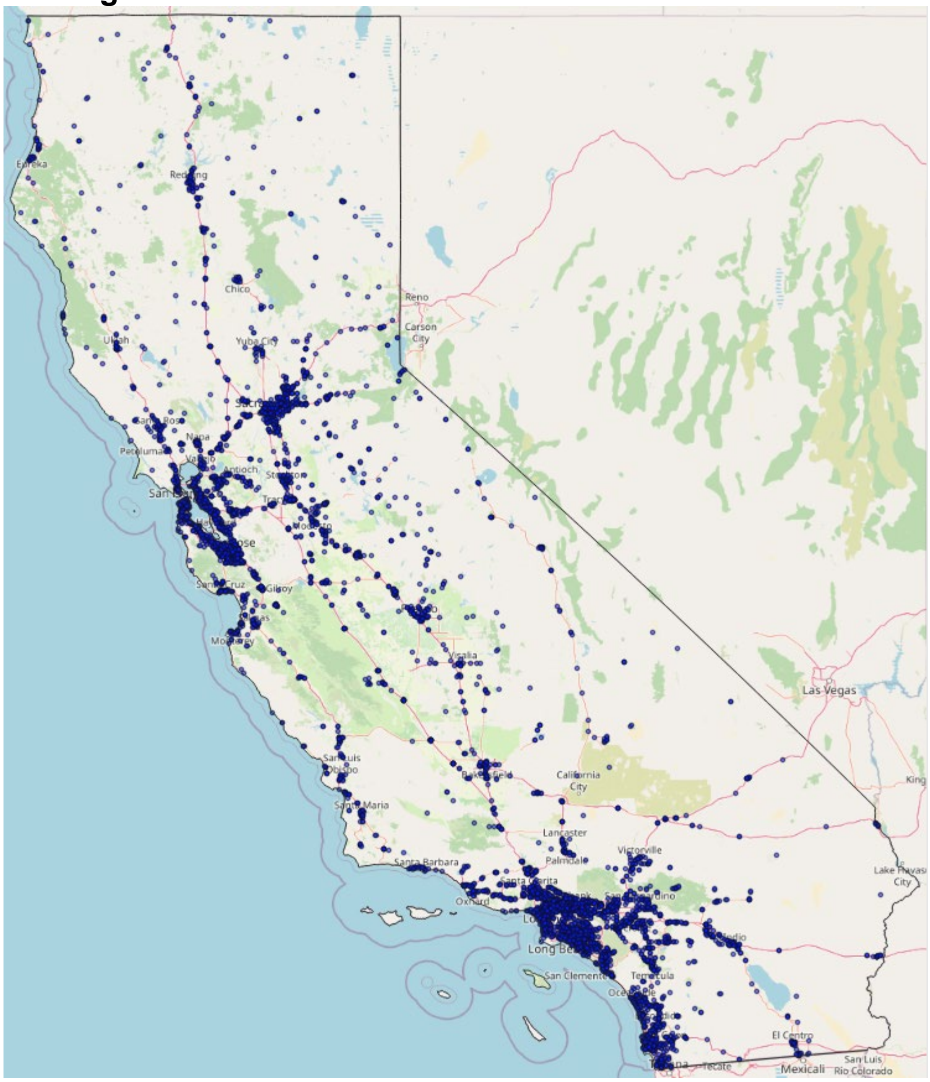
64 Theobald DM (2014) Development and Applications of a Comprehensive Land Use Classification and Map for the US. PLoS ONE 9(4): e94628. doi:10.1371/journal.pone.0094628.

65 OpenStreetMap (OSM). https://www.openstreetmap.org/

Figure 10: Retail Gas Station Locations in California



Source: Adapted from OSM (OpenStreetMap)[66]

Land use types (including gasoline stations) were grouped and prioritized as shown in Table 8. It is assumed that DCFC stations are most likely to be sited in commercial locations, and if not, co-located in gasoline stations. Based on the ranked preferences in Table 8, the area is first searched for the most preferred group of land use types. If those land use types are not available, the next most preferred group is tested and so on until a reasonable DCFC station location is found.

66 OpenStreetMap (OSM). https://www.openstreetmap.org/

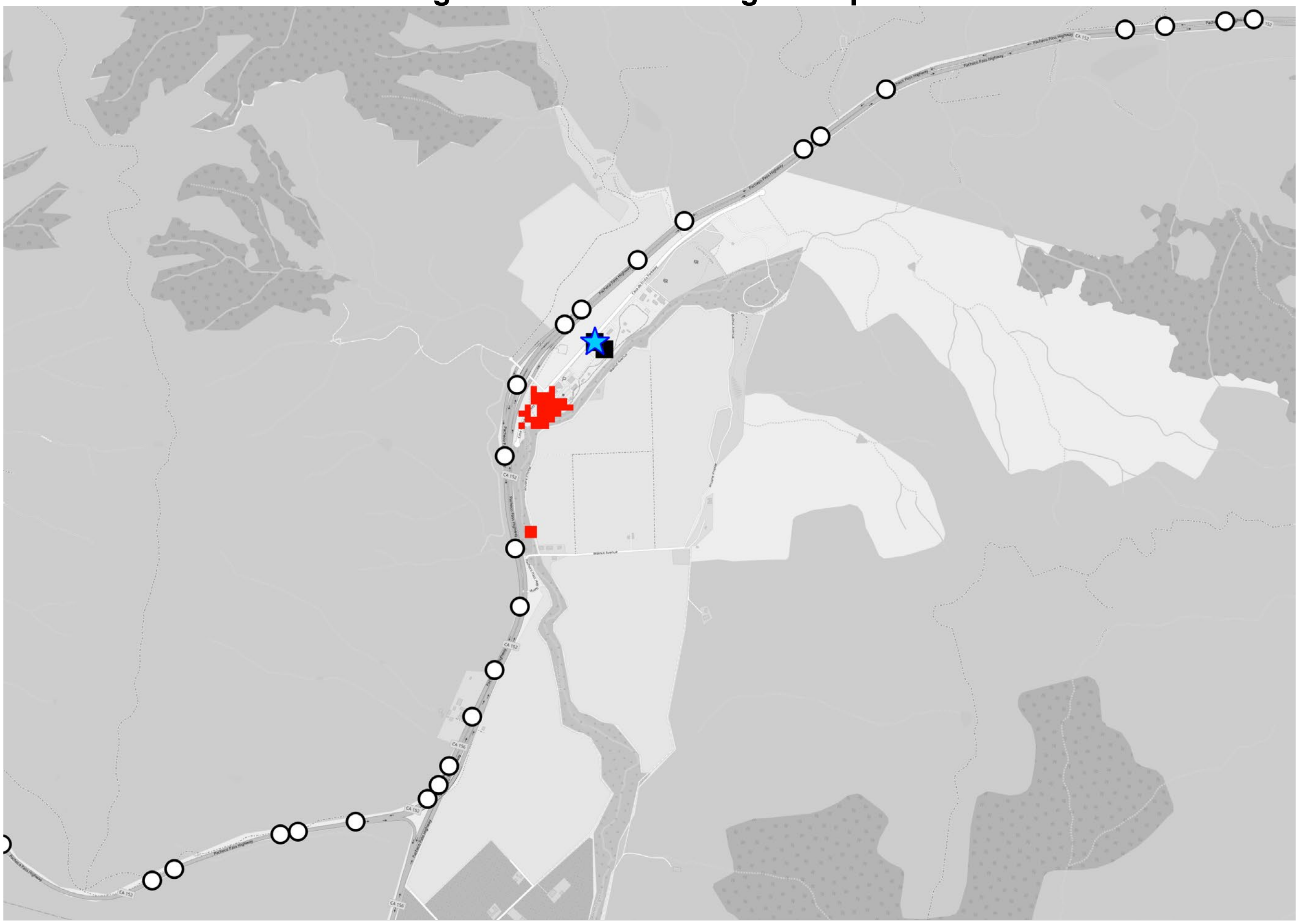
Table 8: Preferred Land Use Types for DCFC Stations

Ranked Preference Group	Land Use Type Code	Land Use Type
1	222	Retail/shopping centers
1	224	Lodge
2	-	Gas stations
3	251	Airports (developed)
3	254	Port, train station
3	411	Urban park
3	410	General park
4	421	Natural park
4	414	OHV staging area/trailhead
4	413	Motorized
4	223	Entertainment (stadiums, amusement, etc.)
4	422	Designated recreation area
4	417	Campground/ranger station
4	416	Marina
4	415	Resort/ski area
4	418	Picnic/trailhead

Source: CEC and National Renewable Energy Laboratory

Figure 11 illustrates the process for determining the location of a charging station in Healdsburg. Individual points of charging demand (white dots) are clustered, creating a center point near the highway. This point is then repositioned to a suitable location (blue star) according to the ranked preferences provided in Table 8.

Figure 11: Station Siting Example



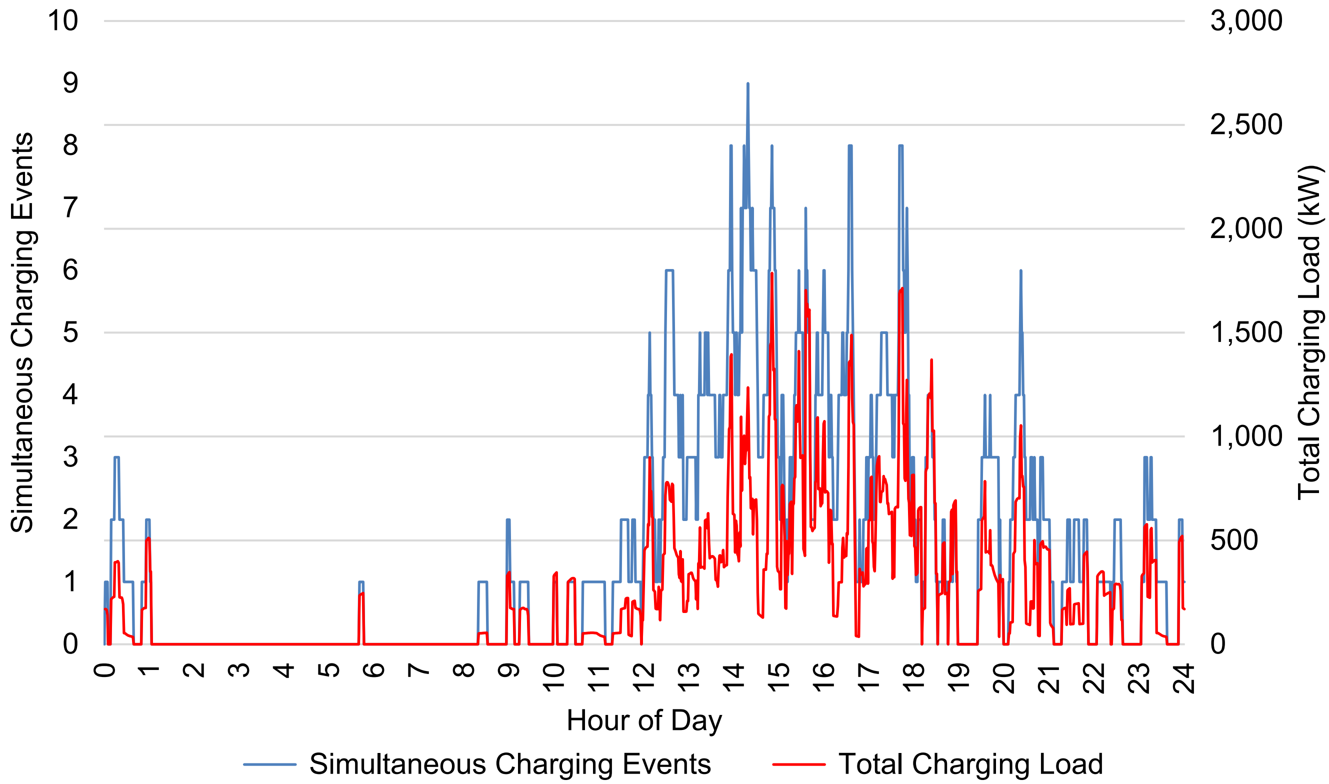
This figure illustrates the process of assigning a station location. White dots indicate the points where drivers realize that they need to charge their vehicles to continue their LDTs. These points are then clustered together, resulting in a center point that is re-positioned to the nearest commercial location (blue star) for the final DCFC station location. In this example, areas marked in red represent commercial sites, while black represents existing gas stations. Source: CEC and NREL

Station Sizing

After the preferred locations are determined for DCFC stations, the number of chargers at each station is estimated based on the profiles of charging events over the course of the day. Figure 12 illustrates an example station where the peak number of chargers simultaneously occupied during the day is nine. The lower bound of chargers at a station is determined by the highest hourly average number of charging events. In the example below, hour 14 to 15 results in the highest hourly average utilization at six chargers occupied. Even though the peak utilization during the day is nine chargers, this is for a short moment in time, and the hourly average utilization approach allows stations to be sized more appropriately. Because long-distance travel is especially common during certain times of year (around major holidays and weekends in the summer), it may be necessary to increase the number of chargers to ensure charging is available at peak times. To account for higher peaks, the upper bound is then calculated by multiplying the lower bound by two, resulting in 12 chargers for the example shown in Figure 12.

