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High-Fidelity Analysis of EV Integration on Real Utility Feeders in Colorado

Shibani Ghosh, Derek Jackson, Mithat John Kisacikoglu, Zhaocai Liu, Nadia Panossian, Priti Paudyal, Erik Pohl, Emin Ucer, and Mingzhi Zhang

National Renewable Energy Laboratory

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Executive Summary

Residential electric vehicle (EV) charging has the potential to alter long-held assumptions about load characteristics impacting distribution grid planning, operations, and design standards. This study identifies analysis and control methods to increase the affordability of residential EV charging both for utility and their customers. The project also provides solutions for more reliable grid interconnection that can support utility business model prepared for increasing EV charging load in the coming years. The main objectives for this project were to:

- Evaluate the suitability of managed charging methods within the study region
- Investigate the impacts of residential charging on grid operation to inform utility standard and program changes
- Perform time-domain feeder impact analysis to improve asset loading visibility
- Develop a software tool to automate analysis of grid impact for the selected feeders.

For this project, we referenced Level 2 alternating current (AC) onboard charging profiles for various vehicle models and high-fidelity charging data collected at the experimental setup established at the EV Research Infrastructure Laboratory at the National Renewable Energy Laboratory (NREL). Next, we developed EV adoption models for 2030 and 2040 for the Boulder and Aurora regions in Colorado. Moreover, we evaluated different smart charging control algorithms and compared their performance. We developed time-of-use (TOU)-based and grid-aware active EV charging control methods and integrated them within the study region to understand field impacts.

Diving deeper, we selected 10 feeders in Boulder and Aurora for high-fidelity grid modeling down to the house level. We executed detailed grid analysis comparing the smart charge management (SCM) algorithms we developed. Finally, we created a novel tool, Electric Vehicle Infrastructure–Distribution System Integration Tool (EVI-DiST), to integrate all the approaches in a single software environment to provide easy integration, fast simulation, and detailed evaluation capability for utility engineers and other stakeholders.

Acknowledgements

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1 Introduction

Today's electric distribution systems have largely grown organically, guided by evolving utility design standards for over a century. A changing energy landscape is creating the need to proactively amend legacy design standards. Distributed energy resources, building electrification, and electric vehicles (EVs) may change the industry's long-held assumptions about the grid-edge dynamic. Historically, utilities have used relatively simple heuristics to forecast load growth and gauge distribution infrastructure requirements, and until today, these methods have proven adequate. However, emerging grid-edge technologies have the potential to considerably alter load dynamics, increase the need for new infrastructure, and lead to overall greater system complexity (Yazdaninejadi et al.; Aguero and Khodaei; Quint et al.). Utilities are grappling with the uncertainty of future load characteristics, adoption levels of new grid-edge technologies, and how to revise design standards such that today's investments prove sufficient for the lifetime of the installed equipment.

As electricity demand increases, particularly during peak hours, utilities are adopting time-of-use (TOU) rates to manage load distribution and enhance efficiency. These rates incentivize consumers to shift their electricity usage to off-peak times, reducing strain on the grid and transformer loading during peak periods. TOU rates have effectively influenced EV charging behavior, with users primarily charging during off-peak hours without significantly altering their plug-in or unplug times. However, this pricing model can inadvertently create issues for the power grid, such as timer peaks, when numerous EVs begin charging simultaneously at the onset of low-rate periods. This surge can cause thermal overload in distribution transformers that are still warm from daytime use. As EV adoption rises, utilities must balance the advantages of TOU rates with the risks of transformer overloading.

To alleviate service transformer overloading from simultaneous charging of multiple EVs, we propose grid-aware active smart charge management (SCM) algorithms to coordinate their charging. We modeled these SCM algorithms in two Xcel Energy service regions in Colorado likely to see increased EV adoption in the near future: Boulder and Aurora.

This study presents data-driven insights into the value of managed EV charging on multiple fronts:

- Effects of different SCM algorithms on individual service transformer loading
- Load coincidence and transformer sizing requirements
- Grid impact analyses under uncontrolled and managed EV charging scenarios.

We also present an analysis of coincidence factors based on advanced metering infrastructure (AMI) data obtained with utility collaboration and how those factors change with the addition of EV supply equipment (EVSE) for residential consumers.

Finally, this study demonstrates an intuitive EV-grid co-simulation tool and user interface called EVI-DiST: Electric Vehicle Infrastructure–Distribution System Integration Tool (*EVI-DiST*) as a new tool for the utility sector to conduct customized analyses of transformer and grid impacts of growing EV charging and charge management controls.

The rest of this report is organized as follows. Chapter 2 discusses the EV adoption modeling for the study regions; Chapter 3 discusses the data collected for grid modeling; Chapter 4 discusses the distribution grid impacts under SCM scenarios; Chapter 5 discusses the load coincidence factor calculations and resulting data-driven transformer sizing considerations; Chapter 6 dives deeper into time-domain grid analysis of different EV integration scenarios; and Chapter 7 presents the EVI-DiST software developed under this work. Concluding remarks and future work are presented in Chapter 8.

2 EV Adoption Modeling for Study Regions

In this section, we develop a data-driven modeling framework to understand residential EV charging demand and apply the framework to the selected Boulder and Aurora service regions.

We leveraged tools previously developed at NREL for this analysis: Transportation Energy & Mobility Pathway Options (TEMPO) model (Muratori et al.) for projecting future EV adoption and Electric Vehicle Infrastructure–Projection Tool (EVI-Pro) for EV charging simulation (*EVI-Pro*). The adoption scenarios were designed as reasonable "what-if" pathways to explore future EV adoption. The developed approach in this study is consistent with practices in available relevant studies in the literature—notably the National Charging Network Study, which presents adoption scenarios using a similar framework (Wood et al.).We integrated diverse data to conduct a thorough analysis, including EV adoption projections, vehicle travel patterns, seasonal and temperature impacts, the probability that EVs have access to residential charging, grid utility data, and all vehicle registrations.

The data-driven modeling framework includes four 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.

Figure 1 shows an overview of the modeling framework. This modeling framework is based those used in previous EV charging demand analyses (Liu et al.).

2.1 Modeling Framework

2.1.1 Data Acquisition & Preprocessing

We used diverse data sources including land use, census, and temperature data; Federal Highway Administration (FHWA) traffic data (*Traffic Volume Trends*); National Household Travel Survey (NHTS) data (*NHTS*); data on EV types; the probability that EVs have access to residential charging; and utility customer data. Land use and census data inform residential charging locations and household-level EV assignments that we use to model the grid-side impact of charging. Weather data from Typical Meteorological Year 3 allow us to estimate ambient temperature impacts on EV energy consumption (*Climate Data Online*). Traffic volume trends provide seasonal adjustment factors, while we use NHTS and NextGen NHTS Origin-Destination (OD) data (*NHTS NextGen OD Data*) to generate region-specific travel itineraries. Additional data on EV types (e.g., battery sizes, charging power) and home charging availability enable accurate simulation of charging scenarios. We modeled monthly variations in travel and energy use for January, July, and September to represent different seasons within a year.

