Analyzing Residential Charging Demand for Light-Duty Electric Vehicles in Colorado

Preprint

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Analyzing Residential Charging Demand for Light-Duty Electric Vehicles in Colorado

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***Abstract*—The past decade has witnessed a remarkable surge in adoption of electric vehicles (EVs). The momentum is expected to continue with strong support from governments and industry. Rapid EV adoption will add significant electricity demand, making it critical to plan for and manage EV charging to avoid causing additional stress and non-negligible risks to the already-aging power grid. To help power grid operators understand the impacts of residential EV charging and identify risk factors, this study presents a data-driven charging demand analysis for light-duty vehicles. This study considers two real-world grid service regions in Colorado and merges multiple data sources and state-of-the-art tools that characterize EV adoption projections, vehicle travel patterns, seasonal variations, residential charging accessibility, ambient temperature impact, EV charging behaviors, grid utility customers, vehicle registration, and household-level EV charging demand distribution. We characterize potential residential charging demand in 2030 for two regions within the state of Colorado: Boulder and Aurora regions. We project that EVs will be 26% of the light-duty vehicle population in Boulder and 16% in Aurora areas. Charging demand is characterized for ten power grid feeders (five for each study region). Across the ten feeders, peak total EV charging powers during wintertime range from less than 1 MW to more than 4 MW.**

***Index Terms*—light-duty electric vehicle, residential charging demand, data-driven analysis**

I. INTRODUCTION

Over the past decade, the automotive industry has undergone a significant shift towards electrified transportation solutions. Electric vehicles (EVs) have taken center stage as a cutting-edge technology alternative to conventional internal combustion engine vehicles. EVs offer environmental benefits by reducing greenhouse gas emissions, lower operating costs due to more efficient operation, and reduce reliance on fossil fuels. Therefore, in 2021, an executive order from the U.S. government set a goal of achieving 50% of U.S. new passenger car and light truck sales as zero-emission vehicles (ZEVs) by the year 2030 [1].

The foreseeable swift and widespread adoption of EVs will result in a substantial increase in charging demand, especially in residential areas as EV users tend to charge their EVs at residential outlets more often [2]. Using extensive real-world data from EV charging, encompassing nearly 6 million charging events from 8,300 EVs across 22 U.S. regions over three years, the Idaho National Laboratory examined the charging habits of American EV users. The analysis revealed that home charging is the predominant charging method, accounting for near 90% of all charges [3]. Thorough examination of EV charging demand is crucial for gaining insights into energy need, assessing the impact on the power grid, and identifying opportunities for smart charging management. A holistic analysis of EV charging demand necessitates the incorporation of various factors, such as the scenarios of EV adoption, travel patterns of EV users, dwelling/charging duration, seasonal travel variations, ambient temperature impacts, and the characteristics of the charging infrastructure [2].

Researchers proposed different methods to address EV charging demand analysis, including modeling based on discrete event simulation [4], Markov process based simulation [5], historical traffic and weather data based forecasting model [6], travel survey data based analysis [7], fluid dynamic traffic model and queuing theory based forecasting method [8]. Recently, National Renewable Energy Laboratory (NREL) researchers developed a data-driven trip-chaining-based modeling framework for EV charging demand analysis [2]. The authors use real-world connected vehicle trip data to construct synthetic travel itineraries to represent the daily travel needs of EV users. EV adoption and charging behaviors are then modeled and simulated using existing tools developed at NREL.

This study develops a data-driven modeling framework for residential EV charging demand analysis, which aims at helping power grid operators predict the impact of EV home charging on the grid and identify risk factors. The modeling framework is constructed based on previous endeavors in the analysis of EV charging demand [2] and leveraging relevant state-of-the-art tools developed at DOE national laboratories, including Transportation Energy & Mobility Pathway Options (TEMPO) model [9] for EV adoption and Electric Vehicle Infrastructure–Projection Tool (EVI- Pro) [10] for EV charging simulation. Two actual grid service regions in Colorado are chosen for analysis. This study integrates diverse data sources and advanced tools, encompassing EV adoption projections, vehicle travel patterns, seasonal variations, residential charging accessibility, the impact of ambient temperature, EV charging behaviors, grid utility customers, vehicle registration, and the distribution of household-level EV charging demand.