Lower and upper bounds are also applied to the number of stations in the network. The lower bound is a direct output from the model simulations and assumes no restrictions on the number of chargers at a station. However, the upper bound assumes no more than 10 chargers can be located at a station. As noted above, the example station shown in Figure 12 has a range of six to 12 chargers, which in turn results in a lower bound of one station and an upper bound of two stations (one with 10 chargers and the other with two).

Figure 12: Simultaneous Charging Events and Total Charging Loads for Simulated Station 150 – 2030, High BEV Adoption, TPM Scenario



Source: CEC and National Renewable Energy Laboratory

In addition to the number of chargers required, the power level of each charger in a station is estimated. In this analysis, it is assumed that chargers will be capable of providing the maximum power that vehicles plugged into it can accept. For example, if two vehicles plug in to a charger over the course of the day, and one of them draws 150 kW, and the other 50 kW, the power rating of that charger is estimated to be 150 kW.

Step 4 – Grid Impact

With the DCFC station network designed at the site-level with latitude-longitude coordinates, the total maximum charging load is then aggregated by TAZ and compared with the existing grid hosting capacity, utilizing the CEC's EVSE Deployment and Grid Evaluation (EDGE) model. EDGE is designed to combine inputs from several data sources and models within four assessment domains: grid conditions, air quality, travel demand, and equity considerations.

The comparison of projected charging load from EVI-RoadTrip with hosting capacity addresses the grid conditions and travel demand domains in EDGE. These results can indicate where and what level of grid upgrade may be necessary to accommodate charging load from LDTs.

EDGE currently leverages investor-owned utility Integration Capacity Analysis (ICA) maps to identify available grid capacity. However, ICA maps only represent a monthly snapshot of a distribution system that frequently changes, and CEC staff is working to incorporate additional data from the Grid Needs Assessment Reports and pending updates to the Uniform Load results.[67] As EDGE is still under development and limited by current grid data availability and quality, this analysis only examined the grid impacts of LDT charging in several utility territories, including Southern California Edison (SCE), Pacific Gas & Electric Company (PG&E), San Diego Gas & Electric (SDG&E), and PacifiCorp, as a proof of concept.

67 CPUC. Administrative Law Judge's Ruling on Joint Parties' Motion for an Order Requiring Refinements to the Integration Capacity Analysis, Rulemaking 14-08-013, January 27, 2021, https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M361/K810/361810169.PDF

CHAPTER 4: Analysis and Results

The main objective of this analysis is to evaluate future DCFC infrastructure requirements for electrified LDTs in California over the next decade, including the number of chargers and their spatial distribution and technological characteristics. In general, charging infrastructure is primarily determined by charging demands or events that are a function of travel activity.

This chapter discusses simulated charging events first, followed by network size estimation results. Load profiles are then shown for the entire state along with hosting capacity analysis for SCE's utility territory.

Simulated Charging Events

As discussed in the previous chapter, it is estimated that approximately 600,000 LDTs will occur on a typical day in California in 2030. Depending on the BEV adoption scenario, the total number of electrified LDTs will vary from 21,000 to 70,300 per day, as summarized in Table 9.

Table 9: Total Number of Simulated Charging Events for Electrified LDTs in 2030

BEV Adoption Scenario	Total Number of Daily LDTs	Total Number of Daily Electrified LDTs	ATO Behavior Charging Events	Hybrid Behavior Charging Events	TMP Behavior Charging Events
Low	583,700	21,000	7,020	7,090	7,860
Mid	583,700	40,700	12,700	12,860	14,160
High	583,700	70,300	18,750	19,100	20,600

Source: CEC and National Renewable Energy Laboratory

As Table 9 implies, not all electrified LDTs require charging along the trip route, depending on the initial SOC, battery capacity, travel distance, and other factors. This analysis indicates that about 40 percent of electrified LDTs require charging at least once between origin and destination in 2020. As battery capacity, and thus range, increases over time, it is predicted that only 24 percent of electrified LDTs would require charging in 2030. For the High BEV adoption scenario, this results in about 17,000 trips that require charging. Furthermore, as Table 9 shows, these trips lead to about 20,000 charging events across the state for the TPM charging behavior, indicating that for trips that do require charging, most only need to charge once to reach the final destination.

In all BEV adoption scenarios, the different charging behaviors result in varying numbers of charging events. The ATO charging behavior always results in the fewest charging events, since this behavior results in charging to 100 percent SOC and thus reduces the potential need to charge again during the remainder of the trip. The TPM charging behavior results in the largest number of charging events, since this optimizes charging duration by cutting charging off at a lower SOC.

Another important consideration for the frequency and duration of on-route charging events is BEV type (Table 10). Looking only at trips that require charging shows that SR-Cars average 1.3 to 1.4 charging events per trip, depending on charging behavior. In contrast, LR-Cars and SUVs average 1 charging event per trip, regardless of charging behavior. This variation of average charging frequency by BEV type is mostly due to the combined effect of battery capacity (Table 6) and energy consumption rate (Figure 6).

Table 10: Average Frequency and Total Duration of On-Route Charging for Trips that Require One or More Charging Events in 2030 – High BEV Adoption Scenario

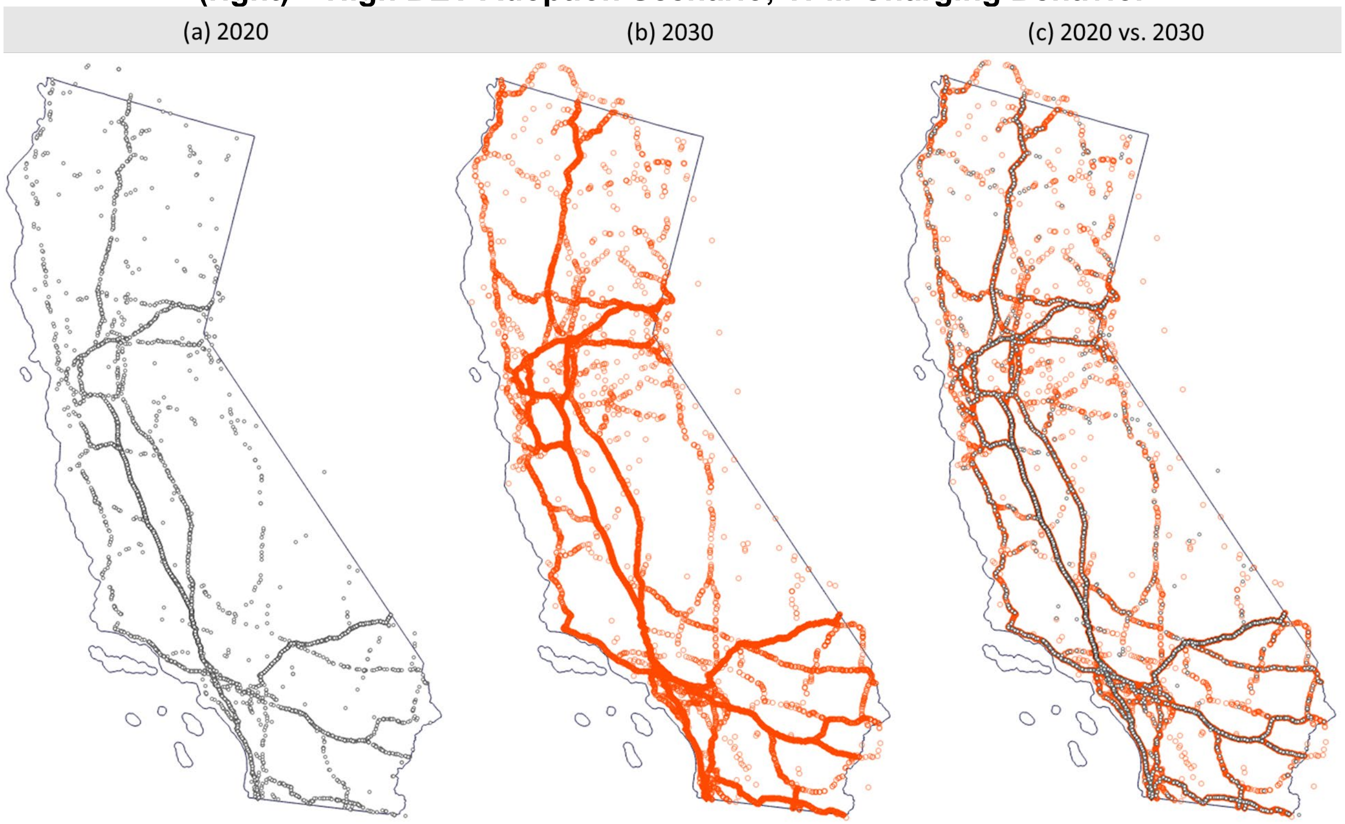
BEV Type	ATO Behavior Average Charging Frequency	Hybrid Behavior Average Charging Frequency	TPM Behavior Average Charging Frequency	ATO Behavior Average Total Charging Duration	Hybrid Behavior Average Total Charging Duration	TPM Behavior Average Total Charging Duration
Short Range Car	1.3	1.3	1.4	39.5 minutes	19.8 minutes	16.0 minutes
Long Range Car	1.0	1.0	1.0	43.6 minutes	7.5 minutes	7.4 minutes
SUV	1.0	1.0	1.0	32.0 minutes	7.0 minutes	7.0 minutes

Source: CEC and National Renewable Energy Laboratory

Table 10 shows that average total duration of on-route charging events is a function of charging behavior, BEV type, model year, and charging power. For all BEV types, Hybrid and TPM behaviors significantly reduce the overall charging time in comparison with ATO. The average total duration of charging for ATO behavior ranges from 32 to 44 minutes, whereas it is 7 to 20 minutes for the Hybrid and TPM behaviors.

Figure 13 shows the spatial distribution of charging events for electrified LDTs in California and its longitudinal evolution from 2020 to 2030. Charging events are mostly concentrated along interstate highways (e.g., I-5, I-80, I-15, and I-10) and around large metropolitan areas (Bay Area, Los Angeles, San Diego, and Sacramento). Charging activities along and around state highways (e.g., CA-101) tend to be sparse in comparison with those along the interstate highways, but the activity level increases notably over time. In addition, charging events are observed outside the state due to trips that start and end in California, but cross the state line due to route efficiency.