2.1.2 EV Adoption Forecast

We used NREL's TEMPO model to develop EV adoption forecasts for 2030 and 2040 (Muratori et al.). According to the TEMPO analysis, Colorado's light-duty vehicle (LDV) fleet will grow from 4.7 million in 2030 to 5 million in 2040, with EVs increasing from 630,000 to 2.8 million. EVs are expected to cluster near Boulder, the Denver metro area, and Aurora.

2.1.3 Synthetic Travel Itinerary Generation

We derived region-specific EV travel patterns using a sampling approach based on NHTS and NextGen NHTS OD data. This process involves fitting gamma distributions, estimating county-level travel distance distributions, and sampling real-world itineraries.

2.1.4 EV Travel and Charging Simulation

The synthetic travel itineraries informed our simulations of EV charging behaviors with NREL's EVI-Pro (*EVI-Pro*). The tool models charging preferences, prioritizing home, workplace, and public stations. Simulations consider one week of travel and charging patterns for various vehicle types (as listed in Table 5 in Chapter 3), leveraging NREL's high-performance computing capabilities to efficiently generate results.

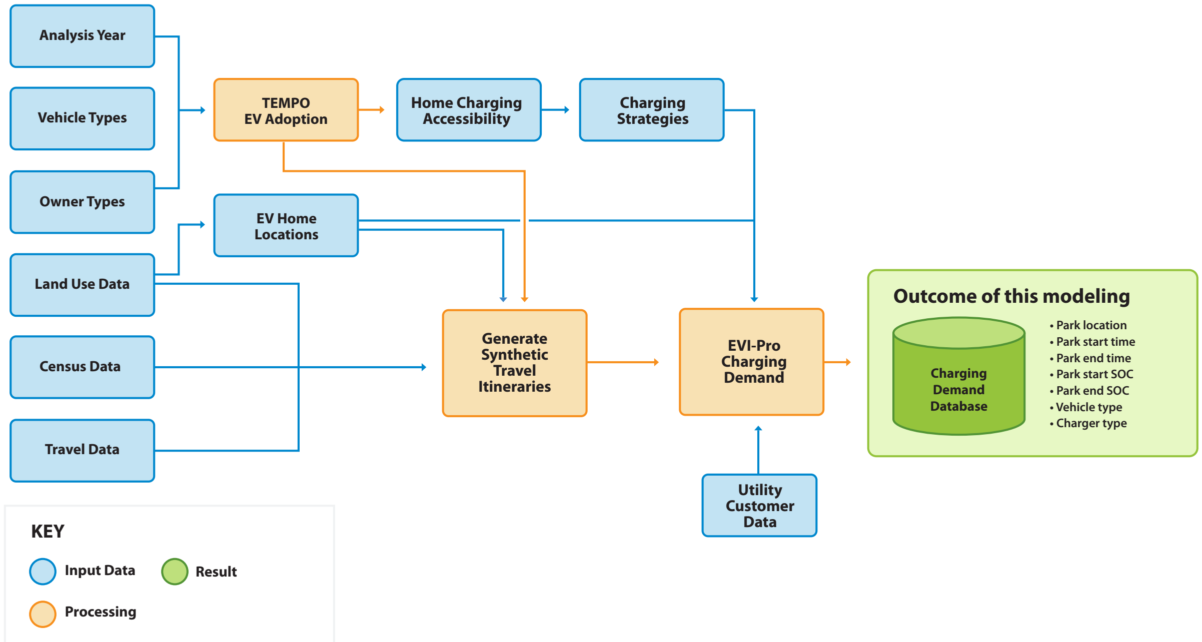


Figure 1. Modeling framework for EV charging demand analysis.

2.2 Analysis Results and Discussion

This study considers two grid service regions in Colorado as shown in Fig. 2: (1) Boulder region (including 5 utility feeders with 12,335 residential customers) and (2) Aurora region (including 5 feeders with 16,787 residential customers). The blue zones in Fig. 2 represent utility customers serviced by the ten feeders.

Colorado is projected to host around 630,000 EVs statewide by 2030, constituting approximately 13% of its total LDV population. Table 1 reports the EV adoption results for the two study regions. Within the study region in Boulder, EVs are anticipated to make up 24% of the total LDV population, while in the study region in Aurora, the percentage of EVs is projected to be 15%.

To conduct our EV adoption modeling analysis, we randomly assigned EVs within each census tract to residential utility customers based on vehicle registration and census data. We randomly assigned EVs to customers because

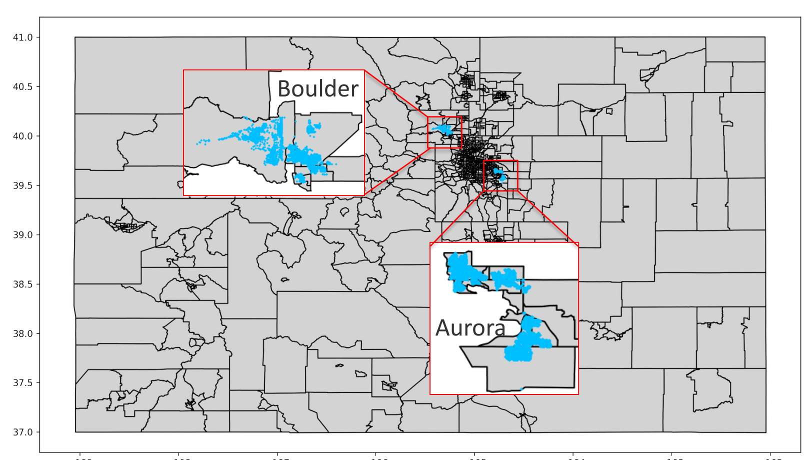
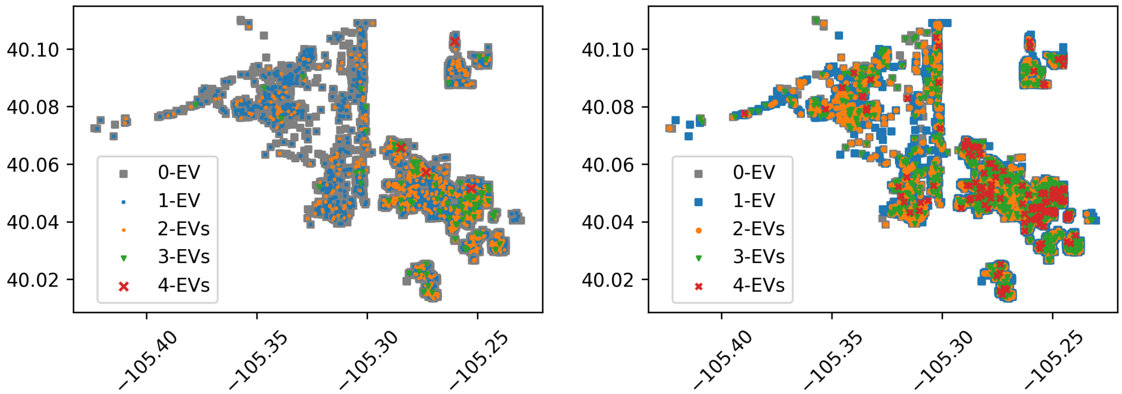


Figure 2. Two study regions in Colorado.