While many studies in the literature have modeled and analyzed the charging demand of EVs, our research makes distinct contributions to the literature in the following ways:

- We developed a region-based travel itinerary synthesis method based on publicly available data. The method allows researchers to consider region-specific trip characteristics without relying on expensive connected vehicle data.

- We developed a high-resolution data-driven method to assign EVs to individual utility customers. This method enables high-resolution transformer and feeder level analysis of EV charging impact.
- We worked with our utility partner and conducted real-world analysis for two regions in Colorado. The insights derived from our study offer valuable contributions to both research and practical applications.

II. Methodology

The data-driven modeling framework includes five key steps: (1) collecting and preprocessing needed data for the chosen study regions; (2) projecting EV adoption by vehicle type for the modeling year; (3) generating synthetic travel itineraries for EV users within the study regions; (4) simulating EV charging demand; (5) generating spatially and temporally resolved EV charging load profiles.

A. Data Acquisition & Preprocessing

Key data sources used in the modeling framework include land use data, census data, temperature data, Federal Highway Administration (FHWA) traffic volume trends data [11], National Household Travel Survey (NHTS) data [12], Next-Generation (NextGen) NHTS National Origin-Destination (OD) data [13], EV technology characteristics data, residential charging accessibility data, and utility customer data. We use land use data to infer potential EV residential charging locations. Fig 1 shows the collected land use data for Aurora in Colorado [14]. Census data provides household and population information that is useful for household-level EV assignment. Fig. 2 shows the census data for Aurora [15]. Historical temperature data was obtained from Typical Meteorological Year 3 (TMY3) weather data [16] and used for estimating the impact of ambient temperature on EV energy consumption. FHWA traffic volume trends data can be used to estimate seasonal adjustment factors for travel frequency. NHTS data and NextGen NHTS OD data enables generation of region-specific travel itineraries. Vehicle archetypes data provides needed data for EV charging simulation, including the EV battery size, energy consumption rate, and acceptable charging power. Residential charging accessibility data is critical for reasonable EV charging simulation and was derived from previous modeling efforts supported by DOE [17].

This study considers three representative months: January, July, and September. To consider the impact of ambient temperature on EV energy consumption, this study uses TMY3 weather data and an ambient penalty factor lookup table generated using a powertrain simulation model FASTSim Hot [18] to estimate the month specific ambient penalty factors. For January, July, and September, the estimated ambient penalty factors are 1.602, 1.059, and 1.093, respectively. To consider the seasonal variations of travel, this study uses FHWA traffic volume data to estimate the month specific adjustment factors. The historical monthly FHWA vehicle miles traveled (VMT) data was extracted for year 2015 to 2019. The monthly

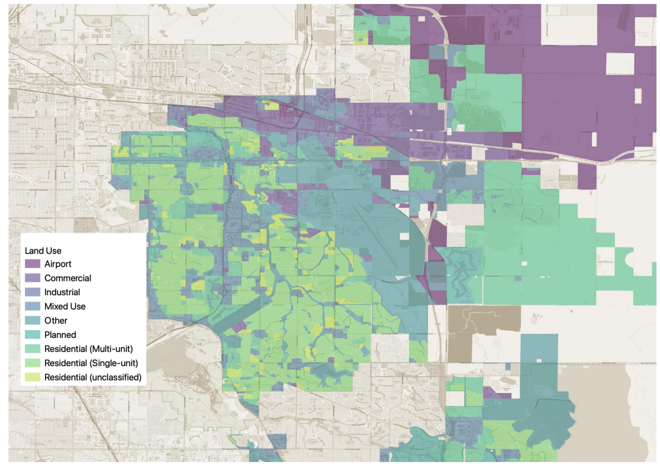


Fig. 1. Land use data for Aurora in Colorado.