Figure 13: Spatial Distribution of Simulated Charging Events from 2020 (left) to 2030 (right) – High BEV Adoption Scenario; TPM Charging Behavior

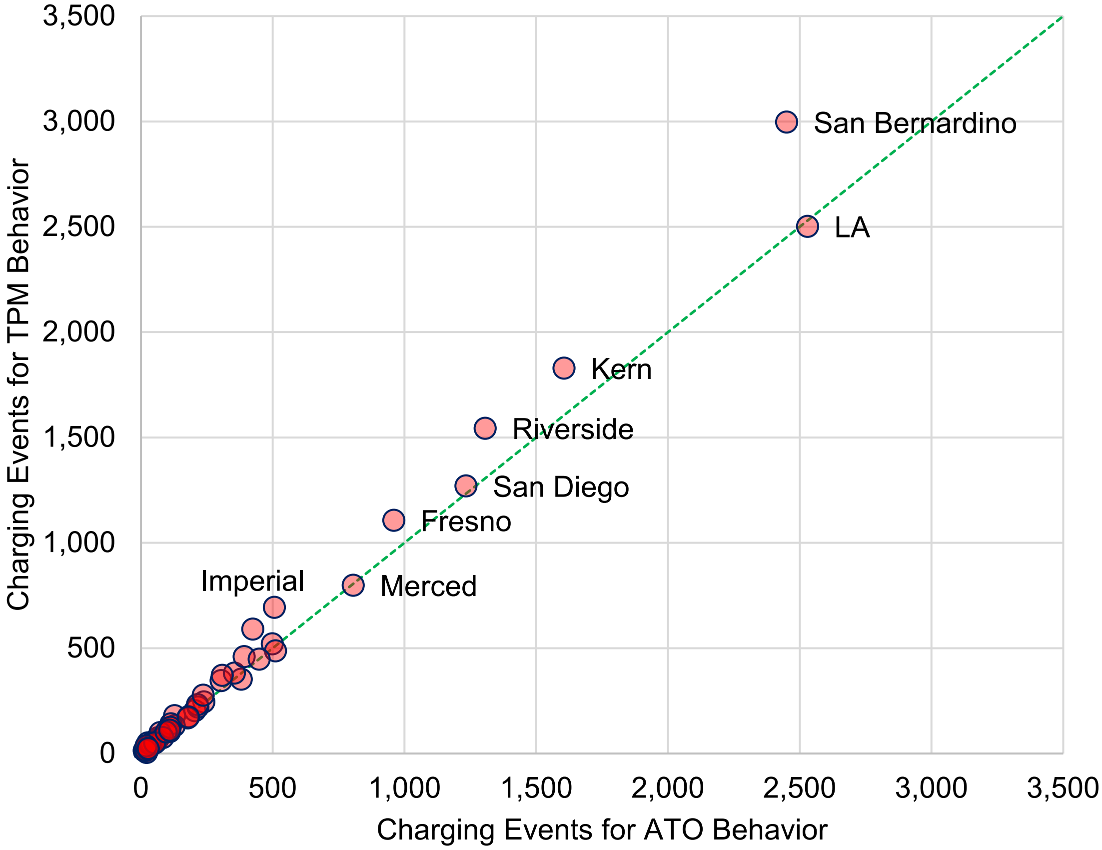


The evolution of charging demand shows that charging events along interstates remain dominant through 2030, but continue to grow along state highways over time. Some charging events are outside the state due to trips that start and end in California, but cross the border for route efficiency. Source: CEC and NREL

Figure 14 indicates that different charging behaviors simulated in this analysis generally do not make a significant impact on the spatial distribution of charging events. Despite the fact that the TPM behavior increases the total number of charging events by 10 percent in comparison with ATO, TPM and ATO behaviors generally result in similar numbers of charging events for each county. The spatial distribution of charging activities is largely correlated with travel activities that are not assumed to be affected by differing charging behaviors.

A few counties represent a small portion of the state population, but account for a significant number of charging events due to the road networks passing through them. For example, San Bernardino County represents about 5.5 percent of the state population, but 14.5 percent of the road trip charging events due to its large size and number of highways connecting the county with California and neighboring states. Similarly, Kern County contains a little over two percent of the population, but nearly nine percent of road trip charging demand due to major highways like the I-5 and CA-99 running through it. In contrast, Los Angeles County, which makes up 25 percent of the California population, only represents 12 percent of total charging events in the state.

Figure 14: Simulated Charging Events per Day by County in 2030 – ATO vs. TPM Charging Behavior

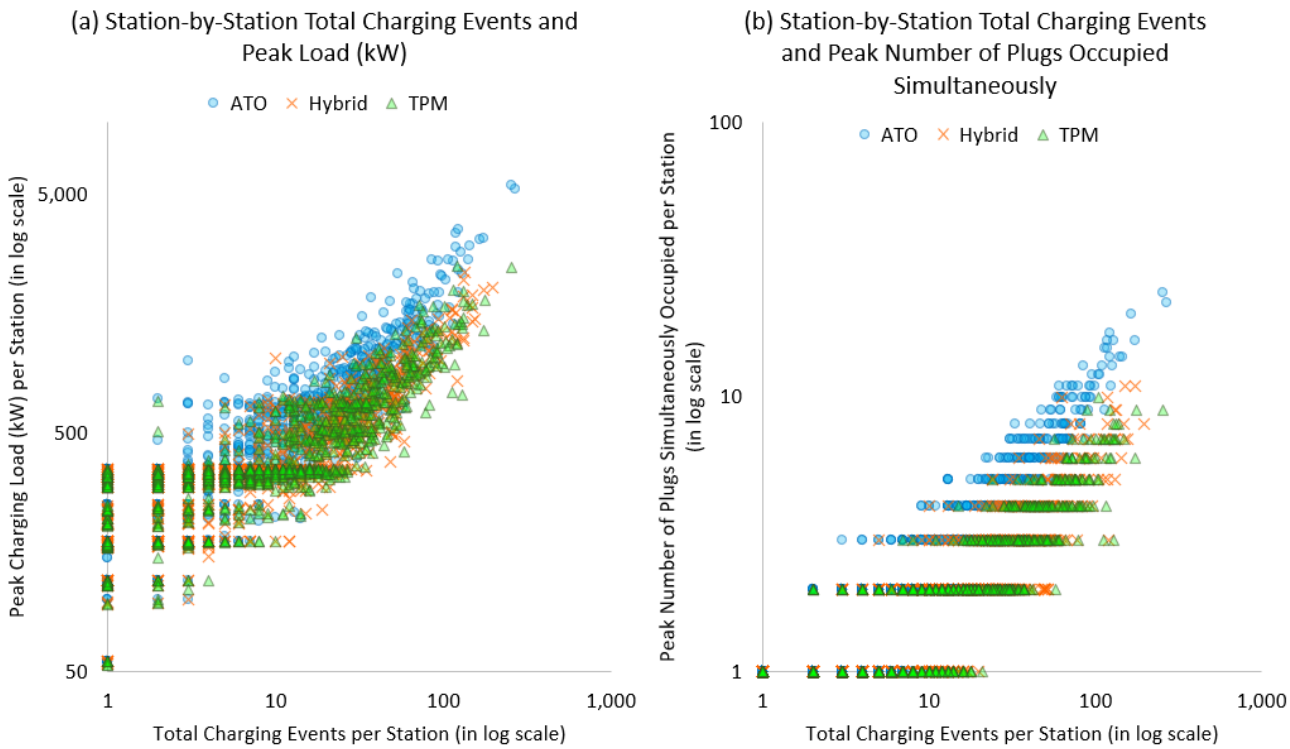


Comparing results for TPM and ATO charging behaviors shows minor spatial differences in charging demand, showing that spatial distribution is more correlated to travel patterns than to charging behavior. Furthermore, charging demand tends to depend more on the road networks in counties than the population of the county. Source: CEC and NREL

Projected Network Size and Distribution

The determination of DCFC infrastructure for electrified LDTs is based on the charging events presented above. Figure 15 illustrates the relationships between simulated charging events for each DCFC station throughout the day and both peak charging load and the maximum number of chargers occupied simultaneously. In general, more simultaneous charging events at a station results in higher peak charging loads and larger stations (in terms of number of chargers).

Figure 15: Station-by-Station Daily Total Charging Events, Peak Charging Load, and Peak Number of Chargers Occupied in 2030 – High BEV Adoption Scenario



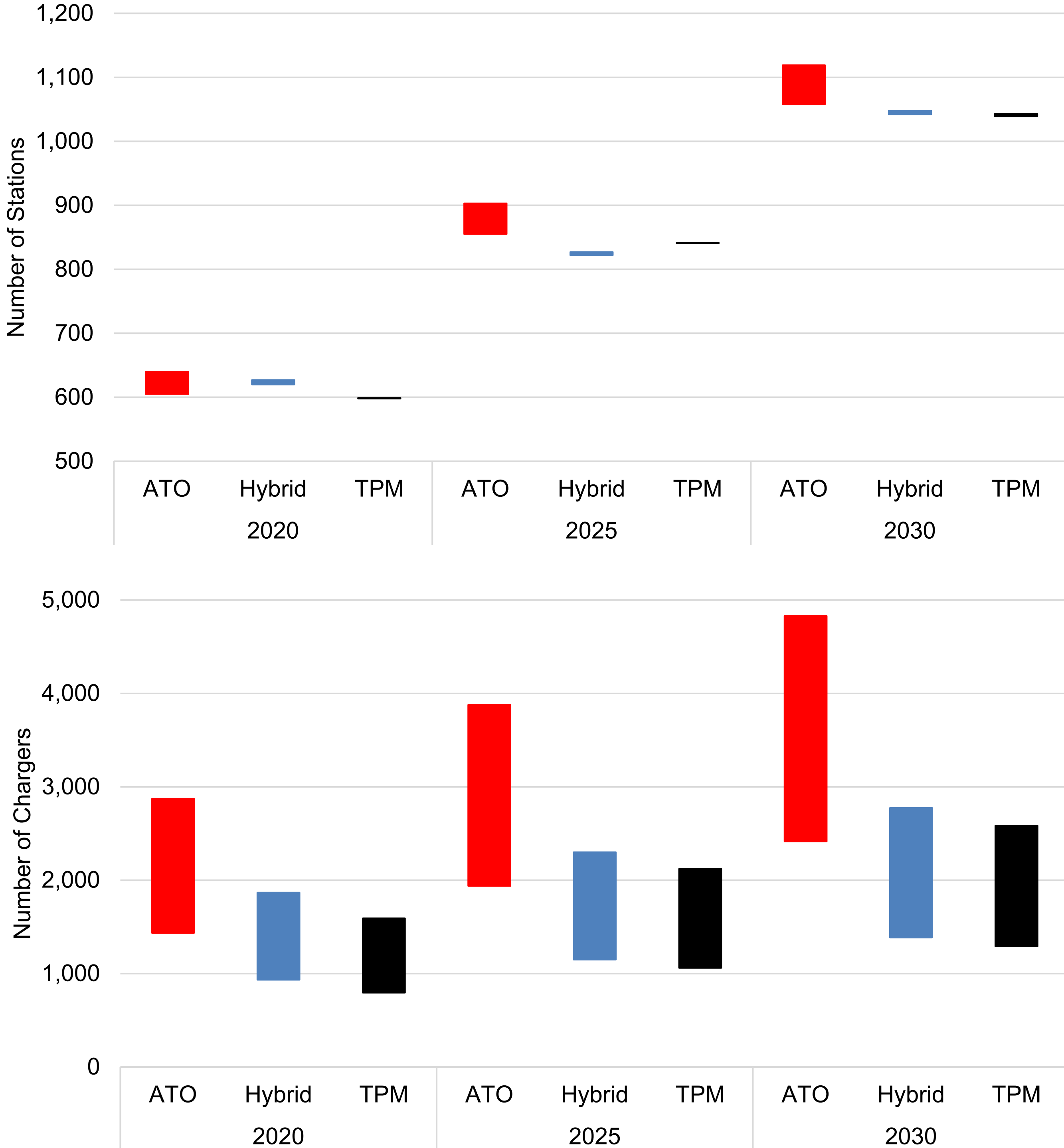
As shown on the left, stations with more total charging events generally result in higher peak charging loads. Similarly, the figure on the right shows that more total charging events leads to more chargers occupied simultaneously. Furthermore, the results show that the ATO charging behavior typically results in higher peak charging loads and more simultaneously occupied chargers. Source: CEC and NREL

In theory, a single charger could serve many charging events throughout the day if those charging activities did not overlap. However, given the vehicle activity pattern for LDTs throughout the day, most stations will have multiple simultaneous charging events at certain times.

