36th International Electric Vehicle Symposium and Exhibition (EVS36)
Sacramento, California, USA, June 11-14, 2023

When Will California's Electric Distribution System Need to be Upgraded to Meet Electric Vehicle Charging Demand?

Yanning Li[1], Alan Jenn 2[2]

[1] *Institute of Transportation Studies,University of California, Davis, 1605 Tilia St, CA 95616, yspli@ucdavis.edu*

[2] *Institute of Transportation Studies,University of California, Davis, 1605 Tilia St, CA 95616, ajenn@ucdavis.edu*

Executive Summary

California's aggressive electric vehicle (EV) policies may generate a large burden of EV charging load on the electric distribution system. In this study, we investigate the development of overloading in the distribution networks, using feeder-level capacity and load data from the grid, and a travel demand model together with empirical EV charging data. We select twelve representative areas across the territories of the three major investor-owned utilities in California. Overloading conditions are highly diverse within our case studies. Three out of the twelve areas that we examine have frequent overloading over 50% of the time starting between 2028 and 2040. Four areas will be challenged by intense overloading, where EV charging load can reach up to 500% of the remaining capacity headroom. Our findings indicate a need for infrastructure upgrade in some parts of the Californian distribution system within the next two decades. However, the spatial heterogeneity in our results suggest a need for large-scale case-by-case analysis.

Keywords: load management, power, prediction, smart grid, user behavior

1 Introduction

An acceleration of electric vehicle (EV) uptake is happening in the transportation sector. According to the International Energy Agency (IEA), the global EV stock has grown over 10 million in the past decade, and is expected to reach as high as 300 million by 2030 [1]. The state of California has been setting ambitious policies for greenhouse gas (GHG) emissions reduction in the transportation sector, including encouraging the growth of EV sales. The state has a goal of 5 million EVs on the road in California by 2030 and recent updates to the Zero Emissions Vehicle rule sets requirements for 100% sales of new passenger vehicles to be electric by 2035. This widespread adoption of EVs in the future will lead to a large growth in electricity charging load, which can contribute to challenges in the operation and planning of the power system.

A vast body of literature has investigated the possible impact of adding unmanaged charging loads to existing power systems, either on the bulk level (generation and transmission)[2]–[4] or on the distribution level [5]–[17]. Since EV charging usually takes place in the distribution grid, before the uncoordinated charging affects the generation dispatch and transmission congestion, the distribution network would likely encounter the challenges first. Furthermore, charging EVs based on wholesale market prices without considering distribution constraints may lead to even more severe congestion than unmanaged charging[5]. Therefore, it is especially important to understand how constrained the distribution grid will be and how much upgrade should be in place for the integration of future EV charging demand into the distribution system.

Many case studies have estimated the potential reinforcement needs of distribution grid infrastructure due to uncoordinated EV charging load. For example, up to 49% of the distribution transformers' capacity thresholds are exceeded in the study by Verzijlbergh et al.[6]; Fernández et al.[7] calculated that with 60% of total vehicles being EV, investment cost on distribution network will increase by up to 15%; 60% of the feeders in San Francisco Bay area will exceed their loading limit according to Coignard et al.[8]; 28% of the distribution network in Great Britain will require upgrade according to Crozier et al.[9]; Borlaug et al.[10] investigated the impact of heavy duty electric truck's depot charging, considering not only the monetary cost of substation upgrade, but also the time needed to implement the reinforcement; González et al.[11] focused on the feeder-level impact of direct current (DC) fast charging.

Results of these studies are highly varied due to the high heterogeneity in the characteristics of the chosen distribution networks. Some of the studies use hypothetical network models instead of real world networks[7], [12]. Majority of the researches are limited in scope, such as a single workplace[13], a single feeder[11], [14], a single distribution network with one substation and several feeders[7], [15]–[17]. Only a handful of studies cover distribution system with several substations: Coignard et al.[8] studied the San Francisco Bay area with 8 substations; Borlaug et al.[10] performed the study for part of the distribution grid in Texas with 36 substations; Verzijlbergh et al.[6] studied part of the distribution grid in the Netherlands with 55 substations; Crozier et al.[9] studied the distribution system of the whole Great Britain but the simulation is based on 3 typical network models. In this study, we examine 12 distribution level areas within California across the utility territories Pacific Gas & Electric (PG&E, covering most of northern California), Southern California Edison (SCE, covering the greater Los Angeles area), and San Diego Gas & Electric (SDG&E, covering the greater San Diego area). The areas are selected in order to cover a combination of residential, commercial, and retail oriented locations that represent a variety of load profiles (both in shape and magnitude).

Another challenge of simulating the real-world impact of future EVs on the distribution system is the uncertainty in charging loads. Many studies use conventional vehicle travel data to simulate the charging demand and pattern of future EVs, usually assuming that EVs would start charging immediately after arrival[5]–[8], [12], [15], [16]. However, real-world EV charging behaviors can be largely different from these simplified assumptions[18]. But very few studies utilize empirical travel and charging data from EVs[9], [13], [14], [17]. In this study, we simulate future EV charging loads from both data loggers and public charging service providers to address the heterogeneity in EV charging behaviors under home charging, public charging, and workplace charging. Uniquely, our work employs the use of a high-resolution state-wide travel demand model that provides vehicle flows based on trip purposes—allowing us to accurately characterize the breakdown of home, public, and workplace charging. The proportion of electric vehicles among the population of vehicles traveling into our regions of study are forecasted based on California's regulatory requirements, allowing us to provide better insight into the timing of distribution grid impacts from additional EV charging load.