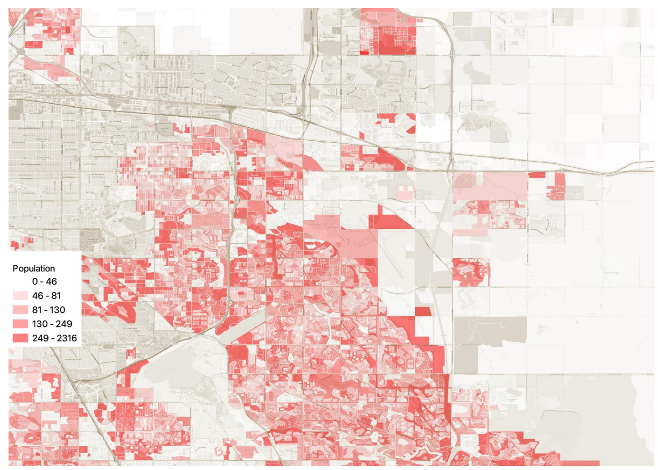


Fig. 2. Census data for Aurora.

daily VMT can be estimated for each month by counting the total number of weekdays and weekends for the month and converting weekends to nominal weekdays using daily weight factors. The month-based scaling factors can be estimated by comparing the monthly average daily VMT with the annual average daily VMT. The calculated scaling factors are 0.89 for January, 1.06 for July, and 1.00 for September. Those scaling factors are used to adjust travelers' daily travel frequency.

B. EV Adoption Prediction

For EV adoption modeling, this study leveraged the Transportation Energy & Mobility Pathway Options (TEMPO) model developed by NREL [9]. TEMPO is a transportation demand model that predicts the decisions of consumers regarding vehicle ownership and technology choices at the household level. An high-level introduction of TEMPO can be found in [19], and the detailed modeling framework can be found in [9]. The target analysis year for this study is 2030. TEMPO projects that Colorado would have around 4.7 million light-duty vehicles (LDVs) by 2030 and around 630k of them will be EVs. Fig. 3 shows the census tract level EV distribution in Colorado by 2030 based on TEMPO analysis. A majority

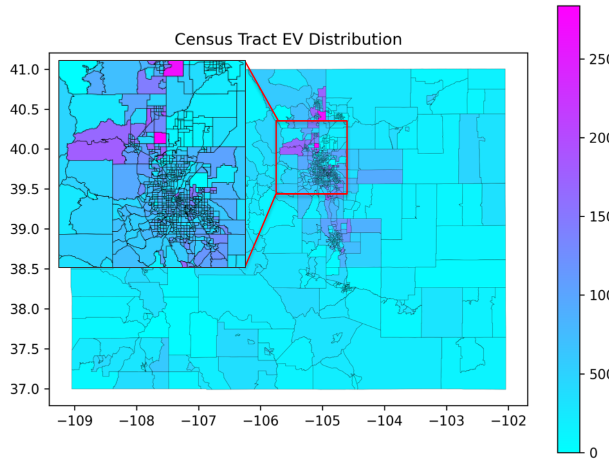


Fig. 3. Expected EV distribution in Colorado in 2030.

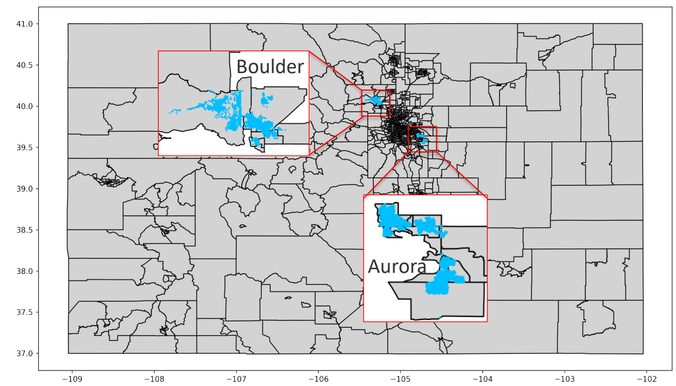


Fig. 4. Two study regions in Colorado.

of EVs are distributed in regions surrounding Boulder, Denver metropolitan area, and Aurora.