Table 1. Region Specific EV Adoption Results for 2030 and 2040

Year	Region	Households	LDVs	EVs	EV Share
2030	Boulder	12,335	24,751	5,998	24%
2030	Aurora	16,787	41,983	6,258	15%
2040	Boulder	12,335	24,751	15,227	62%
2040	Aurora	16,787	41,983	23,001	55%



(a) Year 2030 (b) Year 2040

Figure 3. EV projection for Boulder area.

while we have a projected total number of EVs, it is quite difficult (if not impossible) to forecast an actual distribution of the EVs at the individual household level. To facilitate our grid-side modeling, we needed to assign those projected numbers of EVs to individual households and utility customers. Figures 3 and 4 show the household-level EV assignment results for Boulder and Aurora, respectively. Table 2 reports the number of households with zero to four EVs. Our simulations showed the following projected EV distributions for the year 2030:

- about 30% of households have one EV by 2030
- less than 20% of households with EVs have more than one EV
- less than 1% of households have three EVs

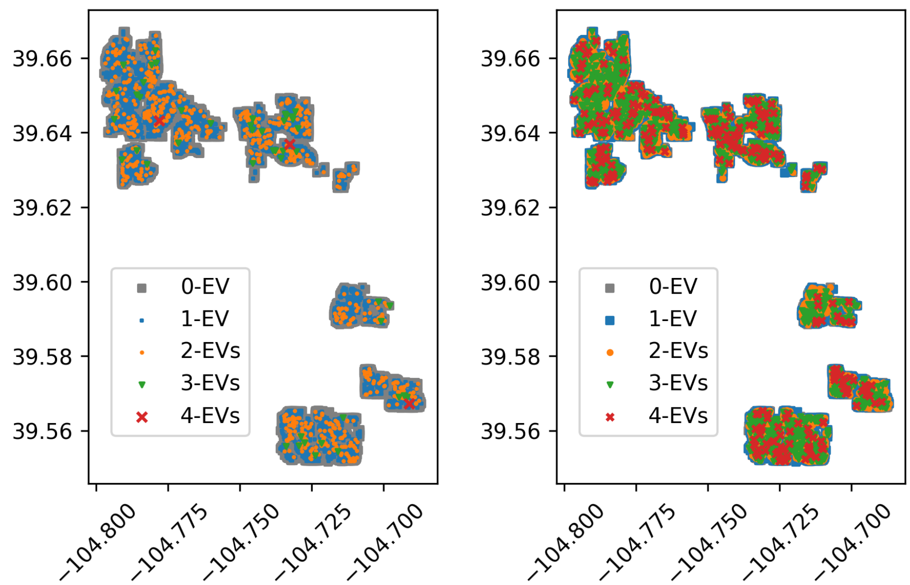
Compared with the year 2030, 2040 has the following projected EV distributions:

- more than 75% of households have one or more EVs by 2040
- more than two-thirds of households have 1 to 2 EVs
- more than 5% of households have 3 EVs
- more than 1% households have 4 EVs.

Table 3 reports the total weekly EV charging energy needs for the two study regions in three representative months for 2030 and 2040. In winter of 2030, the five feeders in Boulder are projected to experience a weekly EV charging demand of around 443 MWh, and the five feeders in Aurora around 428 MWh. It is worth noting that the EV charging demand is lower during the summer. The higher charging needs during the winter are mainly attributed to

Table 2. Household Level EV Assignment Results

Year	Region	0-EV	1-EV	2-EV	3-EV	4-EV
2030	Boulder	7,367	4,033	844	87	4
2030	Aurora	11,353	4,662	723	46	3
2040	Boulder	2,978	4,810	3,365	1,041	141
2040	Aurora	3,206	6,454	5,070	1,821	236



(a) Year 2030 (b) Year 2040

Figure 4. EV assignment for Aurora.

Table 3. Weekly EV Charging Energy Needs

Study Region	EV Charging Needs (MWh)					
	2030 Jan	***2030 Jul***	***2030 Sep***	***2040 Jan***	***2040 Jul***	***2040 Sep***
Boulder	443	339	326	883	634	609
Aurora	428	346	329	1276	969	931

significantly higher EV energy consumption due to heating needs. For each representative month in 2040, the EV charging demand values nearly doubled for Boulder and nearly tripled for Aurora. Note that the residential charging demand increase is not proportional to the increase in EVs because some EV users are unable to or do not charge their EVs at home. Home EV charging access probability will decrease with the increase of EV adoption as more people living in multifamily dwellings adopt EVs. The home charging access probability is derived from our previous modeling efforts (Ge et al.), where multifamily dwellings usually have much less probability to have home charging access than single family dwellings. However, multifamily dwellings like apartments can still have home EV charging by installing EVSE in parking lots. This is the assumption made in our study.

We used the EV charging loads developed in this section in the grid-side modeling. We assigned EVs to utility customers based on household counts and feeder connections, enabling the generation of spatially- and temporally-resolved charging profiles. These profiles detail household, census tract, and feeder-level energy demands for the selected months and enable grid-side modeling and analysis.

3 Description of Selected Feeders and Core Datasets

In addition to the earlier EV adoption modeling results, a core dataset for this study is a set of feeders in Xcel Energy's Boulder and Aurora service regions. The selected feeders represent a diverse set of circuits in terms of number of customers and megawatt (MW) demand, but in general are characterized as suburban, residential areas with a large number of single-phase residential services where behind-the-meter electric vehicle supply equipment (EVSE), or Level 2 EV chargers, may interconnect in the future. Table 4 presents an overview of selected feeder characteristics.

Table 4. Overview of Selected Feeders

Area/Location	**Feeder Name**	**Feeder length** (miles)	**# of Customers†**	**Percent Overhead**	**Demand, MW (planning‡)**
North Boulder	Feeder 1	11.53	4526	53.95	13.87
Boulder	Feeder 2	1.87	2372	53.02	8.25
Boulder	Feeder 3	3.82	5765	16.29	15.92
North Boulder	Feeder 4	4.08	2734	32.24	5.06
Boulder	Feeder 5	2.54	1887	8.55	10.85
Aurora	Feeder 6	4.53	4351	0	11.88
Aurora	Feeder 7	4.24	4260	0	13.57
Aurora	Feeder 8	4.14	1846	0	7.93
Aurora	Feeder 9	9.62	6577	0	11.66
Aurora	Feeder 10	4.41	4241	0.22	10.55

† This represents the total number of premises in the original Premise Report and differs from what was ultimately modeled in OpenDSS due to data conflicts or incompleteness.

‡ This represents the demand values within the original Synergi models and differs from the AMI-informed demand used in the following analyses.

We used these selected feeders as representative grid datasets to showcase multiple, largely independent analysis pathways, each with a unique method to assess the system impacts of EV charging and the value potential of each managed charging strategy. The remainder of this report provides a deeper look into these three types of analysis:

1. An advanced metering infrastructure (AMI)-informed (no load-flow) service transformer loading analysis to assess the impacts of various SCMs on transformer loading, transformer lifespan, and effectiveness of meeting EV charging needs

2. An AMI-informed (no load-flow) load coincidence and transformer sizing analysis to inform utility standards development for an EV future

3. A time domain grid analysis using load-flow models to assess grid impacts of EV charging and the relative values of managed charging.