The remainder of the paper is structured as follows: Section 2 explains the methodology and data sources used in this research. Section 3 presents the primary results on the development of overloading conditions in our case studies. And in section 4, we conclude with a discussion on the major implications and outlook of our work.

2 Methods

The general framework of this study can be seen in Fig. 1. We utilize spatial and temporal empirical data at feeder level from both the grid and the EV side to project the hourly EV charging load and baseload profile by feeder in the future. These results are then compared with the feeder capacities, to determine the frequency and intensity of feeder capacity exceedance resulted from EV uptake.

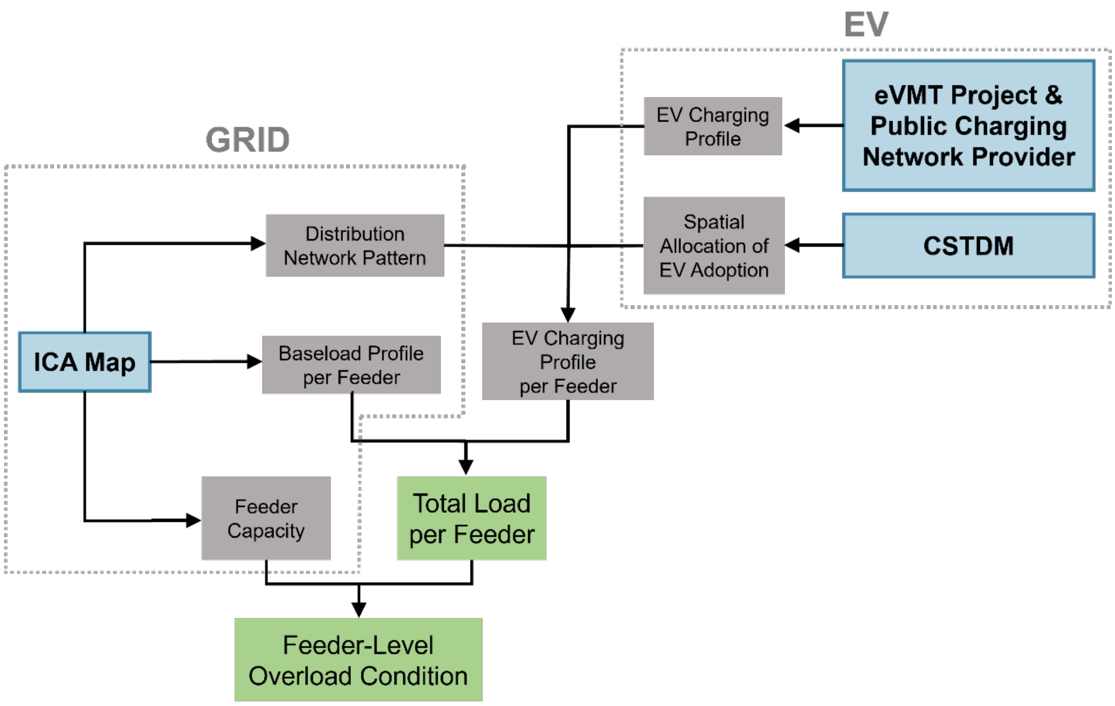


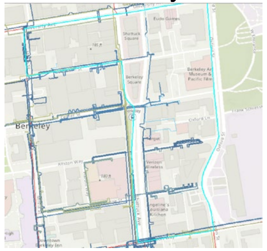
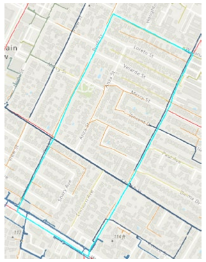
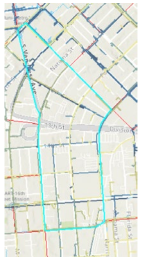
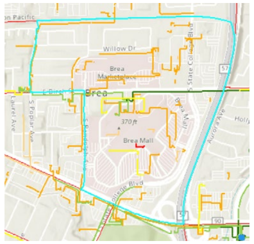
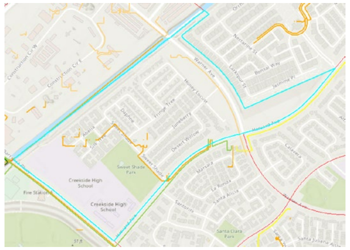
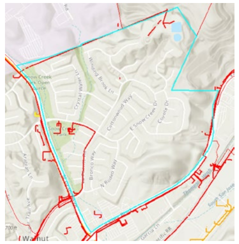
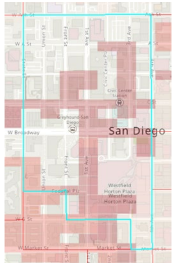
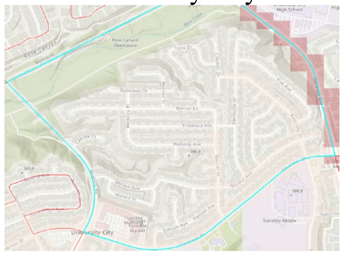
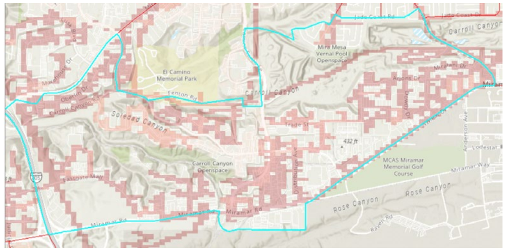
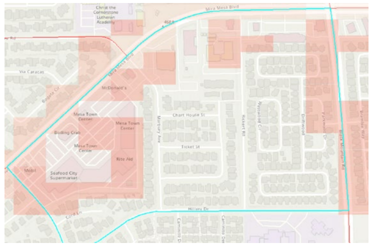
Figure1: Data sources (blue), intermediate data (gray), and outputs (green) in the general research framework