Figure 15 demonstrates that charging behavior, particularly ATO, influences peak load and peak number of chargers simultaneously occupied for a DCFC station. As discussed previously, the ATO charging behavior generally leads to fewer charging events (Table 9) than Hybrid or TPM behaviors. However, since ATO results in longer charging sessions on average, there is a higher probability of charging events overlapping and occurring simultaneously at a station.

On top of the maximum number of chargers simultaneously occupied, charger utilization rate is another major factor affecting the charging infrastructure requirement estimation. As described in Chapter 3, lower and upper bounds of network size are estimated and shown in Figure 16. By 2030, California is projected to need 1,039 to 1,119 DCFC stations composed of 1,292 to 4,830 DC fast chargers to support electrified LDTs for more than 5 million BEVs, depending on charging behavior. The number of stations is relatively consistent across charging behavior types, but the ATO behavior results in a 75 to 90 percent increase in the number of chargers compared to the Hybrid and TPM behaviors, respectively, in 2030.

Figure 16: DCFC Infrastructure Requirements for Stations (top) and Chargers (bottom) by Simulation Year and Charging Behavior – High BEV Adoption Scenario

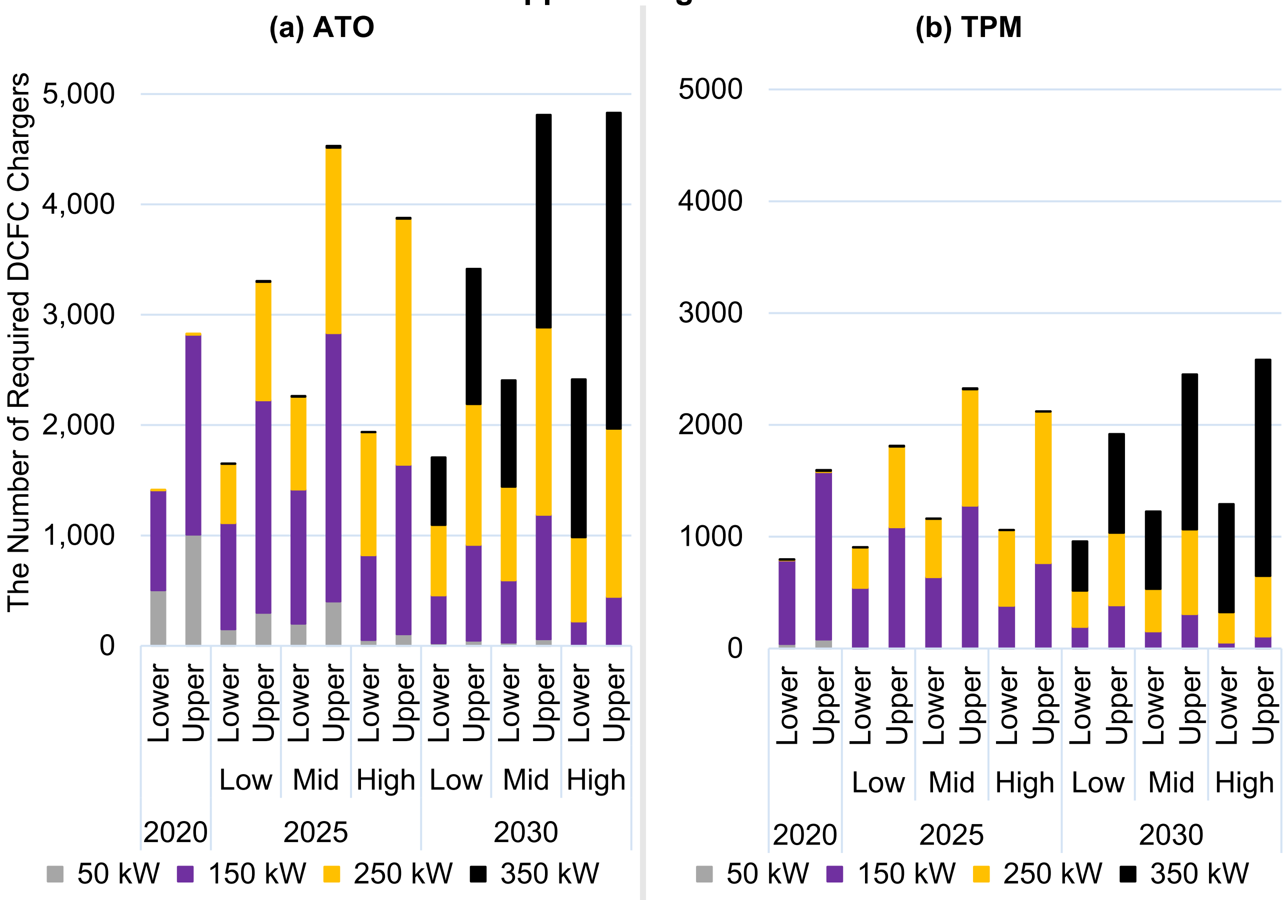


The number of DCFC stations and chargers is expected to increase over time to meet growing BEV travel and charging demand. By 2030, California is projected to need anywhere from 1,039 to 1,119 DCFC stations composed of 1,292 to 4,830

chargers, depending on charging behavior. Under the ideal TPM charging behavior, the infrastructure requirements include an average of about 1,000 stations consisting of nearly 2,000 chargers. Source: CEC and NREL

Along with DCFC infrastructure growth over time, the composition of chargers is also expected to evolve. Since each year is modeled independently, the DCFC infrastructure network is built from scratch each time. Figure 17 shows that later years are more heavily composed of higher-powered DC fast chargers to accommodate the increasing charging power of BEVs, enabling faster charging for the same amount of energy or replenishing more range for the same time spent charging. Moreover, charging behavior could impact the composition of the network. For example, in the 2030 High BEV adoption scenario, ATO leads to 9 percent 150 kW, 32 percent 250 kW, and 59 percent 350 kW chargers, whereas TPM results in 4 percent, 21 percent, and 75 percent, respectively. Thus, TPM suggests a shift in the charger composition towards slightly more powerful chargers. As noted earlier, TPM increases the frequency of on-route charging compared to ATO, increasing the probability of plugging in. If a station is visited by both SR-Cars and LR-Cars, to accommodate both types of BEVs, the charger will be rated for the larger charging power, which explains the shift towards more powerful plugs under the TPM behavior.

Figure 17: The Composition of DCFC Chargers by Maximum Charging Power for Lower and Upper Charger Bounds

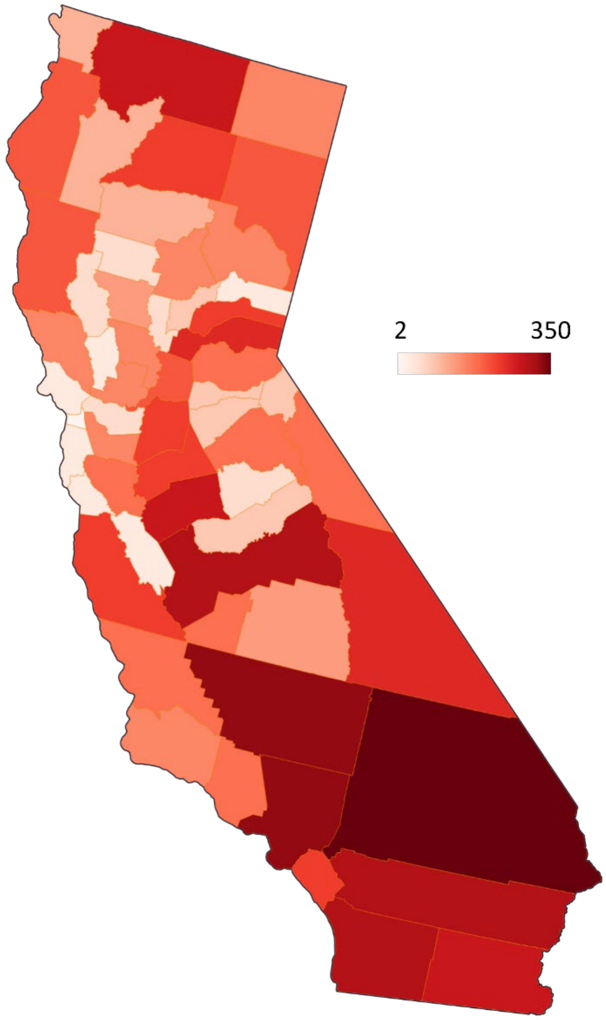


Charger composition evolves over time to favor high-powered charging in parallel with the increasing charging power of BEVs. Charging behavior influences the share of power level distribution, with TPM resulting in fewer chargers overall, but a

larger share of high-powered chargers. Source: CEC and NREL

Figure 18 illustrates how the projected chargers are distributed throughout the state, leading to some interesting observations. For example, in the TPM charging behavior, San Francisco County is estimated to require only 2 chargers for LDTs, whereas San Bernadino County would require over about 350 chargers. This model identifies a smaller need for chargers in some urban areas because it only assigns chargers along the routes of long-distance trips, rather than at the origin or destination, both of which are assumed to already have charging available. Areas like San Francisco are the origin and destination of many long-distance trips but have relatively few other long-distance trips passing through them, and as a result the model assigns relatively few chargers there. Similar to observations made in Figure 15 regarding individual charging events, this is primarily due to the sizes of different counties and their road networks. In the case of San Bernardino County, LDTs from the greater Los Angeles area to Nevada and Arizona are the main driver for the large number of chargers required. Similarly, Sacramento County, while relatively small in terms of land area, is projected to require 320 DCFC chargers, owing to major roads (I-5, I-80, CA-50, and CA-99) crossing through the county.