Several of the datasets informing these analyses are shared across the three pathways, while others are unique. The sections below provide introductions to some of the core datasets and algorithms used, while subsequent chapters of this report will discuss more specific uses, alterations, limitations, and additions to these core datasets.

3.1 EV Allocation

We assigned EVs to customers according to the respective EV adoption scenario (2030 or 2040) and then linked to the relevant service transformers. For example, based on the premises report provided by Xcel Energy, among the 4,260 customers served by the Feeder 7, 4,164 are served by 455 single-phase transformers, while 96 are served by 27 three-phase transformers. This research focuses on residential charging, which more widely uses single-phase transformers. It is projected that by 2030, 401 of the 455 single-phase transformers will serve customers with EVs, totaling 1,171 EVs, resulting in an adoption rate of 28.12% among all single-phase residential customers. Assigning projected numbers of EVs to service area customers provides us the final critical data to begin our grid-side modeling.

Following our example, Table 5 displays different types of EVs along with their key parameter assumptions for Feeder 7. According to our EV adoption forecast, 30.7% of EV users use the 120 V Level 1 EVSE, providing up to 12 A (1.4 kW), while 69.3% have access to the 240 V Level 2 EVSE, which supports up to 80 A (19.2 kW). Our analysis incorporates the onboard charger power (AC/DC charger power electronics rating on the EV) for each vehicle type, which is essential in determining the maximum grid power drawn by EVs. The table shows that newer models (Gen2) generally have higher onboard charging power. For example, the EV SUV/Truck (Gen2) features a 17 kW on-board charger; when charged on an 80 A EVSE, it reaches its maximum charging power, imposing substantial strain on the distribution transformer and feeder.

Table 5. Vehicle Types and Key Parameters for Feeder 7 (2030 Adoption Scenario)

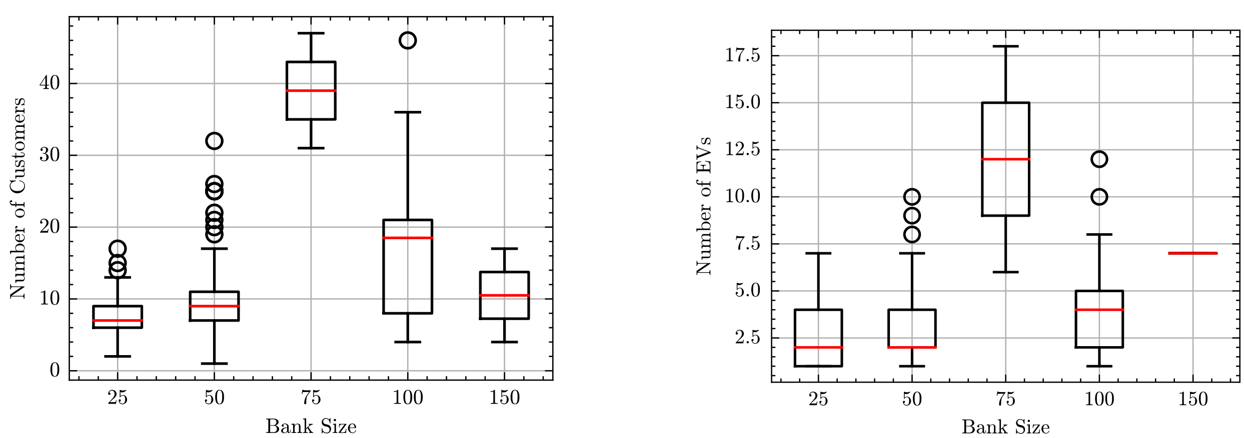
Vehicle Type	Vehicle Number	Battery Size (kWh)	Onboard Charger Power(kW)
EV Compact (Gen1)	72	45	8
EV Compact (Gen2)	55	45	11
EV Midsize (Gen1)	153	82.5	9
EV Midsize (Gen2)	87	97.5	12
EV SUV/Truck (Gen1)	293	95	12
EV SUV/Truck (Gen2)	212	118.75	17
PHEV† Midsize (Long Range)	112	15.5	7
PHEV Midsize (Short Range)	31	5	5
PHEV SUV/Truck	156	23.75	10

†PHEV stands for plug-in hybrid electric vehicle.

All 1,171 EVs in the Feeder 7's service area were assigned to customers and linked to their respective service transformers. Table 6 shows the sizes of transformer banks, along with the number of customers served and EVs projected for 2030. The most frequently used transformer sizes are 25 kVA and 50 kVA, which together serve 3,344 customers, accounting for 78.3% of the total. Figure 5 illustrates the distribution of customers and EV numbers by transformer bank size.

Table 6. EV Adoption by Bank Sizes for Feeder 7 (2030 Adoption Scenario)

Bank Size (KVA)	25	50	75	100	150
Service Transformer Count	266	139	2	46	2
Customer Count	1964	1368	78	733	21
EV Count	596	365	24	179	7



(a) Number of customers **(b) Number of EVs**

Figure 5. Distribution of customers and EVs by bank size for Feeder 7.

3.2 AMI Datasets

With EVs mapped to the customer level, we employed a bottom-up modeling approach to evaluate the impacts of EV grid integration. AMI is "an integrated system of smart meters, communications networks, and data management systems that enables two-way communication between utilities and customers" (*AMI*). It is providing first-of-its-kind empirical data for evaluation of load coincidence at the grid edge. In this study, we collected AMI-meter measurements from over 19,000 predominantly residential customers across ten distribution feeders. AMI measurements used in this analysis ranged from September 2 through September 8, 2023, including active and reactive power measurements at a 15-minute temporal resolution. It is important to note that the selected week may not coincide with the system peak load; nor does the data delineate customers with rooftop solar, energy storage, or pre-existing EVSEs (which is likely to be small compared to the assumptions in this study). This dataset only represents *net load* measurements during a late summer week in Colorado. The high-resolution field measurement data provides valuable insights into the load characteristics in the area, forming a foundation for the following EV grid integration analysis.

Even with increasing replacement and rollout of smart meters, there are still some customers who lack AMI recording. For the premises with missing AMI profiles, the U.S. residential building sector stock energy model (ResStock™) is used to represent the households' loading profiles (*ResStock Data*). ResStock is a U.S. Department of Energy model of the residential building stock of the United States, developed and maintained by NREL. This detailed, bottom-up model utilizes various data sources, statistical sampling, and advanced energy simulations to analyze the residential building stock across the contiguous United States. Using ResStock, we incorporated the loading characteristics of residential customers in the Boulder and Aurora areas into the missing data imputation process.

We integrated the EV charging profiles with household load profiles to evaluate their potential impacts on the distribution system. Alongside the base uncontrolled charging scenario, we propose several SCM algorithms in Chapter 4.