2.1 Distribution Grid Data

In 2016, the California Public Utilities Commission (CPUC) required utilities to perform Integration Capacity Analysis (ICA) for the distribution system. The ICA maps from PG&E, SCE, and SDG&E provide publicly available data on the spatial pattern of the distribution network down to the circuit level, feeder capacities, as well as hourly load profiles per feeder. The datasets also include future upgrade plans of the distribution grid, along with projections on the growth of feeder-level distribution energy resources (DER) such as rooftop photovoltaic (PV). The ICA data contains both thermal and voltage load allowances for their distribution circuit segments across each of the three major utilities in California. These load allowances are provided on an hourly basis by the maximum and minimum load days observed in each month of the year. These are the primary elements of interest that allow us to observe whether additional charging loads exceed these load allowances and the extent to which they are exceeded on the basis of magnitude and time.

In this study, we select a total of twelve census block group areas, four block groups in each of the utilities of PG&E (Berkeley, West Davis, San Francisco, and Mountain View), SCE (Brea, Irvine, Manhattan Beach, and Walnut), and SDG&E (downtown San Diego, Mira Mesa, La Jolla, and University City). These areas were selected based on their diversity and variation of building types including residential, commercial, shopping areas, and schools. A map and basic characteristics of each of the areas can be found in Table 1. Due to discrepancies in the load profile data from SCE, we scaled the data to ensure it is consistent in magnitude with the load data at circuit segment level in other utilities and that the ratio of load to the thermal load threshold is also consistent.

Table 1 Study Areas in Three Major Utilities

PG&E	Berkeley  Urban; residential, commercial, and retail	Mountain View  Suburban; residential	Mission District  Urban; residential, commercial, retail	Davis  Rural; residential, school
SCE	Brea  Urban; residential, retail	Irvine  Urban; residential, school	Manhattan Beach  Urban; residential, commercial	Walnut  Suburban; residential
SDG&E	Downtown SD  Urban; residential, commercial, retail	University City  Suburban, residential	La Jolla  Urban; commercial, residential	Mira Mesa  Suburban; residential, retail

2.2 Mobility Data

To determine the additional load for charging electric vehicles in each of the selected regions seen in Table 1, we first calculate the number of EVs traveling in each of the regions per day and their respective purposes for travel based on the California Statewide Travel Demand Model (CSTDM). This model allows us to obtain the counts of vehicles traveling through each of the study areas and whether they would be traveling to residential areas, workplaces, or other public use locations (dining, shopping, school, recreation, etc.). The extent to which the vehicles in the region are electrified is determined as a proportion of the total number of electric vehicles in California relative to the total number of light-duty vehicles in the state. This proportion is calculated by assuming a linear growth in EV sales, up to 100% EVs within all new light-duty vehicles sold in 2035, which aligns with California's newly proposed standard[1]. This assumption projects a state-wide EV adoption of nearly 7 million by 2030 - which is more than 30% above the 5 million goal to be reached by 2030 - and over 21 million EVs on the road by 2045.

With the number of EVs that travel to each of the regions on different purposes (categorized as home, work, and public), we are able to simulate the EV charging profiles in these areas from empirical EV charging data. For home charging and workplace charging, we employ data from the eVMT project, which is collected from data loggers on a total of 300 EVs in multiple utility areas(19). And for public charging, we adopt a dataset consisting of charging records from several charging network providers (including EVgo, Chargepoint, and Electrify America) from 2014 to 2019. The datasets contain information of each single charging event, including the start and end time and energy charged. The distribution of the start hour of the charging events in different locations are depicted in Fig. 2. We can see that workplace charging mostly start around 8:00 in the morning, when people arrive at work; and home charging usually start after 18:00 when EV owners get back; the start time of public charging tend to be distributed in the middle, when people are running errands. Table 2 shows some other statistics of the charging data. In general, the duration of public charging events are significantly shorter than home and workplace charging events. And the energy charged per charging event in public charging tends to be a lot higher than those in home and workplace charging. This is due to the higher proportion of DC fast chargers in public charging stations than among the charge points at home or work.

With these charging data, we first calculate the average number of charging events per day per EV, for home, workplace, and public charging separately. This is then multiplied with the number of EVs that travel into each region for the same purpose, to obtain the number of charging events that occur in each region in different charging locations per day. Lastly, we bootstrap the charging events in each day from the empirical data, and calculate the hourly EV charging load profile.

The spatial allocation of EV charging demand is then connected with the network pattern of the distribution grid. Each of the regions correspond to several feeder lines. The aggregate capacity threshold of the feeders within each region can be compared with the aggregate baseload and EV load, to examine whether the addition of EV charging demand violates the capacity constraint. And if overloading takes place in an area, we can quantify when it starts, how frequent it happens, and how intense it is.