C. Synthetic Travel Itinerary Generation

To capture the travel needs of EVs, this study developed a region-based sampling approach to randomly sample real-world travel itineraries from the NHTS data while considering the region-specific trip features captured in the NextGen NHTS National OD data. The 2017 NHTS data covers about 130,000 households, representing about 0.1% of U.S. households. The data consists of real-world daily travel itineraries with trip times, distances, purposes, and other details. The NextGen NHTS OD data was collected from multiple telematics providers for each month in 2021. The data covers 270 million monthly active users with more than 80% coverage in Colorado. The data provides aggregate information such as work and non-work trip volumes by distance bin for each Core Based Statistical Area (CBSA) OD pair. The travel itinerary sampling approach includes four key steps: (1) using nation-level NextGen NHTS OD data to fit a gamma distribution and then calculating deciles of estimated distribution, (2) using Colorado county-level NHTS OD data to estimate monthly travel distance distributions and compute distributions of county data over national level deciles, (3) determining the number of EVs for each county based on the TEMPO projection, and (4) using county-level trip distance distributions to sample from NHTS itineraries.

D. EV Travel and Charging Simulation

With EV adoption projection and synthetic travel itineraries, this study then simulated EV charging using the Electric Vehicle Infrastructure–Projection Tool (EVI- Pro) developed by NREL [10]. EVI-Pro considers characteristics of EVs and charging stations and simulates the travel and charging behaviors of EVs based on the given travel itineraries and the charging cost minimization assumption. In this study, it is assumed that EV drivers give precedence to home charging, followed by workplace and public slow charging, and finally public direct current fast charging. Access to home charging is determined using information obtained from prior modeling endeavors [17]. This study generated one-week charging demands for the months of January, July, and September in the designated regions. NREL's high-performance-computing (HPC) system Eagle was used to enable parallel EVI-Pro simulation. In total, 378 groups of simulation scenarios are generated, with each scenario representing one vehicle type and one month. For each scenario, separate configuration file and batch scripts can be generated and run on one HPC node with 36 cores. Each simulation job can be finished in about half an hour. Simulation results from EVI-Pro report the parking start and end times, parking duration, charging energy, start and end EV battery state of charge, and charger type information.

E. EV Charging Load Development

Last, to generate spatially and temporally resolved EV charging load profiles, this study acquired power grid feeder data from the utility collaborator and developed a household-level EV assignment method to distribute EVs to individual utility customers. The assignment is a three-step process: (1) Total PEVs are first distributed based on number of households; (2) Residential utility customers are extracted based on the grid feeder data and land use data; (3) Lastly, PEVs are randomly assigned to residential utility customers. By aggregating EV charging loads, this study generated week-long EV home charging power profiles at feeder level for the months of January, July, and September. Total EV charging energy needs can also be obtained at household level, census tract level, and feeder level.

III. EV Residential Charging Demand Analysis Results

This study considers two grid service regions in Colorado (as shown in Fig. 4): (1) Boulder region (including 5 utility feeders with 12335 residential customers), (2) Aurora region (including 5 feeders with 16787 residential customers). These regions were selected based on their high risks of increased EV penetration. The blue zones in Fig. 4 represent utility customers serviced by the 10 feeders. Census-tract-level EV adoption projection was obtained from the TEMPO model

TABLE I
REGION SPECIFIC EV ADOPTION RESULTS FOR 2030

Region	Households	LDVs	EVs	EV Share
Boulder	12,335	25,380	6,493	26%
Aurora	16,787	42,683	6,754	16%