4 SCM Algorithm Development

For this study, we developed and evaluated five SCMs broken out into two categories. The first category consists of three TOU-based SCMs aimed at minimizing energy costs for each EV while meeting charging needs without coordination (i.e., no communication between EVs or between EV and grid authority other than fixed TOU rates). The second category includes two grid-aware active SCMs, where the available capacity for EV charging at each transformer is determined by a load monitoring system using direct or indirect AMI data. That available capacity is allocated to the EVs connected to the same transformer based on various power allocation strategies, facilitating local coordination among EVs. We evaluated the following control methods in this study:

- **Uncontrolled**: Customers begin charging as soon as they plug in, continuing until their energy needs are met.
- **TOU-based SCMs**:
  - **TOU ASAP (As-Soon-As-Possible)**: Minimize total charging costs while meeting energy requirements under a TOU rate, prioritizing completion of charging as soon as possible within the vehicle's dwell period (the time a vehicle spends stopped without moving).
  - **TOU ALAP (As-Late-As-Possible)**: Minimize total charging costs while meeting energy requirements under the TOU rate, prioritizing charging completion as close to departure time as possible within the dwell period.
  - **TOU Random**: Minimize total charging costs while satisfying energy needs under the TOU rate, with random charging periods chosen within the dwell period.
- **Grid-aware Active SCMs**:
  - **First-Come First-Served (FCFS)**: The available transformer capacity is allocated to EVs based on their plug-in order. The first EV to charge receives its full power request, subject to EV charging equipment limits and available transformer capacity. Subsequent EVs receive power according to their plug-in time until the transformer capacity is exhausted.
  - **Equal Sharing (ES)**: The available transformer capacity is equally shared among all active charging EVs served by that transformer.

4.1 TOU-Based SCM Algorithms

This section proposes three TOU-based SCMs with varying charging timing preferences. The TOU-based rate structure adopted by Xcel Energy currently divides the day into on-peak, mid-peak, and off-peak periods:

- On-peak hours: Weekdays from 3 p.m. to 7 p.m.
- Mid-peak hours: Weekdays from 1 p.m. to 3 p.m.
- Off-peak hours: Daily before 1 p.m. and after 7 p.m.; Weekends and holidays are priced at off-peak rates.

The goal of the TOU-based SCMs is to minimize charging costs under the TOU rate while satisfying each EV's energy requirements. Additionally, the charging power of an EV is constrained by its maximum charging capacity, determined by the lower ratings of its charging equipment and onboard charger.

To account for the charging timing preferences of different EVs, we included a timing preference weight in the objective function (the SCM formula). The approach that prioritizes finishing charging as soon as possible is named TOU ASAP. In contrast, the one that prefers to finish charging as late as possible before the next departure is named TOU ALAP. Random selection of charging periods during the dwell period is referred to as TOU Random. More details regarding the mathematical formulations of the SCMs are available in our paper (Zhang et al.).

All three SCMs can effectively minimize EV charging costs under the TOU rate structure while complying with energy and charging power constraints. Their differences are only in the preferred timing of the charging process, without compromising cost minimization or operational requirements.

Figure 6 illustrates the weekly aggregated EV charging profiles at the feeder level (Feeder 7) for different SCM strategies, comparing three TOU-based SCM schemes (TOU ASAP, TOU ALAP, and TOU Random) with an uncontrolled charging scenario where EVs charge immediately upon connection. The first two weekend days display similar peak charging profiles among the SCMs, mainly differing in peak timing. In contrast, the following five weekdays reveal significant variations in both the magnitude and timing of the charging profiles across the different SCMs.

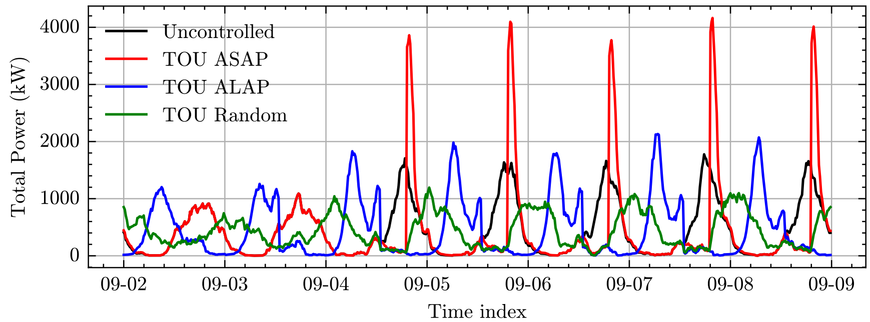


Figure 6. Feeder-level weekly aggregated EV charging profiles.

In uncontrolled charging scenarios, all EVs begin charging immediately upon plugging in, causing a peak around 7 p.m. The TOU ASAP program encourages EVs to delay charging until 7 p.m. to benefit from off-peak rates. However, the demand for quick charging results in a secondary peak after 7 p.m., reaching about 4 MW of EV charging load. Both TOU ALAP and TOU Random effectively shift charging loads to later times, reducing coincident charging compared to TOU ASAP. Nonetheless, TOU ALAP may create a coincident peak in the early morning as it aims to complete charging before daily commutes. Among these strategies, TOU Random is the most effective at flattening EV charging loads, resulting in significantly lower peaks of around 1 MW. More detailed grid impacts analysis of EV charging loads under different SCMs can be found in our technical papers (Pohl et al.; Zhang et al.).

TOU-based SCMs can shift EV charging to low-demand periods. However, uncoordinated charging may occur when these low-price periods start, risking overload of the service transformer.

4.2 Grid-Aware Active SCM Algorithms

Service transformer overloading is a significant concern for large-scale EV integration. Customer herding behavior in response to TOU-based SCMs may result in simultaneous charging, exacerbating transformer overloads. To tackle this issue, we propose grid-aware active SCMs to coordinate EV charging on the secondary side of the service transformer to alleviate the potential overload caused by EV charging. The proposed grid-aware active SCMs are illustrated in Fig. 7.

The utility can assess the loading of the service transformer with a direct metering device on the service transformer or through indirect virtual metering from local household-level AMI measurements. Based on this loading, and transformer capacity constraints, the utility can determine and allocate available capacity for EV charging to all connected EVs requesting power. Depending on the allocation method, grid-aware active SCM can either use FCFS or ES control methods, distributing available capacity to EVs based on their connection order or equally among them, respectively.

Using a 25 kVA service transformer as an example, which is forecasted to support three EVs in our 2030 adoption scenario, we assume the upper loading limit is the nameplate capacity. The goal of grid-aware SCMs is to coordinate EV charging on the same transformer to prevent overloading. We implemented grid-aware SCMs into this example transformer. Figure 8 displays the available capacity, power allocation among the EVs, and the total EV charging power across uncontrolled, FCFS, and ES scenarios.