Table 2 Statistics of charge event duration and energy per charge event in different charging locations, from empirical EV charging data

Value	EV Charging Location	Mean	Standard Deviation
Charge Event Duration [Hours]	Home	3.58	3.00
	Work	3.04	2.70
	Public	0.52	0.52
Energy Per Charge Event [kWh]	Home	7.59	8.27
	Work	7.30	7.28
	Public	12.73	7.95

[1] California Code of Regulations, Section 1962.4 Draft, December 2021. "Zero-Emission Vehicle Standards for 2026 and Subsequent Model Year Passenger Cars and Light-Duty Trucks".

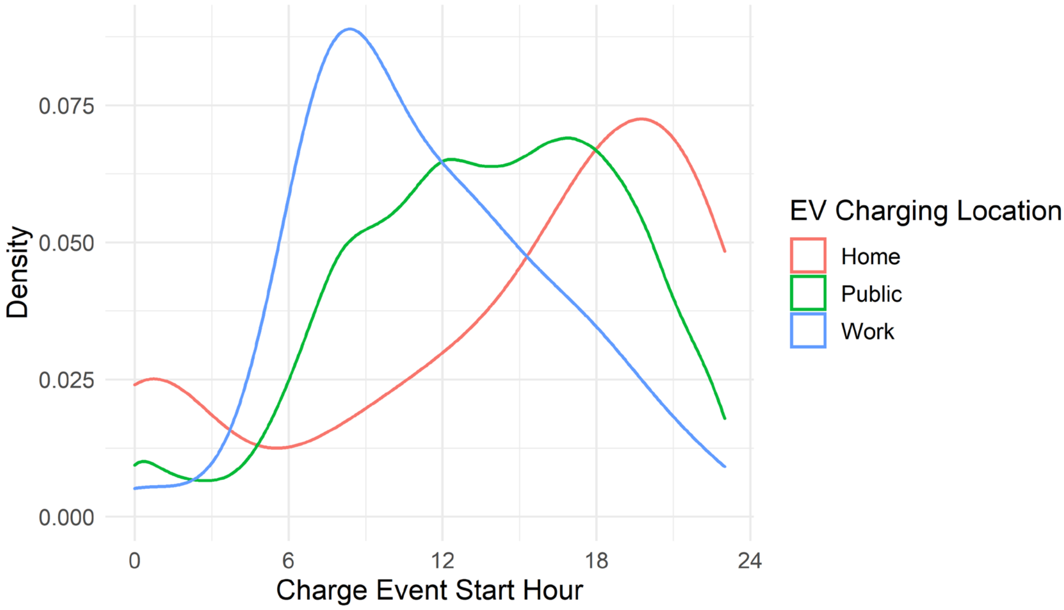


Figure 1 Distribution of charge event start hour in different charging locations, from empirical EV charging data

3 Results

3.1 Overload Frequency and Intensity

We run the model from 2022 to 2045, and simulate the hourly EV charging profile in each area on the maximum load day of each month, when overload is most likely to happen. In Fig. 3, the EV charging load (red line) is compared with the feeders' thermal load allowance (blue line) provided in the ICA dataset, which is the remaining feeder capacity after excluding baseload in the circuit segments. Overload happens when the red line goes above the blue line. We can observe that in 2022 (the top figure), the red line is almost always below the blue line, indicating very rare overloading in the areas that we examine. In 2045 (the bottom figure), however, in many areas, the EV load grows to exceed the remaining capacity from time to time. The extent of overloading can be very diverse across different areas. For example, in Berkeley and Mira Mesa, the red line is completely beyond the blue line all the time; While in Mission and Downtown San Diego, the EV load remains well below the thermal limits; In places like La Jolla and University City, overload happens regularly at certain hours of each day.