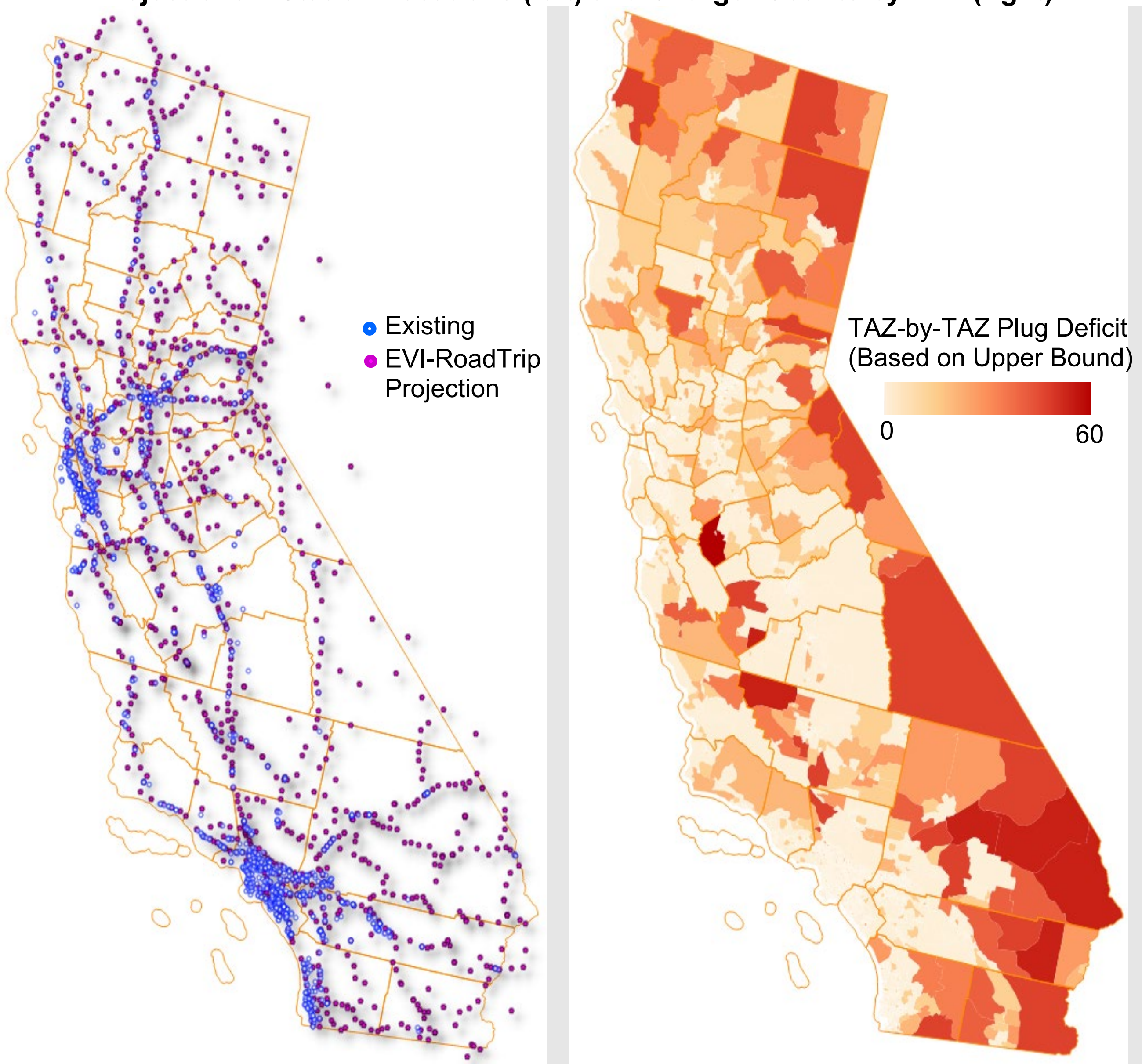
Figure 18: Number of Chargers (Upper Bound) by County in 2030 – High BEV Adoption; TPM Charging Behavior



Chargers are predominantly located in larger counties, especially those with major interstates and highways crossing through them. San Francisco County requires the fewest chargers (2) and San Bernardino County contains the most (about 350). Source: CEC and NREL

Comparing the projected 2030 DCFC station locations against existing stations published by the Alternative Fuels Data Center (AFDC) in Figure 19 yields several notable takeaways. Existing stations are largely concentrated in the major metropolitan areas of the state, with a sparser distribution along the major highways. This analysis suggests that stations need to more thoroughly cover California's road network by 2030 to enable long-distance travel. In addition, many of the projected stations are in rural and less-traveled areas that have so far not been targeted in the market. One caveat is that an existing fast charging station on the AFDC list may not be a suitable substitute for a projected nearby EVI-RoadTrip station; for example, it may not have enough chargers. It will be important to consider the evolution, both in terms of the number of chargers at stations and related power levels, to support the travel demand modeled in EVI-RoadTrip.

Figure 19: Comparison between Existing DCFC Infrastructure and EVI-RoadTrip 2030 Projections – Station Locations (left) and Charger Counts by TAZ (right)



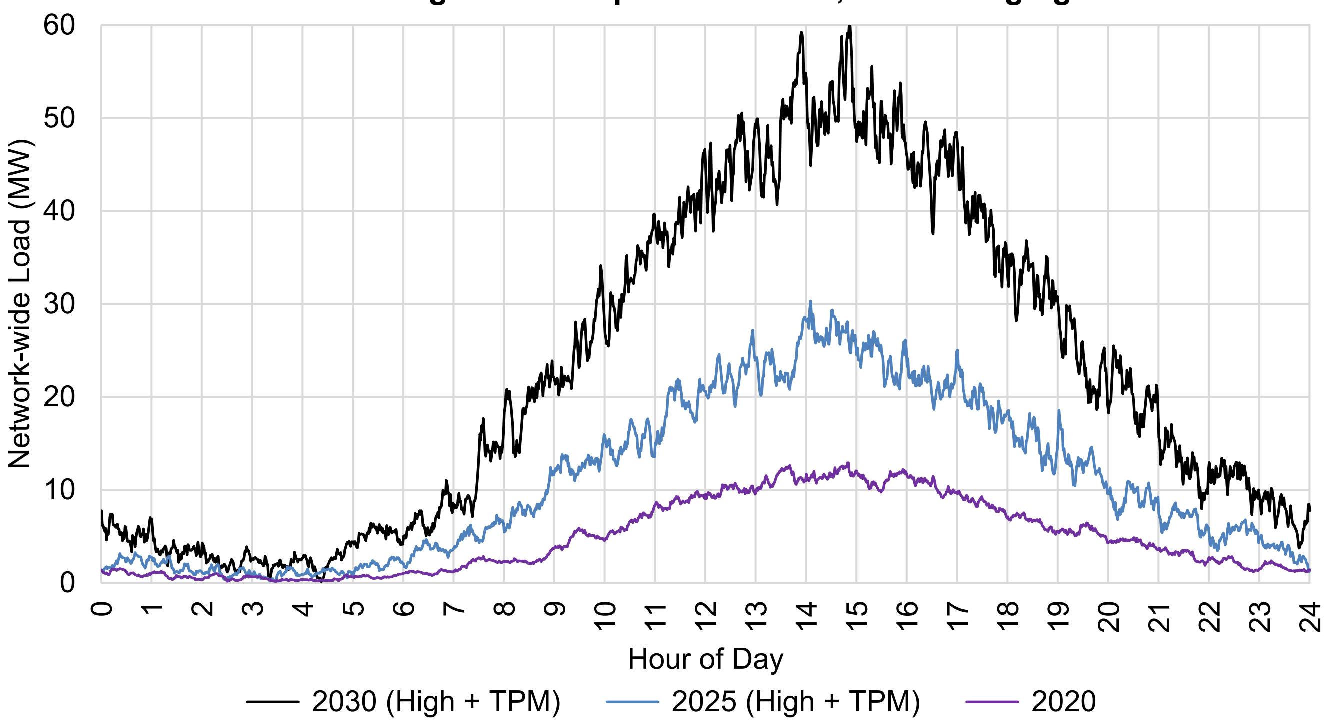
On the left, EVI-RoadTrip results for the TPM charging behavior in 2030 show that DCFC stations will need to cover California's road network more thoroughly than existing stations do today. On the right, a TAZ-by-TAZ analysis shows that the largest projected gaps in charger counts are concentrated in more rural areas of the state that have not been targeted as much in the market. However, many areas have minimal or no charger deficit, especially in urban areas and along major corridors. That said, these results do not consider the power level of existing chargers compared to projected chargers in the future. Source: CEC and NREL

Charging infrastructure for LDTs can be disproportionately large on a per-trip basis, in comparison with the corresponding infrastructure for daily or short-distance travel. According to the CSTDM, LDTs only account for around 0.5 percent of total daily light-duty personal vehicle trips in California. This analysis projects electrified LDTs would need 1,292 to 4,830 DC fast chargers by 2030, compared to about 30,000 projected by EVI-Pro 2 for short-distance travels and 2,100 projected by WIRED for transportation network company operations.[68] Despite such a small share of LDTs in daily vehicle activity on the road, these trips demand anywhere from 4 to 13 percent of the total DCFC network. It is important to caveat that EVI-RoadTrip and EVI-Pro 2 do not currently consider co-utilization of DCFC infrastructure for short- and long-distance travelers, which could decrease the required DCFC network size.

Load Profiles

Figure 20 shows the statewide aggregated charging load profiles for the High BEV adoption scenario and the longitudinal change from 2020 to 2030. The scale of charging load profiles tends to be proportional to the assumption of electrification rates, which varies between simulation years and BEV adoption scenarios. In addition, regardless of simulation year, the network-wide load peaks during the early afternoon around 2 p.m. and can take advantage of solar generation. This is a result of the temporal pattern of LDT activity over the course of the day mentioned previously. In 2030, LDT charging demand is expected to peak around 60 MW.

Figure 20: Longitudinal Evolution of Network-Wide Charging Load Profiles for Electrified LDTs – High BEV Adoption Scenario; TPM Charging Behavior

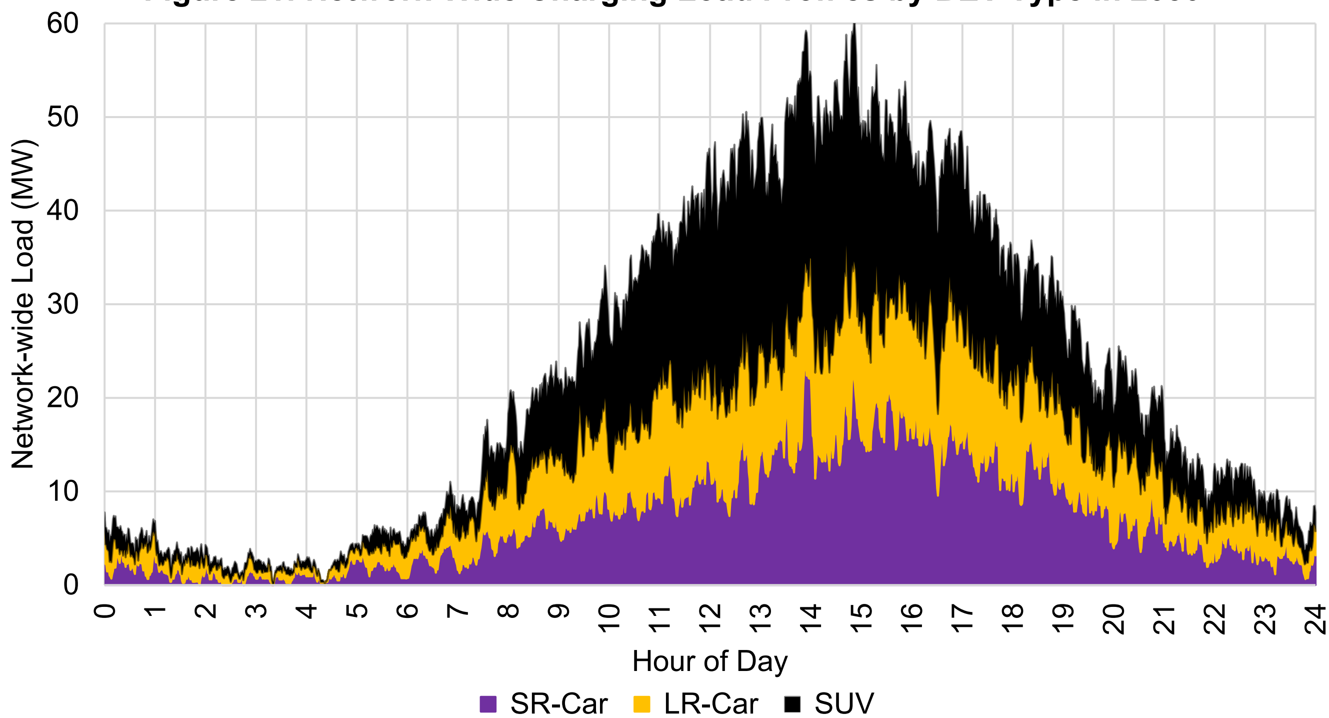


Charging load is generally proportional with electrification rates, growing over time as the BEV population increases. The timing of the peak load remains consistent around 2 p.m. due to travel patterns, and by 2030 the peak load is estimated to reach nearly 60 MW. Source: CEC and NREL

68 Alexander, Matt, Noel Crisostomo, Wendell Krell, Jeffrey Lu, and Raja Ramesh. July 2021. *Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment: Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030 – Commission Report*. California Energy Commission. Publication Number: CEC-600-2021-001-CMR.