The power allocation results show that without control, the total EV charging power (green dashed line) significantly increases with the plug-in of all three EVs (Fig. 8a), easily overloading the transformer. In contrast, both the FCFS (Fig. 8b) and ES (Fig. 8c) methods can coordinate EV charging based on transformer loading, effectively preventing transformer overload while meeting the charging needs of EVs. The primary difference between these two strategies

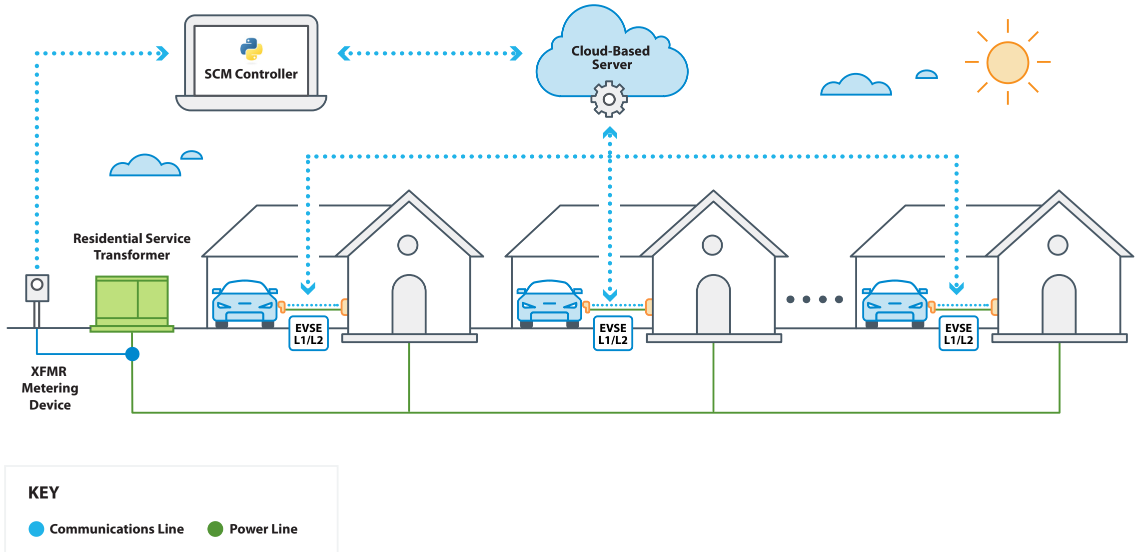
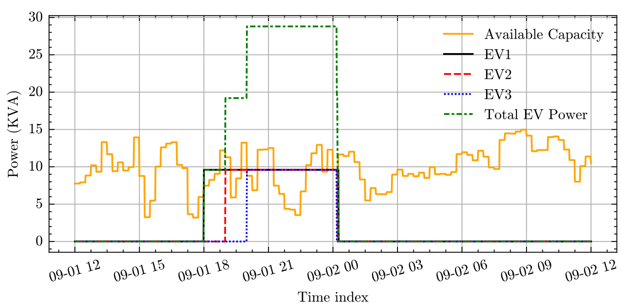
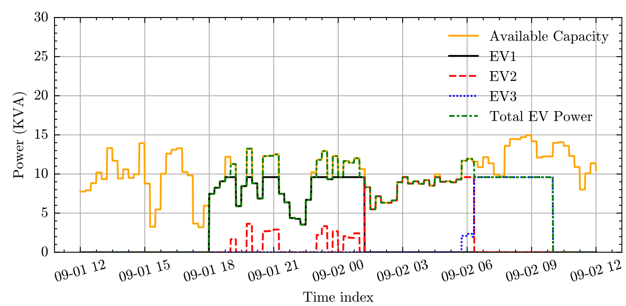


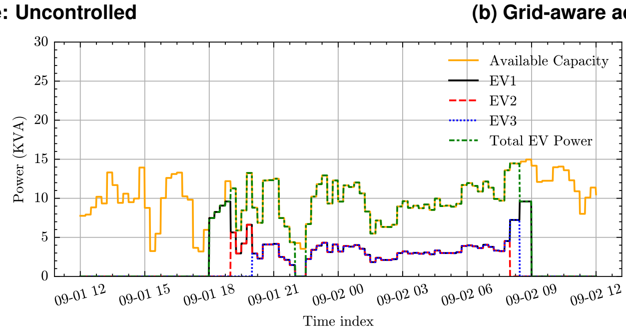
Figure 7. Implementation diagram of grid-aware active control-based SCMs.



(a) Base case: Uncontrolled



(b) Grid-aware active SCM: FCFS.



(c) Grid-aware active SCM: ES.

Figure 8. EV power allocation outcomes with grid-aware active SCMs.

lies in how available capacity is allocated to various EVs. It is worth mentioning that this active control prioritizes mitigating transformer overloads, which may restrict customers' charging needs due to capacity limits. In the following section, we discuss performance related to balancing grid operation constraints with customer charging needs.

4.3 Service Transformer Loading Analysis under Different SCMs

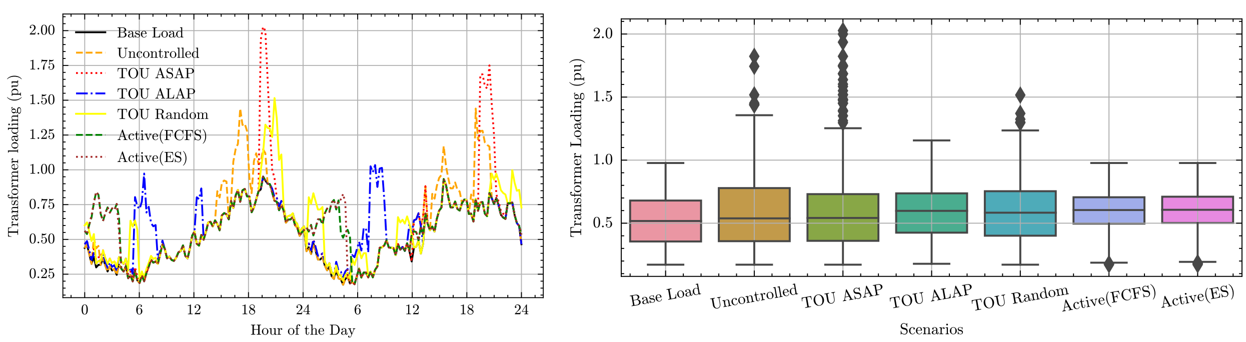
4.3.1 Transformer-Level EV Integration Analysis

25 kVA and 50 kVA transformers are the most commonly used in distribution systems. Due to their limited capacity, they are more likely to be overloaded from EV grid integration. In this section, we present a 50 kVA transformer as

an example. This transformer is expected to support 8 EVs with varying mobility and charging characteristics based on our 2030 EV adoption scenario.

Figure 9a shows the transformer load over two consecutive days. Uncontrolled charging, TOU ASAP, and TOU Random can all lead to transformer overloading. Uncontrolled charging begins when an EV is plugged in at home during peak nighttime hours, resulting in a maximum loading of 1.46 pu (per-unit) of the rated capacity. TOU ASAP charging peaks at 2.01 pu as all EVs start charging at 7 p.m. to benefit from lower rates, exacerbating the loading issue. In contrast, TOU Random typically prevents multiple EVs from charging simultaneously, shifts charging to nighttime, and helps avoid overloading the transformer. However, the lack of coordination among EVs on the same transformer led to overloading during peak hours on the first night, with the transformer reaching to 1.51 pu of its rated capacity. In contrast, the grid-aware active SCMs (i.e., FCFS and ES) successfully shift EV charging loads to off-peak times and manage power distribution among EVs, effectively regulating transformer loading.