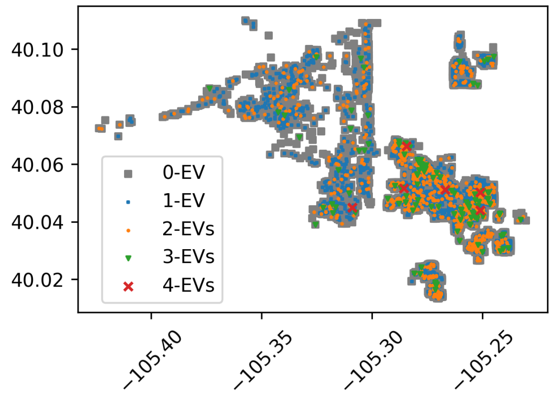


Fig. 5. EV assignment for Boulder.

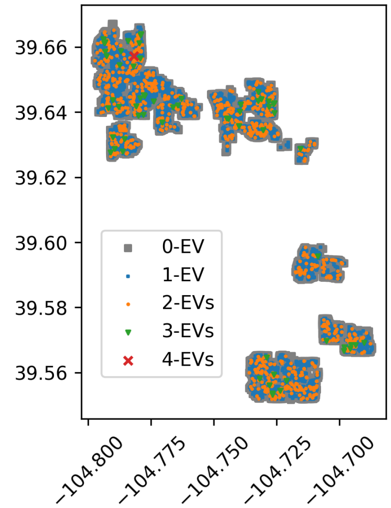


Fig. 6. EV assignment for Aurora.

TABLE II
WEEKLY EV CHARGING ENERGY NEEDS

Study Region	EV Charging Needs (MWh)		
	January	*July*	*September*
Boulder	483	373	359
Aurora	463	377	356

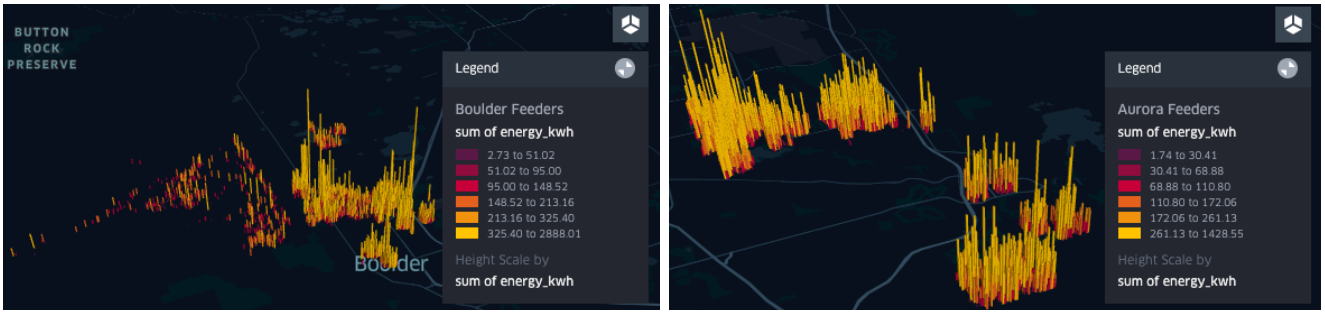
for a target analysis year 2030. The projection specifies vehicle body type, battery range, and powertrain technology. Colorado is projected to host around 630k EVs, constituting approximately 13% of its total LDV population. Table I reports the EV adoption results for the two study regions. Within the study region in Boulder, EVs are anticipated to make up 26% of the total LDV population, while in the study region in Aurora, the percentage of EVs is projected to be 16%.

EVs within each census tract are randomly assigned to residential utility customers based on vehicle registration and census data. Figs 5 and 6 show the household level EV assignment results for Boulder and Aurora, respectively. The following observations can be made: (1) majority of households have no EVs by 2030, (2) majority of households with EVs only have one EV, (3) few houses have three EVs, (4) only a handful of houses have four EVs.