Charging load profiles are also a function of BEV classification and LDT type, as shown in Figures 21 and 22, respectively. SR-Cars account for 41 percent of total energy from charging, followed by SUVs at 32 percent and LR-Cars making up 27 percent in 2030. The dominance of SR-Cars in load profiles is attributable to their battery capacity, which is smallest among the BEV types considered and requires more frequent charging for the same travel distance. SUVs consume more energy than LR-Cars principally due to their lower energy efficiency. While LR-Cars make up a larger share of the 2030 BEV fleet, and both LR-Cars and SUVs are assumed to have the same battery capacity, SUVs consume roughly 40 percent more energy than LR-Cars for highway driving, leading to increased charging.

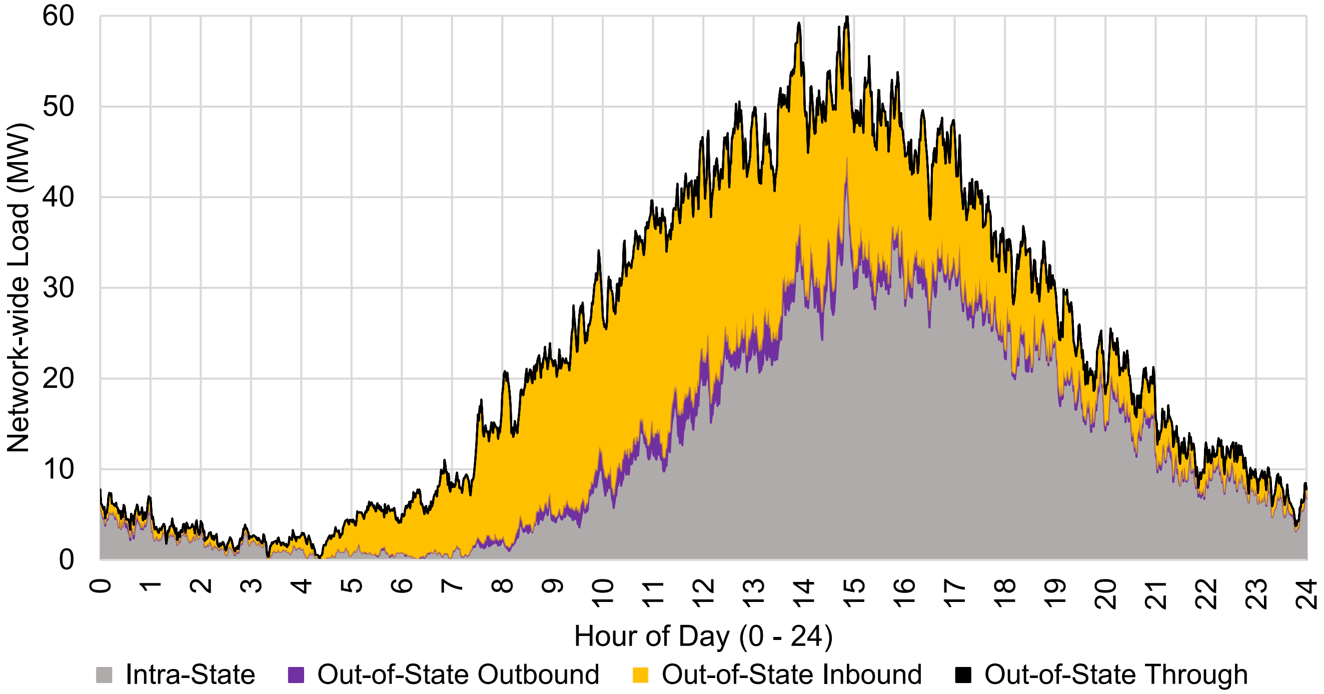
Figure 21: Network-Wide Charging Load Profiles by BEV Type in 2030



SR-Cars, which have the smallest battery capacity, contribute the most charging load (41 percent), followed by SUVs (32 percent) and LR-Cars (27 percent). Despite LR-Cars making up a larger fraction of the BEV population than SUVs, SUVs are modeled to consume roughly 40 percent more energy, requiring more charging. Source: CEC and NREL

Figure 22 illustrates the load profiles broken down by LDT type. Intra-state LDTs account for the majority of charging load (55 percent) throughout the day, followed by out-of-state inbound trips (41 percent). Load profiles for intra-state trips peak between 3 and 4 p.m., whereas the peak load for out-of-state inbound trips occurs around midday. This is mainly due to the assumption about timing of trips. Most LDTs start around 10 a.m., and it is assumed that out-of-state inbound trips will arrive at their destinations in the afternoon, based on the travel survey data. The other two types of out-of-state LDTs, out-of-state outbound and through, represent a very small share of charging load: 4 percent and less than 1 percent, respectively. Although out-of-state outbound trips are not expected to require much charging inside California, these vehicles are very likely to require charging along the rest of the route, indicating the importance of regional and national approaches to electrifying corridors. While out-of-state through trips have much longer travel distances than the other three types of LDTs, their overall travel volume is very small, contributing to their insignificant contribution to the load profiles.

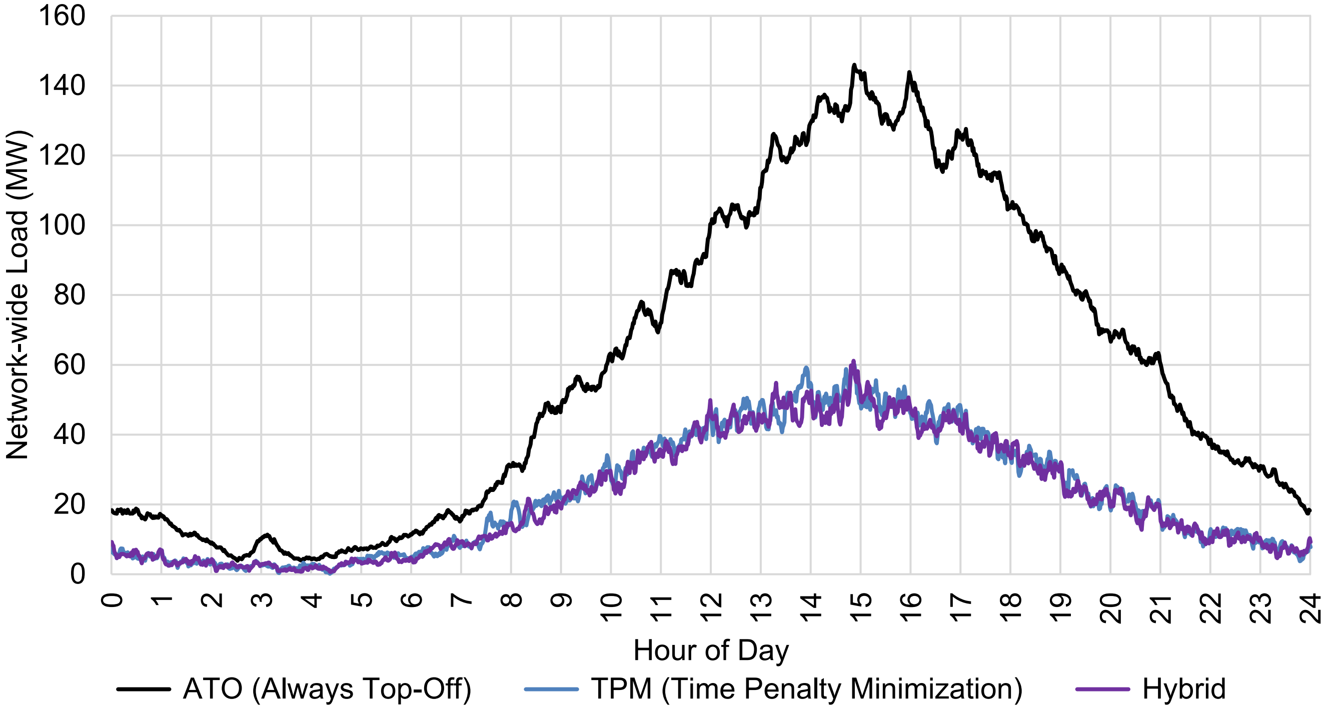
Figure 22: Network-Wide Charging Load Profiles by LDT Type in 2030



Intra-state LDTs account for the most charging load (55 percent) followed by out-of-state inbound trips (41 percent). Out-of-state outbound trips are not expected to require much charging in California but are very likely to charge along the rest of their routes. Source: CEC and NREL

Finally, Figure 23 highlights the impact of charging behavior on the load profiles. The ATO behavior can more than double the peak load compared to the TPM and Hybrid behaviors, due to the increased coincidence in charging from longer charging session durations. The insignificant difference between TPM and Hybrid load profiles is primarily because most LDTs only require one charging event. Since the Hybrid scenario adopts the TPM behavior for the last charging event of a trip, trips with only one charging event will exhibit no difference between the Hybrid and TPM scenarios. The impact of charging behavior on load profiles also affects the local load profiles at destinations. For example, the ATO behavior results in a higher average SOC at the final destination than the Hybrid or TPM scenarios, meaning that charging load at destinations would be lower.

Figure 23: Network-Wide Charging Load Profiles by Charging Behavior in 2030



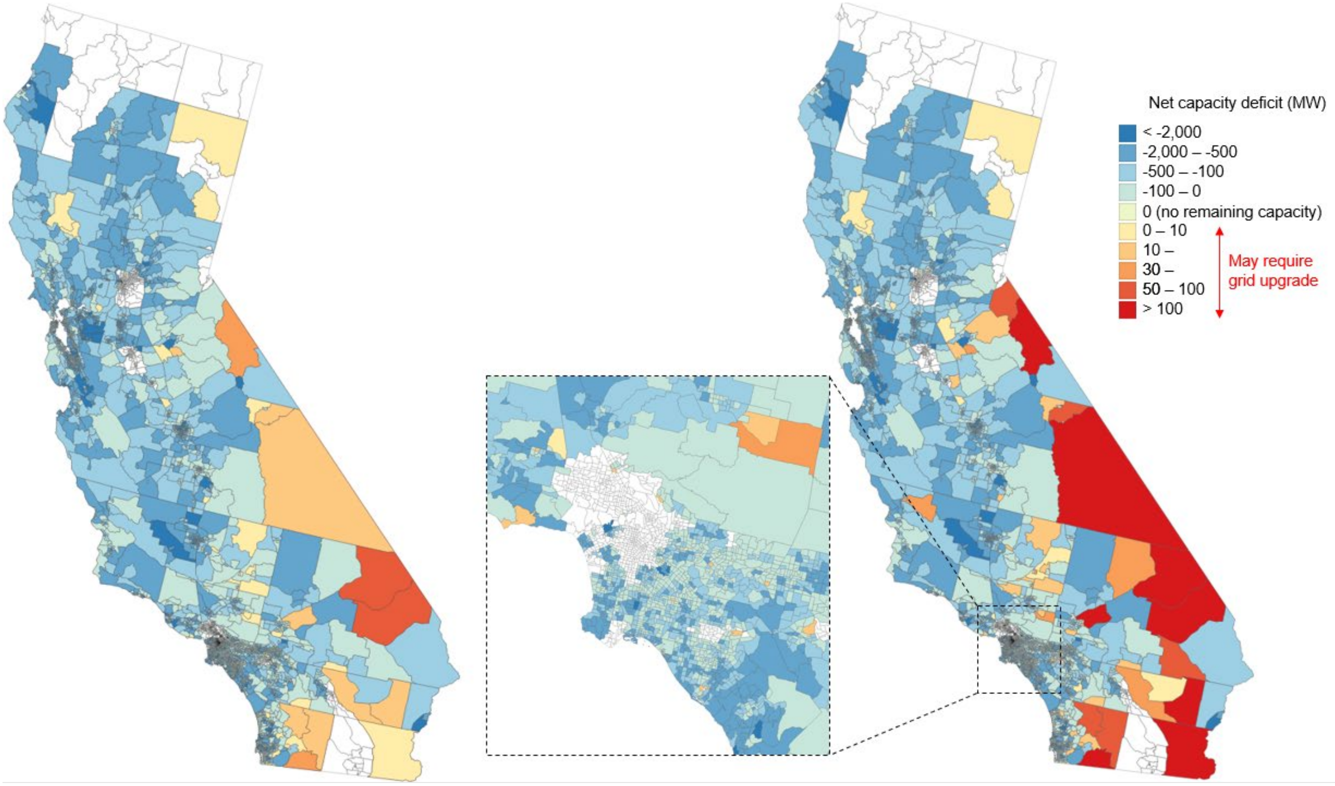
Charging behavior can have a significant impact on charging load, as the ATO scenario results in more than doubling the peak load compared to TPM. Source: CEC and NREL

Electric Grid Hosting Capacity Analysis

Figure 24 shows the results of TAZ-by-TAZ hosting capacity analysis using the EDGE model to evaluate net capacity deficits in MW for lower and upper charger bounds. Positive values indicate that the existing hosting capacity would not be enough to support increasing DCFC demand from electrified LDTs. Note that some TAZs (shown as blank) are removed due to data availability or quality issues.