Figure 9b shows the weekly loading distribution of the 50 kVA service transformer with EV integration across various SCMs. Similar to the previous daily variation case, uncontrolled EV charging and TOU-based SCMs can overload the transformer due to utility's lack of awareness of loading conditions and lack of coordination among EVs. In contrast, grid-aware active SCMs manage EV charging by considering the dynamic loading conditions of the transformer, shifting loads to low-loading periods, and preventing overloading.



(a) Transformer loading variations (2 days) **(b) Weekly transformer load distribution**

Figure 9. Service transformer (50 KVA) loading with EV integration.

4.3.2 Feeder-Level EV Integration Analysis

We extended the previous transformer-level EV integration analysis to the entire feeder (Feeder 7), encompassing 455 service transformers. We analyzed the charging profiles of 1,171 EVs and the corresponding loads of 401 transformers to assess loading conditions for all service transformers with EV integration. Figure 10 shows the hourly loading distribution of service transformers under different SCMs during the peak load week of our study.

Table 7 provides statistics on overload and EV energy satisfaction, defined further in this subsection, for the feeder. The second column contains the count and ratio of overloaded transformers exceeding the 160% nameplate threshold, the third column shows the accumulated overload time for all 455 service transformers, and the fourth column indicates EV energy satisfaction ratio of EV owners across different SCMs. We chose the 160% overload threshold of the nameplate capacity since service transformers can be safely overloaded above rated capacity for a limited duration in practice.

As in the earlier analysis, results show that both uncontrolled and TOU-based SCM strategies notably increase the number of overloaded transformers and the total duration of overloads. The TOU ASAP greatly exacerbates overloading, while both TOU ALAP and TOU Random help alleviate it by spreading EV charging throughout the night. However, they still lead to overloading due to insufficient coordination between different EVs.

In contrast, as before, grid-aware active SCMs efficiently manage EV charging under the same service transformer by coordinating and shifting loads to off-peak periods, thus preventing transformer overload from EV integration. The number of overloaded transformers and total overload time remain unchanged compared to base load scenarios, indicating that these grid-aware SCMs can completely eliminate transformer overload due to EV grid integration.

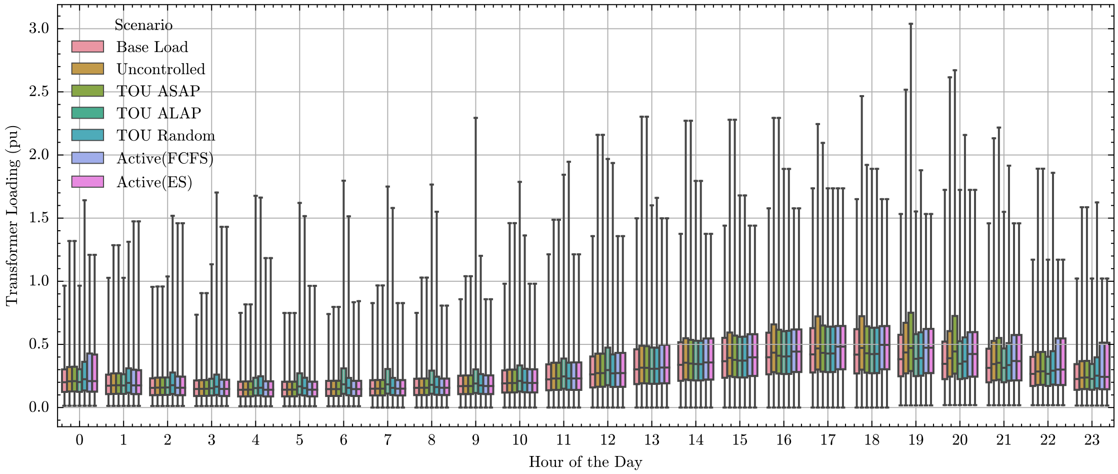


Figure 10. Hourly distribution of transformer loading with EV integration.

Table 7. Service Transformer Overload (>160% Nameplate Capacity) and EV Energy Satisfaction Statistics

Scenarios	Overload Transformer Count (Ratio)	Accumulated Overload Time (Hour)	EV Energy Satisfaction Ratio
Base Load	3 (0.66%)	0.75	NA
Uncontrolled	65 (14.29%)	115.25	100%
TOU ASAP	73 (16.04%)	159.50	100%
TOU ALAP	24 (5.27%)	18.50	100%
TOU Random	26 (5.71%)	22.50	100%
Active(FCFS)	3 (0.66%)	0.75	94.99%
Active(ES)	3 (0.66%)	0.75	94.57%

Under the FCFS strategy, EV owners who connect later may be penalized, creating a risk of not receiving sufficient energy. To address this issue, a modified strategy could incorporate a minimum energy guarantee in the algorithm. Meanwhile, the ES strategy equally distributes the available power capacity among all connected EVs. However, when transformer capacity for EV charging is limited, users may not fully charge their EVs, overall.

Given the limitations of capacity, the question is whether the charging needs can be met during dwelling periods. To quantify this, we defined the EV energy satisfaction index as the proportion of charging sessions that fully meet the EV's energy needs out of all charging sessions. Thanks to the long dwelling times typically available for residential charging, both grid-aware active SCMs (FCFS, ES) can satisfy over 94% of charging events.

There is little difference between these two power allocation strategies; the distinction lies in user perception. Fairness in power distribution plays a critical role in shaping consumer acceptance of these SCM programs. Accurately modeling consumer choices and behaviors is essential for enhancing the effectiveness of SCM program design. By gaining deeper insights into consumer decision-making processes and the factors influencing their behaviors, utilities can develop more targeted and efficient SCM strategies that better align with grid requirements. Utilities should also explore the use of advanced analytics to gain deeper insights into consumer preferences. These analysis can uncover patterns and forecast reactions to different SCM strategies, allowing utilities to address potential issues proactively. Additionally, clear and transparent communication about the decision-making process can enhance trust and boost user satisfaction. Educating consumers on the advantages of these programs while emphasizing a commitment to fairness can strengthen customer relationships, ultimately supporting the long-term success of SCM programs.

5 Load Coincidence Analysis and Transformer Sizing to Inform Standards Development

The objective of our analysis in this chapter is to inform service transformer design standards for residential services with increasing EV adoption. Distribution design assumptions largely depend on typical load coincidence, or the degree to which individual loads contribute to systemwide peak load. Prior to the industrywide rollout of AMI, utilities had little data accessible to gauge load coincidence, relying mostly on high-level system data (e.g., substation-level SCADA measurements, customer counts) and engineering judgement. Notably, evaluating load coincidence at the granularity of a single service transformer is especially challenging, given the lack of data at this scale. Enhanced grid edge visibility can aid in prescribing design standards to appropriately size service transformers.