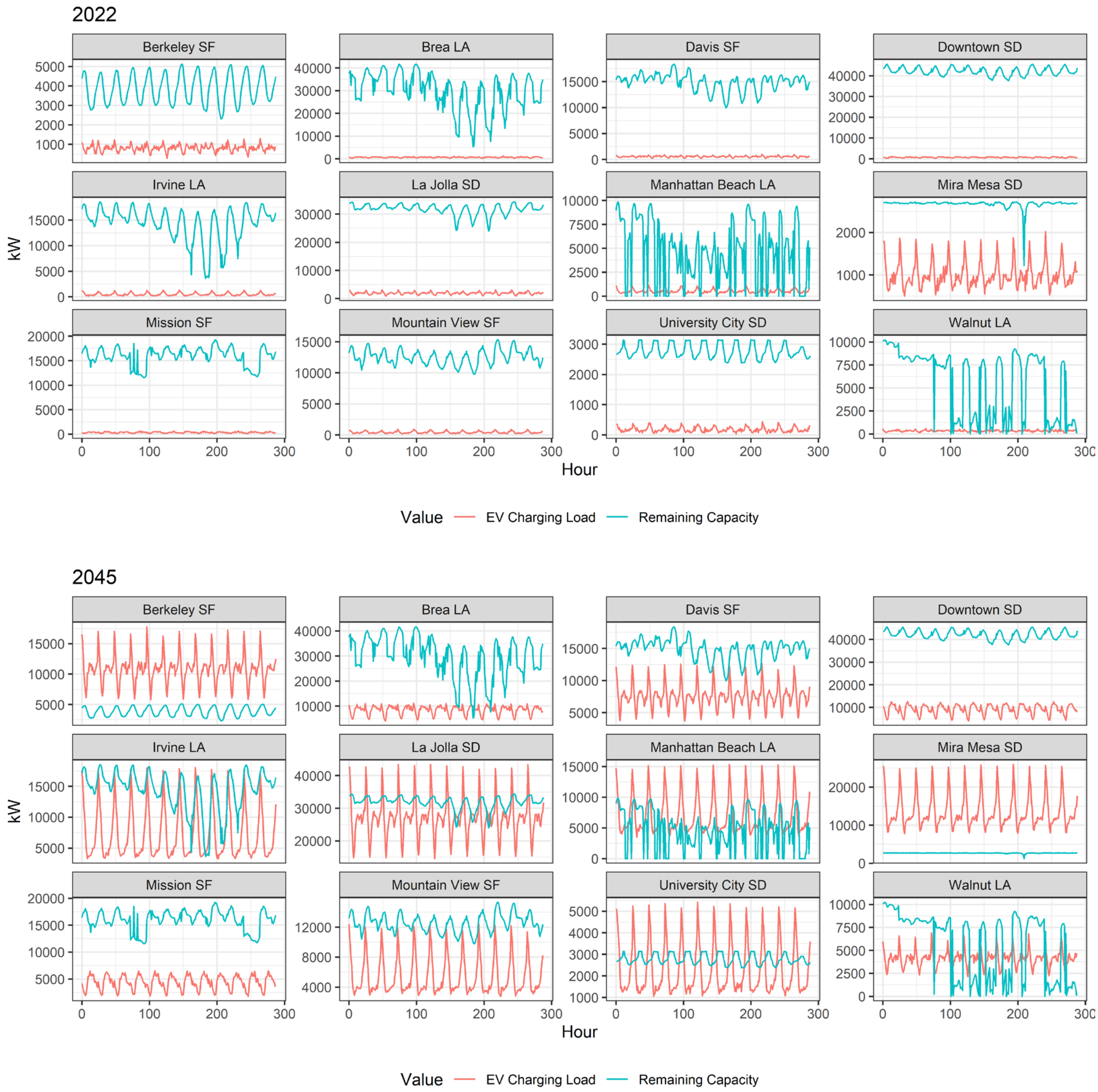


Figure 2 Hourly EV charging load profile and remaining feeder capacity, in the peak load day of each month, in different areas, in 2022 (top) and 2045 (bottom)

To further quantify the frequency of overload in the distribution system, we calculate the share of the number of hours where EV load exceeds remaining feeder capacity within the total number of hours in the days simulated each year. As illustrated in Fig. 4, this share indicates how often the distribution network in each area is stressed by the growth of EV charging load in each year. A flat line of 0 over all the years represents the local distribution network not challenged by overloading at all, as can be seen in Davis, Downtown San Diego, Mission, and Mountain View. In some areas (Irvine, La Jolla, University City, and Walnut) we can see a relatively mild increase in overload frequency, up to less than 50% of the time, as the EV charging load increases over the years. But the year that this increase starts can be varied: Irvine and La Jolla start to have overload from 2038, while University City starts to be overloaded from 2033, and Walnut's overload frequency increases from as early as 2025. There are also areas that risk severe overloading in the future – Berkeley, Manhattan Beach, and Mira Mesa, where the frequency of overload can reach over 50% of the time. Mira Mesa and Berkeley's distribution networks will be overloaded 100% of the time after 2030 and 2040 respectively.