Figs. 7a and 7b show the spatial distribution of one-week EV residential charging energy needs during winter for Boulder and Aurora, respectively. For the Boulder region, one can see from Fig. 7a that the right region has denser residents and relatively larger energy needs. For the Aurora region, one can see the spatial variation is not as strong as that in the Boulder area.

Table II reports the total weekly EV charging energy needs for the two study regions in three representative months. In the winter season, the five feeders in Boulder are projected to experience a weekly EV charging demand of around 483 MWh, whereas for Aurora, the corresponding figure is around 463 MWh. It's worth noting that the EV charging demand is lower during the summertime. The higher charging needs during wintertime are mainly attributed to the significantly higher EV energy consumption due to heating needs. Aggregated residential charging power profile during a wintertime week for each power grid feeder is shown in Fig. 8. One can see from Fig. 8 that the peak charging power for the ten feeders range from less than one megawatt to more than four megawatts. Note that the EV charging simulation in this study assumes uncontrolled charging. By further merging the EV charging data with the existing baseload data, this study finds that the uncontrolled charging could bring significantly high peak power and lead to overloading risks. As an example, Fig. 9 shows the real power profiles for one representative feeder under base case and EV integrated case. One can see that the EV charging load will significantly increase the base power consumption during the weekly peak demand period by almost 50%. In addition, we have observed 6 out of 10 feeders were loaded more than 1.3 pu within this 2030 scenario. Nevertheless, effective coordination and management of EV charging has the potential to address these issues while supporting the load growth. Controlled EV charging can facilitate demand-side flexibility and support power system planning and operations under normal and extreme conditions.

Besides the feeder data, our utility partner also provided two real-world EV charging datasets. The first set of data was collected from May 2022 to April 2023, with 439 EVs and more than 11 thousands charging sessions. The second dataset was collected from July 2021 to April 2022, with 278 Tesla EVs and more than 39 thousands charging sessions. These two charging datasets are controlled EV charging. Figs. 10 and 11 respectively show the plug start and unplug time distributions for our simulation data and the two real-world EV charging datasets. One can see our simulation results and the real-world charging data have similar plug start time and unplug



(a) Boulder (b) Aurora

Fig. 7. Spatial distribution of EV charging load for Boulder and Aurora.

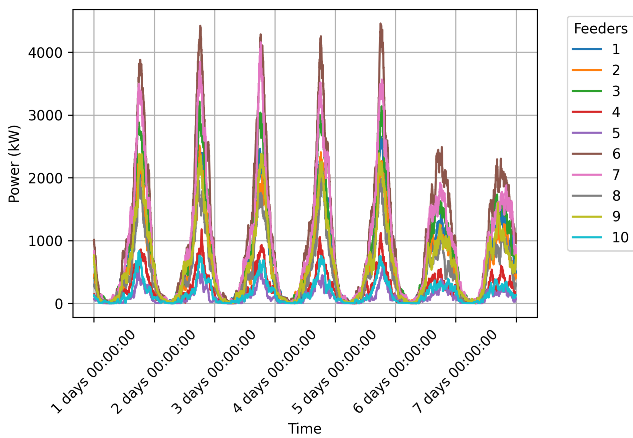
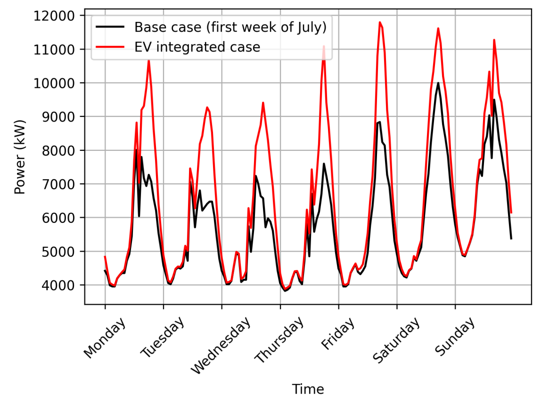
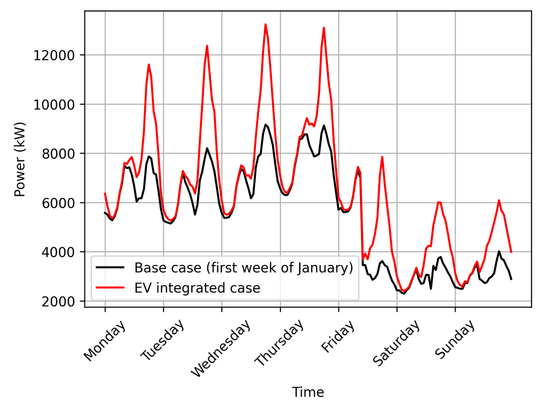