Two key takeaways can be drawn from the hosting capacity analysis results. First, most of the TAZs are estimated to have enough capacity to host increasing DCFC demand for electrified LDTs. However, TAZs in rural or suburban areas along the popular interstate highways, including those near the eastern and southern state borders, may require capacity upgrades to meet the increasing DCFC demand for electrified LDTs. Critically, this analysis does not account for other charging demand from other use cases such as local travel and may not fully reflect hosting capacity constraints.

Figure 24: Net Capacity Deficit by TAZ in 2030 – Lower (left) and Upper (right) Charger Bounds



Integrating the EVI-RoadTrip load results with the CEC's EDGE model allows net grid capacity deficits by TAZ to be evaluated for lower (left) and upper (right) bounds on chargers. Positive values indicate a capacity deficit. The results suggest that most LDT charging load could be accommodated by the current grid infrastructure, though more rural regions on the eastern and southern borders of the state may require grid upgrades. Source: CEC and NREL

Sensitivity Analysis

The results presented thus far are based on a specific set of assumptions, although different scenarios were considered for BEV adoption (Low, Mid, and High) and charging behavior (ATO, Hybrid, and TPM). To evaluate the impact of different assumptions from those used in previous sections, nine cases (described in Table 11) were adopted for sensitivity analysis. DCFC network size and characteristics (e.g., plug composition), as well as load profiles, for all nine sensitivity cases (except gas station-centric siting) are compared with the baseline case. Since the gas station-centric siting approach is primarily related to station siting, only the change in land use types is shown.

Table 11: Sensitivity Analysis Cases[69]

Sensitivity Case Name	Description
Cold Temperature	Decrease ambient temperature from 75° F to 35° F.
ECR: Low	Vehicles are assumed to be more efficient and follow the lower bound of ECR in Figure 7.
ECR: High	Vehicles are assumed to be less efficient and follow the upper bound of ECR in Figure 7.
Station Buffer: 2 Miles	Decrease distance buffer between the point where drivers realize they need to charge and DCFC stations from 5 miles to 2 miles.
Station Buffer: 10 Miles	Increase distance buffer between the point where drivers realize they need to charge and DCFC stations from 5 miles to 10 miles.
BEV Fleet: Equal	The BEV fleet is composed of equal shares of SR-Cars, LR-Cars, and SUVs.
BEV Fleet: LDV	The BEV fleet composition is the same as the overall light-duty vehicle (LDV) fleet composition.
SUV Battery Capacity	SUVs are assumed to have 180 kWh batteries in 2030 instead of 125 kWh.
kW-SOC Curves	Use alternative kW-SOC curves that are similar to Tesla Version 3 supercharging.[70] This type of charging is unique and includes an initial spike at lower SOC, followed by a linear decrease afterwards, while maintaining the same charging speed as in Figure 9.
Gas Station-Centric	Gas stations are the most preferred land use type for DCFC stations (Table 8).

Source: CEC and National Renewable Energy Laboratory

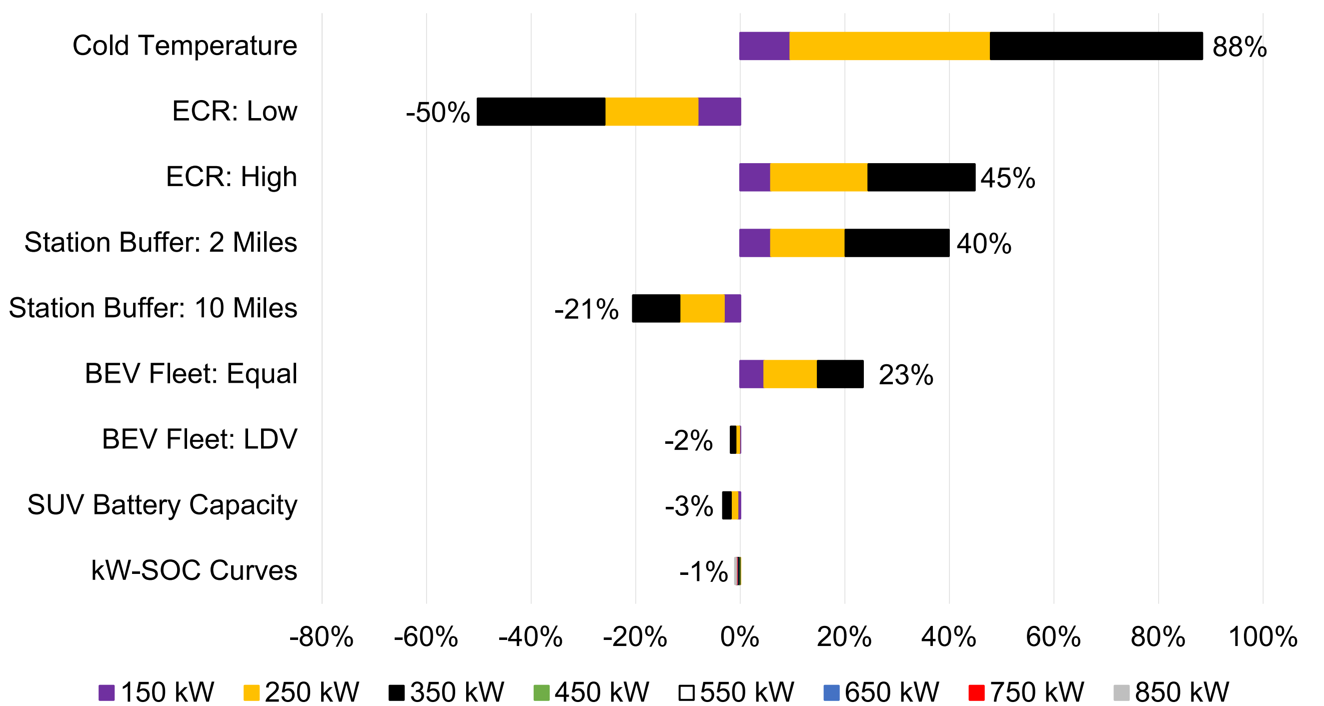
Figure 25 illustrates the impact of these scenarios on the number and power level of chargers required to support electrified LDTs in 2030. All values are relative to the baseline scenario with Mid BEV adoption and TPM charging behavior. There is a wide range of differences in the results, varying from a 1 percent change to 88 percent. Among the nine sensitivity cases, cold temperature leads to the largest increase in network size, at 88 percent. Vehicle efficiency has the second-largest impact, increasing or decreasing network size by 50 or 45 percent, respectively, as efficiency decreases or increases. Modifying the distance buffer for stations has the third largest impact, increasing or decreasing the network size by 40 percent and 21 percent, respectively, as the distance buffer is decreased to 2 miles or increased to 10 miles.

69 Lee, D.-Y. and Wood, E. 2020. DC Fast Charging Infrastructure for Electrified Road Trips. Available at: https://www.energy.ca.gov/event/workshop/2020-08/session3-modeling-and-projecting-charging-infrastructure-commissioner.

70 Tesla. Introducing V3 Supercharging. https://www.tesla.com/blog/introducing-v3-supercharging.

Splitting the BEV fleet composition evenly between the three vehicle types results in a 23 percent increase in the network size due to a shift towards SR cars that require more charging. Distributing the BEV fleet to reflect the composition of the overall light-duty fleet results in a 2 percent decrease in the network size. Increasing the battery capacity of SUVs from 125 kWh to 180 kWh results in a 3 percent decrease in the network size. The use of alternative kW-SOC curves leads to almost no difference in terms of the overall number of chargers, though the composition by power level could change drastically.

Figure 25: Percentage Change in Network Size and Charger Composition by Sensitivity Analysis Case in Year 2030

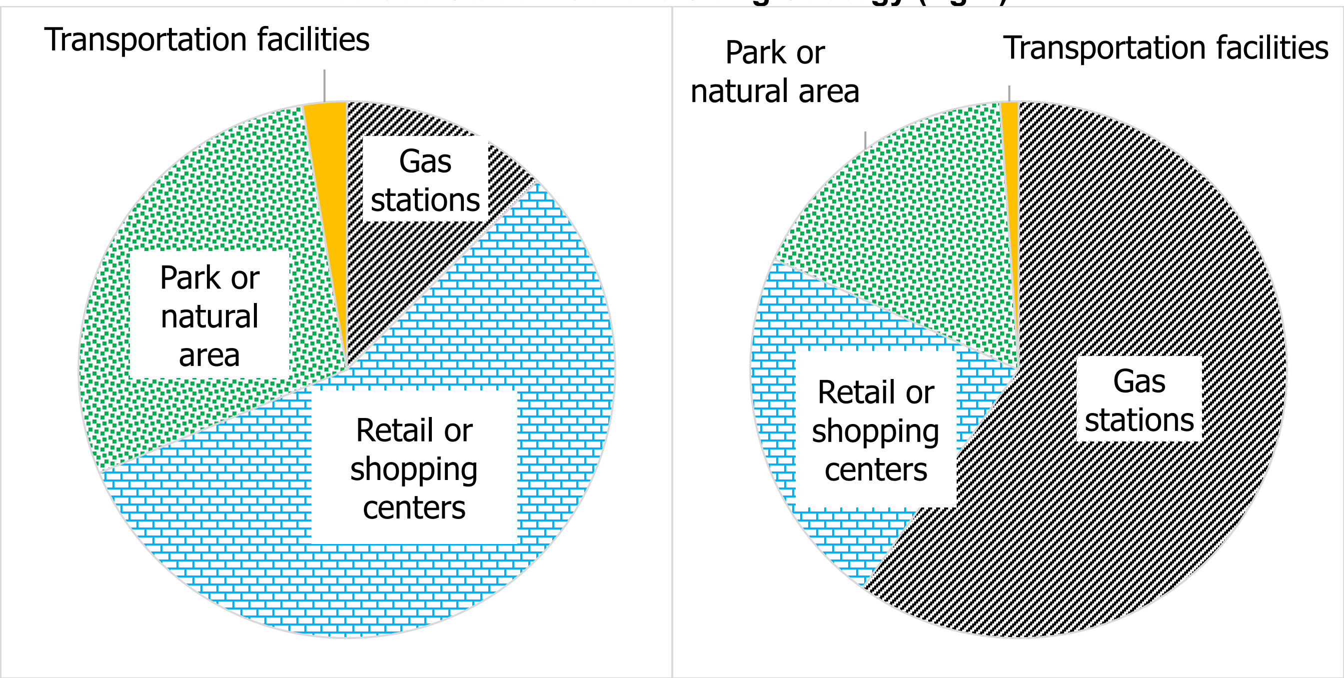


The sensitivity analysis shows a wide range of increases and decreases in the network size. Cold temperatures results in the largest change, increasing the network size by 88 percent. The ECR of BEVs also makes a noticeable impact, emphasizing the importance of vehicle efficiency. Modifying the station buffer demonstrates the effect of driver decision-making for when to seek out a charger on the network size. Doubling the station buffer, which could reflect more proactive planning amongst drivers, results in a 21 percent decrease in the network size. Other scenarios result in more modest changes. Chargers above 350 kW are only present in the kW-SOC Curve scenario. Source: CEC and NREL

Charging load profiles fluctuate over the course of the day, but the overall impact of these sensitivity scenarios is similar to the network size results. Once again, cold temperature makes the largest impact, increasing load by up to 250 percent. Vehicle efficiency has the second-largest impact, increasing load by 50 to 150 percent in the low efficiency case and decreasing load by 50 to 100 percent in the high efficiency case. All other sensitivities lead to smaller impacts within a 50 percent increase or decrease.