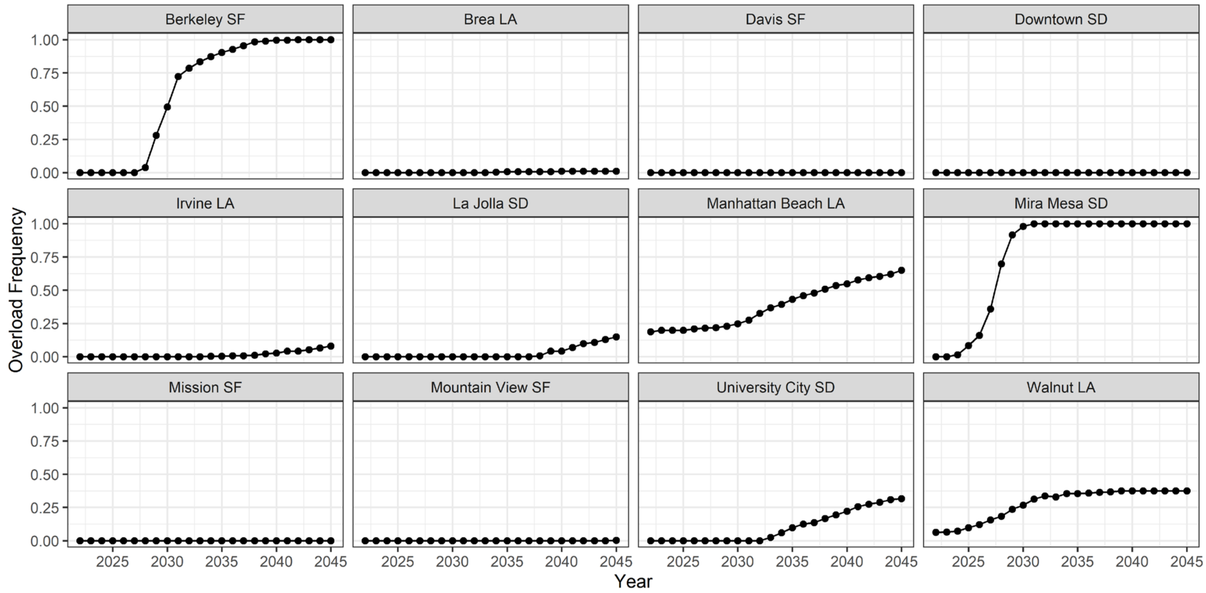


Figure 3 Overload frequency of the distribution network in each area by year

We also want to evaluate how intense the future EV charging load contribute to the reduction of capacity headroom. The headroom reduction share in each hour is calculated by dividing the remaining feeder capacity by the EV charging load. Fig. 5 shows the average headroom reduction share in each area by year, and we categorize the 12 regions into mainly residential and mainly commercial areas. The share that EV charging demand takes up in the remaining feeder capacity increases as the EV uptake grows over the years. When the headroom reduction share goes beyond 1, it means that on average, the EV load level in this area is higher than the remaining capacity, which indicates overloading. Among the residential areas, EV charging demand in Mira Mesa and Walnut can reach as high as 5 times and 3 times as much as their remaining feeder capacities respectively. Mira Mesa's headroom reduction share exceeds 100% in 2027, and this happens later in Walnut in 2030. In the commercial areas, overloading is generally less intense and happens later. EV loads in Berkeley and Manhattan Beach exceed 100% of their remaining feeder capacities on 2030 and 2036 respectively, and reach up to 3 times and 1.5 times as much as their capacity headroom respectively.

Overloading can also exist in the areas with headroom reduction share below 1, such as University City and La Jolla. While the EV loads exceed remaining capacity at certain hours in each day, the relatively lower overload frequency and intensity reduces the headroom reduction share on average. Among those areas that have no overload until 2045, some of them have a lot more capacity headroom left after integrating EV charging demand, such as Downtown San Diego and Mission, both are commercial areas; while others can have peak EV loads taking up majority of the remaining capacities, such as Davis, Mountain View, and Irvine, all of which are residential areas.

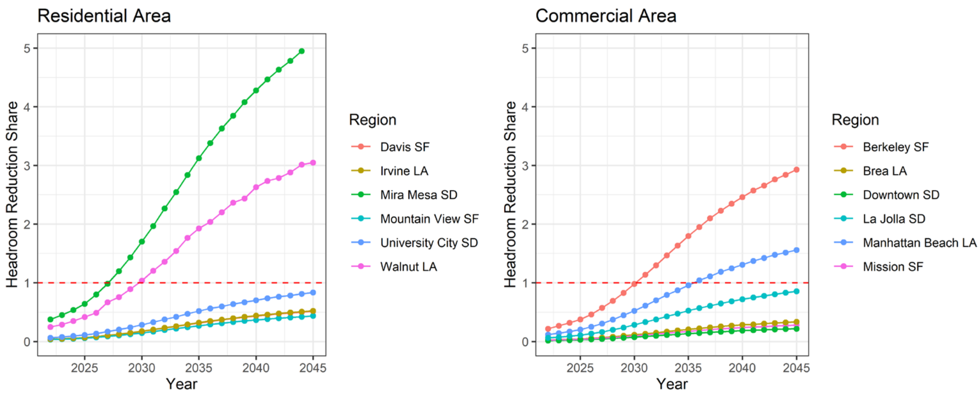


Figure 4 Yearly average feeder capacity headroom reduction share caused by EV charging load, in residential areas (left) and commercial areas (right)

3.2 Load Patterns

Temporal patterns of EV load and baseload can influence the overloading conditions in the distribution system. In Fig. 6, we show the load patterns in different areas on the peak load day of August 2045. The composition of EV load is different between residential and commercial areas, leading to a difference in the general pattern of EV charging profiles. In residential areas, majority of the EV charging demand comes from home charging, which makes the charging load at night a lot higher than that in the day. Most of the residential areas that we examine have only one peak charging load during the night. In commercial areas, the proportion of public charging is a lot higher than that in residential areas, which generates another peak in the charging load in the middle of the day. Baseload patterns are also affected by the characteristics of the area. In residential areas, baseload usually peaks around 18:00; while in commercial areas, baseload peak tends to start earlier during the day, usually from around noon. The synergy of baseload and EV load patterns influence the time that overloading tends to happen. In residential areas, overload tends to take place at night, such as University City and Irvine. In the areas that do not have overloading problems yet, such as Davis and Mountain View, nighttime is also when total load gets the closest to feeder capacity threshold. Similar trend can be seen in the middle of the day in most of the commercial areas that we examine.

Despite this general trend of difference between commercial and residential areas discussed above, it is worth noting that the extent of overloading in each specific distribution network is far more complex and needs to be analyzed case by case. This heterogeneity can be observed in our case studies among the areas within the residential or commercial category. When and how much overload takes place in a feeder is not only related to people's energy consumption behaviors, but also largely affected by the amount of capacity headroom left when the distribution infrastructure is built, as well as the overall scale of local EV charging load.