Fig. 8. Residential aggregated EV charging power profile for each feeder during Winter.



(a) Summer



(b) Winter

Fig. 9. Power profiles for one representative feeder during Summer and Winter.

time distributions, verifying that the travel itineraries used in the charging simulation might represent the real-world travel patterns well in terms of home arrival and departure time. Note that the real-world controlled EV charging might delay actual EV charging start time to reduce charging cost for EVs, which is not considered in our simulation.

IV. Conclusions

This study presents a data-driven residential charging demand analysis framework for light-duty EVs. Multiple data sources are merged to capture EV penetration, EV charging simulation, household-level EV distribution, residential charging demand, and potential impact on power grid. NREL's TEMPO model is used to provide EV adoption prediction. NREL's EVI-Pro model is used to simulate EV travel and charging behaviors. Working with the utility grid partner, this study examined two real-world grid service regions in Boulder and Aurora, CO, each with five power grid feeders. The Boulder region is projected to have 26% of its light-duty vehicles being EVs while the figure for Aurora is 16% in 2030. Feeder data and land use data are combined to enable household level assignment of EVs. Household-level EV charging data are aggregated to generate feeder level EV residential charging load profiles.

The ten feeders are estimated to have peak charging powers ranging from less than 1 MW to more than 4 MW during wintertime. The residential charging load values are highest during wintertime due to large heating needs. In addition, we have observed 6 out of 10 feeders were loaded more than 1.3 pu within the 2030 scenario. The analysis will help grid operators better understand the potential risk factors brought by rapid EV penetration and develop mitigation strategies such as smart charging control, tailored time-of-use electricity rate structure for EVs, grid infrastructure enhancement or upgrade. Our future study will further refine and enhance the data-driven EV charging load analysis framework, with the objective of reducing the data acquisition burden and extending the study to other regions.

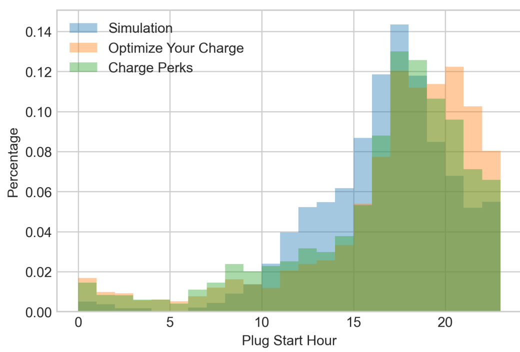


Fig. 10. Plug start time distributions.

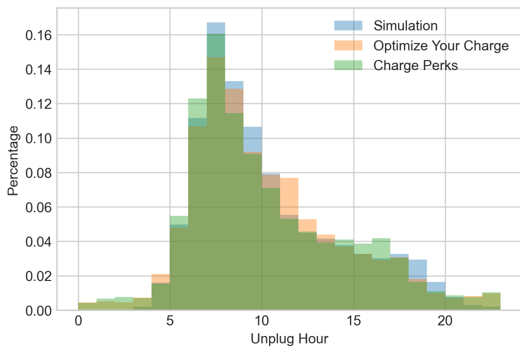


Fig. 11. Unplug time distributions.

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