The gas station-centric sensitivity scenario primarily altered the locations of projected DCFC stations. Figure 26 shows how this re-prioritization results in existing gas stations hosting about 70 percent of the required DCFC stations. Furthermore, this transition alters the composition for the remaining DCFC stations as well, as the gas stations primarily absorb demand from commercial locations and general parks.

Figure 26: Change in DCFC Station Locations from Default Station Siting Strategy (left) to Gas Station-Centric Siting Strategy (right)



Prioritizing gas stations for DCFC station siting shows that existing gas stations can host about 60 percent of the required DCFC stations. Furthermore, the new gas station locations primarily displace DCFC stations at commercial locations and general parks. Source: CEC and NREL

CHAPTER 5: Conclusions and Future Work

This novel model and analysis address an under-researched, but increasingly important use case for transportation electrification: personal on-road long-distance travels. To accelerate and maximize the transition to EVs, it is critical to have a fast charging network connecting regions within and outside California to reduce range anxiety and the desire to keep ICE vehicles.

The results of this analysis show the potential infrastructure network requirements to achieve this vision. Assuming drivers optimize charging behavior, an average of 1,041 DCFC stations and nearly 2,000 DC fast chargers are projected to support the electrified interregional travel of more than 5 million BEVs in 2030. Charging from electrified LDTs in this scenario is projected to result in a peak load of about 60 MW around 2 to 3 p.m. and aligns with solar generation. However, this analysis highlighted how these results can significantly vary depending on vehicle population, charging behavior, and other conditions.

Policy Implications

Several policy implications emerge from this work:

1) **Investments should be targeted in under-served areas to support electrified interregional travel.**

   As shown in Figure 19, existing DCFC stations are largely concentrated in the major metropolitan areas of the state, with a sparser distribution along major highways. The EVI-RoadTrip results indicate that by 2030, stations will need to cover California's road network more thoroughly, particularly in rural and less-trafficked areas that have so far not been targeted in the market. However, the assumption that drivers will proceed until their batteries are nearly depleted and will need to charge very soon afterwards leads to a denser network in Figure 19 than may be realistically needed or feasible. This assumption will be revisited in future work.

2) **Future-proofing infrastructure and encouraging interoperability of charging connectors should be a priority.**

   Even with a growing BEV population, EVI-RoadTrip finds that technology improvements such as longer-range vehicles and higher charging power moderate the growth in the needed number of stations and plugs over time. Since each analysis year is simulated independent of the others, later years show low-powered DC fast chargers replaced with higher-powered infrastructure. Given the lifetime of DC fast chargers, this suggests that installing high-powered chargers should be prioritized today to meet the needs and capabilities of future BEVs. The model also assumes perfect interoperability, where any BEV can plug into any charger and successfully charge. Since this is not the case in practice today, EVI-RoadTrip may underestimate the DC fast charging needs if a fragmented infrastructure network persists.

3) **Further research and collaboration are needed to fully understand potential grid impacts.**

   The proof-of-concept SCE case study using EDGE (discussed in the "Electric Grid Hosting Capacity Analysis section of Chapter 4) indicates that road trip charging demand may not be accommodated by the current grid infrastructure depending on the region. It is critical for state agencies to continue working and engaging with utilities and researchers on the EDGE tool to accurately reflect grid conditions and the impact of future load and to proactively plan for increased ZEV penetration.

4) **Optimized charging and driving behavior can minimize grid impacts and infrastructure requirements.**

   As the ATO charging behavior illustrated, always charging to 100 percent SOC creates ripple effects that could more than double peak load and require significantly more chargers due to the increased coincidence in charging from longer charging sessions. Educating drivers about charging behavior or proactively limiting plug-out SOC for DC fast charging through vehicle or charger controls could minimize grid impacts and infrastructure requirements.

   Furthermore, the sensitivity analysis demonstrated the impact of driver decision-making on the network size. Doubling the maximum distance from when a driver needed to charge to the station site from 5 to 10 miles resulted in a 21 percent decrease in the network size.

5) **Infrastructure in neighboring states and countries is needed to fully support electrified interregional travel.**

   EVI-RoadTrip identifies several station sites in neighboring states to accommodate routes that include out-of-state travel. However, these are only for trips that begin and end in California. As noted in previous sections, the model does not consider charging demand outside of California for trips that begin or end outside the state. To fully enable electrified interregional travel, a sufficient DC fast charging network will be needed across states and in countries such as Mexico and Canada. Regional collaboration has the potential to accelerate and improve deployment of this network.

Future Work

Although this analysis represents a significant step forward for charging infrastructure modeling, there are some limitations and refinements that will be addressed in future work.

EVI-RoadTrip will be combined with EVI-Pro 2, which focuses on intraregional travel and community charging infrastructure needs. Since these two models are currently separate, it is possible that the DC fast charging infrastructure modeled in each could overlap. For example, chargers designed in EVI-RoadTrip for long-distance travel could also be used for local travel, or vice versa. The development of EVI-Pro 3 will aim to bridge this gap either through co-simulating the travel and charging needs of both use cases or through post-processing. Also, EVI-RoadTrip does not currently generate charging loads at origins or destinations. Including these in a single model will provide a more accurate and holistic depiction of LDT charging.

In addition, the independent nature of simulation years is an area that will be investigated. As mentioned previously, the charging infrastructure designed in one year is not assumed to still exist in a later year. This results in a model that may not reflect infrastructure planning and installations in practice. Capturing these real-world properties may better illustrate costs and benefits, such as future-proofing equipment mentioned above.

Further integration with the EDGE model as it is refined will be a critical step towards understanding grid impacts and properly planning for growing charging load. While this analysis presented a case study demonstrating the value of EDGE, there are still notable data gaps and uncertainties that will require continued coordination between state agencies, utilities, and researchers.

Several assumptions about travel demand, driver behavior, vehicle characteristics, and charging session characteristics were made in this analysis. Higher-quality data on travel behavior (including multi-day LDTs) and detailed charging session data will be needed to more accurately estimate infrastructure requirements and charging load. Also, relationships between vehicle characteristics and LDTs (e.g., bias towards longer-range or larger BEVs, pulling trailers) could be incorporated to improve the realism of the analysis. As mentioned above, the assumption on trip planning and when drivers decide to charge makes a significant impact on the network size and design and will be investigated more robustly in future work.

Future analysis should continue to consider market evolution and policy goals to reevaluate infrastructure needs. These include factors such as vehicle attributes, charging technologies, consumer behavior and preferences, BEV adoption trajectories, sales goals, and more. As the different fleet scenarios and sensitivity analyses showed, the infrastructure results can vary depending on the specific conditions, and it will be necessary to continue benchmarking infrastructure needs for this use-case as part of the CEC’s AB 2127 assessments.

Glossary

ALTERNATING CURRENT (AC) — Flow of electricity that constantly changes direction. Almost all power produced by electric utilities in the United States moves in current that shifts direction at a rate of 60 times per second.

BATTERY-ELECTRIC VEHICLE (BEV) — Also known as an “all-electric” vehicle, BEVs use energy that is stored in rechargeable battery packs. BEVs sustain power through the batteries and therefore must be plugged into an external electricity source to recharge.

CALIFORNIA AIR RESOURCES BOARD (CARB) — The state's lead air quality agency consisting of an 11-member board appointed by the Governor and more than 1,000 employees. CARB is responsible for attainment and maintenance of the state and federal air quality standards, California climate change programs, and motor vehicle pollution control. It oversees county and regional air pollution management programs.

CALIFORNIA ENERGY COMMISSION (CEC)—The state agency established by the Warren Alquist State Energy Resources Conservation and Development Act in 1974 (Public Resources Code, Sections 25000 et seq.) responsible for energy policy. The CEC's five major areas of responsibilities are forecasting future statewide energy needs; licensing power plants sufficient to meet those needs; promoting energy conservation and efficiency measures; developing renewable and alternative energy resources, including providing assistance to develop clean transportation fuels and infrastructure; and planning for and directing state response to energy emergencies.

CALIFORNIA PUBLIC UTILITIES COMMISSION (CPUC) — A state agency created by a California constitutional amendment in 1911 to regulate the rates and services of more than 1,500 privately owned utilities and 20,000 transportation companies. The CPUC is an administrative agency that exercises legislative and judicial powers; its decisions and orders may be appealed only to the California Supreme Court. The major duties of the CPUC are to regulate privately owned utilities, securing adequate service to the public at rates that are just and reasonable to customers and shareholders of the utilities; and the oversight of electricity transmission lines and natural gas pipelines. The CPUC also provides electricity and natural gas forecasting, and analysis and planning of energy supply and resources. Its headquarters are in San Francisco.

DIRECT CURRENT (DC) — A current of electricity that flows in one direction and is the type of power that comes from a battery.

DIRECT CURRENT FAST CHARGER (DCFC) – Electric vehicle charging that uses direct current anywhere from 200 to 1000 volts and can reach a maximum power output of 450 kilowatts.

ELECTRIC VEHICLE (EV) — A broad category that includes all vehicles that can be fully powered by electricity or an electric motor.

ELECTRIC VEHICLE CHARGING STATION — A location where one or more EVSEs are installed to charge EVs.

ELECTRIC VEHICLE SUPPLY EQUIPMENT (EVSE) -- Equipment designed to supply power to EVs. Most EVSEs can charge BEVs and PHEVs.

GREENHOUSE GAS (GHG) — Any gas that absorbs infrared radiation in the atmosphere. Greenhouse gases include water vapor, carbon dioxide (CO2), methane (CH4), nitrous oxide (NOx), halogenated fluorocarbons (HCFCs), ozone (O3), perfluorinated carbons (PFCs), and hydrofluorocarbons (HFCs).

KILOWATT (kW) — One thousand watts, a measure of power. On a hot summer afternoon, a typical home — with central air conditioning and other equipment in use — might have a power demand of 4 kW.

KILOWATT-HOUR (kWh) — One kilowatt of electricity supplied for one hour, that is, a measure of energy. It is the most used unit of measure telling the amount of electricity consumed over time.

MEGAWATT (MW) — A unit of power equal to 1 million watts.

NITROGEN OXIDES (OXIDES OF NITROGEN, NOx) — A general term for compounds of nitric oxide (NO), nitrogen dioxide (NO2), and other oxides of nitrogen. Nitrogen oxides are typically created during combustion and are major contributors to smog formation and acid deposition. NO2 is a criteria air pollutant and may result in numerous adverse health effects.

PLUG-IN ELECTRIC VEHICLE (PEV) — A general term for any car that runs at least partially on battery power and is recharged from the electricity grid. There are two types of PEVs: pure battery-electric and plug-in hybrid electric vehicles.

PLUG-IN HYBRID ELECTRIC VEHICLE (PHEV) — PHEVs are powered by an internal combustion engine and an electric motor that uses energy stored in a battery. The vehicle can be plugged 107 into an electric power source to charge the battery. Some can travel nearly 100 miles on electricity alone, and all can operate solely on gasoline (like a conventional hybrid).

TRAFFIC ANALYSIS ZONE (TAZ)

VEHICLE-GRID INTEGRATION (VGI) — Methods to align electric vehicle charging with the needs of the electric grid. To do this, electric vehicles must have capabilities to manage charging or support two-way communication between vehicles and the grid.228

ZERO-EMISSION VEHICLE (ZEV) — Vehicles that produce no emissions from the onboard source of power (for example, hydrogen fuel cell vehicles and electric vehicles).