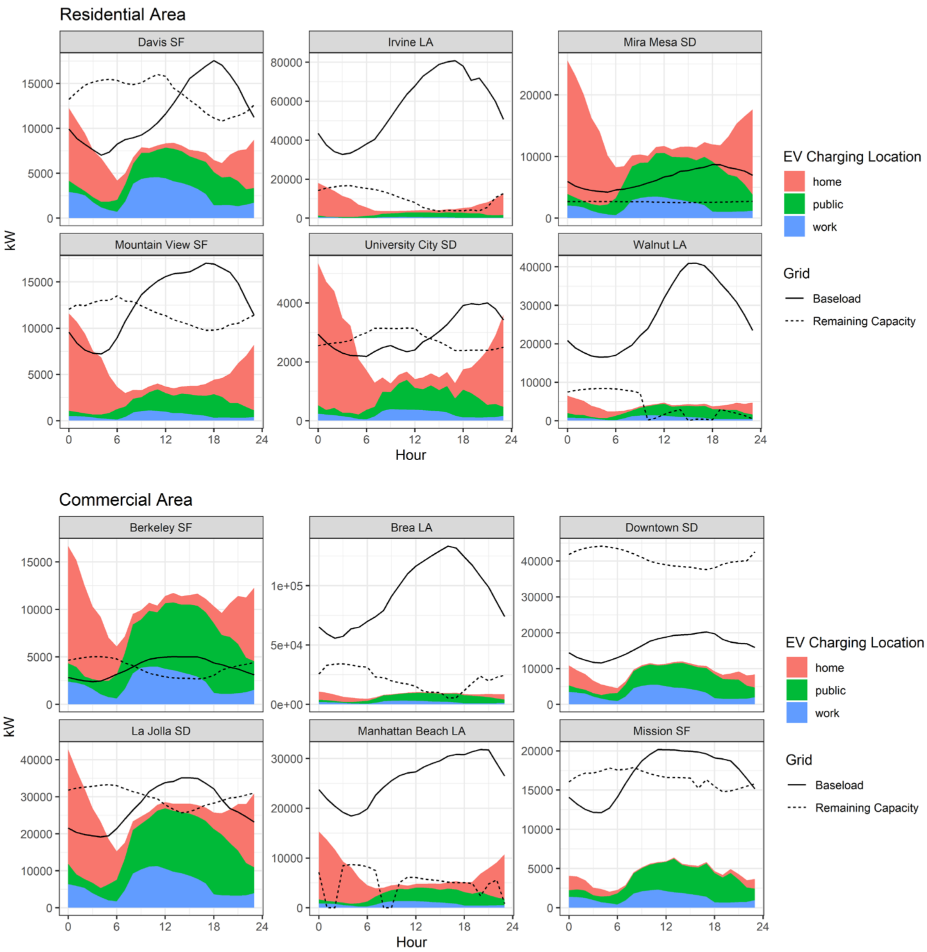


Figure 5 Breakdown of hourly EV charging load by location, feeder baseload profile, and remaining feeder capacity, in residential areas (top) and commercial areas (bottom), on the peak load day of August in 2045

4 Conclusion and Discussion

In this study, we utilize spatial and temporal empirical data from both the grid and the EV side, to investigate when the electric distribution system of California will be stressed by the growing EV charging load, and to what extent the overloading will develop. We cover the spatial heterogeneity and diversity of building types by examining twelve representative areas across the territories of the three major investor-owned utilities in California. The simulation of EV charging profile is conducted uniquely with travel demand model and empirical EV charging data, with the EV uptake projections reflecting California's aggressive policies.

Across the regions that we examine, generally, the distribution networks in residential areas are more intensely stressed than commercial areas. As future EV charging demand grows, overload tends to occur during the night in residential areas, and during the day in commercial areas. These trends are caused by the general difference in load patterns, which is related to the characteristics of an area that influence people's energy consumption habits, travel purposes, and charging behaviors.

However, our case studies also reveal that the development of overloading in each specific region is more diverse than a generalized conclusion. In some areas overloading starts to occur from as early as 2022, while in other areas total load remains below capacity threshold until 2045. Three out of the twelve areas that we examine have frequent overloading over 50% of the time, starting between 2028 and 2040. Four areas will be challenged by intense overloading, where EV charging load can reach up to 500% of the remaining capacity headroom. The scale of feeder capacity headroom in each area is determined when the distribution network is built, and can fluctuate with real time temperature and voltage conditions. The magnitude of local EV charging demand, on the other hand, is influenced by many factors such as travel demand, vehicle ownership, charging infrastructure availability, etc. These diversities make the impact of EV charging demand on existing distribution system highly varied and need to be analyzed on a case-by-case basis.

Our next step would be to expand the case studies into a larger scale, in order to cover a wider heterogeneity and better understand the time, frequency, and intensity of possible capacity exceedance caused by future EV charging load. Another limitation of this study is the simplification of the spatial heterogeneity in the average number of charging events per EV per day, and in the electrification rate of light duty vehicles. Additionally, projections on the demand side development of the grid – such as rooftop solar generation and energy efficiency – could further improve the accuracy of our analysis.

Acknowledgments

We would like to thank the California Resilient and Innovative Mobility Initiative (RIMI) for providing funding for this project.

References

[1] International Energy Agency, "Electric Vehicles," 2021. https://www.iea.org/reports/electric-vehicles

[2] C. Zhang, J. B. Greenblatt, P. MacDougall, S. Saxena, and A. Jayam Prabhakar, "Quantifying the benefits of electric vehicles on the future electricity grid in the midwestern United States," *Applied Energy*, vol. 270, p. 115174, Jul. 2020, doi: 10.1016/J.APENERGY.2020.115174.

[3] T. T. Mai *et al.*, "Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States," Jun. 2018, doi: 10.2172/1459351.

[4] M. Wolinetz, J. Axsen, J. Peters, and C. Crawford, "Simulating the value of electric-vehicle–grid integration using a behaviourally realistic model," *Nature Energy 2017 3:2*, vol. 3, no. 2, pp. 132–139, Feb. 2018, doi: 10.1038/s41560-017-0077-9.

[5] E. Veldman and R. A. Verzijlbergh, "Distribution grid impacts of smart electric vehicle charging from different perspectives," *IEEE Trans Smart Grid*, vol. 6, no. 1, pp. 333–342, Jan. 2015, doi: 10.1109/TSG.2014.2355494.

[6] R. A. Verzijlbergh, M. O. W. Grond, Z. Lukszo, J. G. Slootweg, and M. D. Ilic, “Network impacts and cost savings of controlled EV charging,” *IEEE Trans Smart Grid*, vol. 3, no. 3, pp. 1203–1212, 2012, doi: 10.1109/TSG.2012.2190307.

[7] L. Pieltain Fernández, T. Gómez San Román, R. Cossent, C. Mateo Domingo, and P. Frías, “Assessment of the impact of plug-in electric vehicles on distribution networks,” *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 206–213, Feb. 2011, doi: 10.1109/TPWRS.2010.2049133.

[8] J. Coignard, P. Macdougall, F. Stadtmueller, and E. Vrettos, “Will Electric Vehicles Drive Distribution Grid Upgrades?: The Case of California,” *IEEE Electrification Magazine*, vol. 7, no. 2, pp. 46–56, Jun. 2019, doi: 10.1109/MELE.2019.2908794.

[9] C. Crozier, T. Morstyn, and M. McCulloch, “The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems,” *Appl Energy*, vol. 268, p. 114973, Jun. 2020, doi: 10.1016/J.APENERGY.2020.114973.

[10] B. Borlaug *et al.*, “Heavy-duty truck electrification and the impacts of depot charging on electricity distribution systems,” *Nature Energy 2021 6:6*, vol. 6, no. 6, pp. 673–682, Jun. 2021, doi: 10.1038/s41560-021-00855-0.

[11] L. G. González, E. Siavichay, and J. L. Espinoza, “Impact of EV fast charging stations on the power distribution network of a Latin American intermediate city,” *Renewable and Sustainable Energy Reviews*, vol. 107, pp. 309–318, Jun. 2019, doi: 10.1016/J.RSER.2019.03.017.

[12] A. G. Anastasiadis, G. P. Kondylis, A. Polyzakis, and G. Vokas, “Effects of Increased Electric Vehicles into a Distribution Network,” *Energy Procedia*, vol. 157, pp. 586–593, Jan. 2019, doi: 10.1016/J.EGYPRO.2018.11.223.

[13] S. Powell, E. C. Kara, R. Sevlian, G. V. Cezar, S. Kiliccote, and R. Rajagopal, “Controlled workplace charging of electric vehicles: The impact of rate schedules on transformer aging,” *Appl Energy*, vol. 276, no. March, 2020, doi: 10.1016/j.apenergy.2020.115352.

[14] M. Muratori, “Impact of uncoordinated plug-in electric vehicle charging on residential power demand,” *Nature Energy 2018 3:3*, vol. 3, no. 3, pp. 193–201, Jan. 2018, doi: 10.1038/s41560-017-0074-z.

[15] M. Kühnbach, J. Stute, T. Gnann, M. Wietschel, S. Marwitz, and M. Klobasa, “Impact of electric vehicles: Will German households pay less for electricity?,” *Energy Strategy Reviews*, vol. 32, p. 100568, Nov. 2020, doi: 10.1016/J.ESR.2020.100568.

[16] A. Dubey and S. Santoso, “Electric Vehicle Charging on Residential Distribution Systems: Impacts and Mitigations,” *IEEE Access*, vol. 3, pp. 1871–1893, 2015, doi: 10.1109/ACCESS.2015.2476996.

[17] N. B. G. Brinkel, W. L. Schram, T. A. AlSkaif, I. Lampropoulos, and W. G. J. H. M. van Sark, “Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits,” *Appl Energy*, vol. 276, p. 115285, Oct. 2020, doi: 10.1016/J.APENERGY.2020.115285.

[18] A. Jenn and J. Highleyman, “Distribution grid impacts of electric vehicles: A California case study,” *iScience*, vol. 25, no. 1, p. 103686, 2022, doi: 10.1016/j.isci.2021.103686.

Presenter Biography

Yanning Li is currently a PhD candidate at the Plug-in Hybrid and Electric Vehicle (PH&EV) center of the Institute of Transportation Studies (ITS) at the University of California, Davis. She graduated from ETH Zurich with a MSc in Energy Science and Technology, and has an undergraduate degree in Electrical Engineering from Tsinghua University. Yanning's research is focused on grid integration of plug-in electric vehicles.