Load coincidence is quantified using a coincidence factor, which is "the ratio of the maximum coincident demand of a group of consumers to the sum of the maximum power demands of individual consumers comprising the group both taken at the same point of supply for the same time" (*AIEE*). The coincidence factor can vary across load types, customer classes, or times of the year.

We used the customer-level AMI dataset to create a basecase load characterization of residential loads in the study area during the time period captured in the AMI dataset described in Chapter 3. The basecase represents only the customer AMI data and no added EV charging loads for the single week in September 2023. Once again, note that this week of data may not coincide with the system peak day and as a result may underestimate customer-level peak load values. However, this can still provide insights into real-world load characteristics and the adequacy of today's design standards. Coincidence factors generally decrease with increasing customer sample sizes—with larger customer sample sizes, the impact of any individual load on the systemwide peak load is smaller and approaches a single value. We capped our maximum sample size to 50 customers, as a larger number would likely not be served by a single transformer of the evaluated single-phase sizes: 25 kVA, 50 kVA, and 100 kVA.

We calculated coincident and non-coincident peak load[1] across the modeling time frame for each customer sample size (1 to 50) using 1,000 random customer samples for each sample size. For example, given a sample size of ten customers, we make 1,000 random selections of ten customers from the AMI dataset and calculate coincident and non-coincident peak load for each selection. Figure 11 compares coincidence factors under the basecase, uncontrolled charging, and the three TOU-based SCMs. The values in Figure 11 represent the top-quartile means across the 1,000 randomized samples in our 2030 adoption scenario. This includes all customers in the AMI sample set, including those with and without EVs. Figure 12 shows the customer counts at which the calculated coincident peak load reaches 100% of the nameplate rating for the three evaluated transformer sizes.

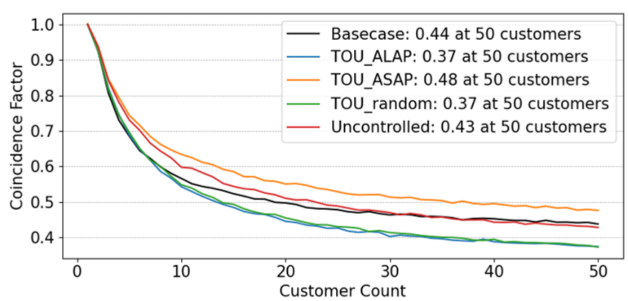


Figure 11. Calculated load coincidence factors.

Within the basecase, we see our coincidence factor asymptotically approach 0.44 for a 50 customer sample, yielding 6-, 16-, and 36-customer limits for a 25, 50, and 100 kVA transformer, respectively. Under the four SCM algorithms, including uncontrolled charging, we see notable differences in transformer customer limits. Relative to the basecase, the addition of EVs using uncontrolled charging increases coincident loading, though the coincidence factor is largely unchanged. The higher coincident loading requires a reduction in the allowable transformer customer limits. For smaller transformers (25 and 50 kVA), the customer limit is about halved with uncontrolled charging. TOU-ASAP results in a higher coincidence factor and higher coincident load, given that EVSEs start their charge cycle

[1] Coincident peak load is calculated by taking the peak value of the sum of all AMI load profiles in a given customer sample across the weeklong modeling timeframe. Non-coincident peak load is calculated by taking the sum of the individual peak loads of each AMI meter in a given customer sample across the weeklong modeling timeframe.

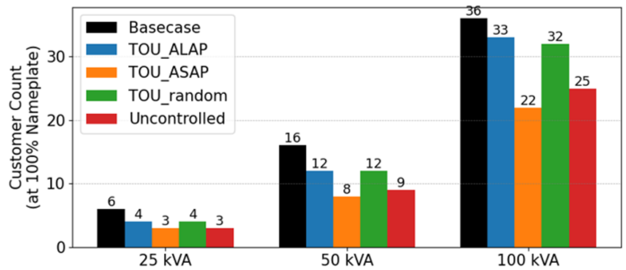


Figure 12. Customer count limits for residential service transformers.

at the same time to minimize charging cost, *further* reducing transformer customer limits relative to uncontrolled charging. This indicates that uncontrolled charging may actually outperform a TOU-ASAP strategy. Both TOU-Random and TOU-ALAP effectively spread out charging throughout the night, reducing load coincidence compared with uncontrolled charging, and increasing the transformer customer limits.

We have chosen not to include a similar coincidence analysis on the grid-aware active SCMs like FCFS or ES described in Chapter 4. Including active, transformer-specific SCMs in this type of analysis can be somewhat misleading, as the randomized customer sampling done here to get average coincident loads does not include any consideration of existing transformer groupings of customers and is focused on characterizing the larger AMI sample set as a whole. Instead, one can intuitively conclude that with an active SCM that implements a hard limit on charging at the transformer nameplate rating, one could allocate the same number of customers on each transformer size as one could in the basecase (e.g., 36 customers with grid-aware FCFS on a single 100 kVA service transformer). The caveat to this approach is that for a transformer that is heavily loaded in the Basecase, the allocated EV customers may experience more significant charging curtailment, potentially resulting in lower EV energy satisfaction ratios, as explained in the Table 7. Conversely, for a lightly loaded transformer with plenty of capacity for added EV loads, the grid-aware active SCMs like FCFS or ES may not curtail EVs very often or at all, and thus EV charging for those customers would look largely the same as an uncontrolled charging scenario.

The improvements in load coincidence and transformer customer limits under TOU-ALAP and TOU-Random represent one of the value propositions for indirect managed charging. These programs, as modeled, show promise in reducing potential transformer overloads of *existing* distribution assets as EVSEs are added to existing services and reducing the number of *new* transformers and accompanying infrastructure needed to serve new residential services with EVs. This type of non-load flow AMI analytics can easily be replicated as more widespread or more granular AMI datasets are made available in the future. The resulting calculations of such an analysis can be used to inform distribution design standards such as how many customers to allocate to a single transformer when designing new distribution or how to appropriately derate connected load when evaluating loading levels of other grid assets like conductors, protective devices, or substation equipment. Having a better understanding of what typical coincidence factors are across different customer classes, times of the year, or for customers participating in utility programs can improve the accuracy of design assumptions used in distribution engineering and customer program design.

6 Time Domain Grid Analysis

In this section, we examine broader distribution grid impacts of EV adoption, and the stacked value proposition of SCM strategies investigated, before using an EPRI-developed open-source load flow solver (*OpenDSS*) to create load flow models of the selected feeders.

6.1 Model Overview

The NREL team obtained several datasets from Xcel Energy to construct distribution models in OpenDSS, including both primary (medium voltage) and secondary (low voltage) lines. We converted primary-only (i.e., not including service transformers or low voltage secondaries) Synergi load-flow models for the previously selected 10 feeders into OpenDSS using NREL's DiTTo tool (*DiTTo*). DiTTo, an open-source tool, extracts all of the circuit's assets, attributes, and connectivity from the Synergi model and translates this into a roughly equivalent OpenDSS model. While this translation is rarely perfect, we conducted model validation efforts to ensure reasonably similar results between the original Synergi models and the translated OpenDSS models. Figure 13 depicts the overall process of feeder conversion and modeling implemented in this study.

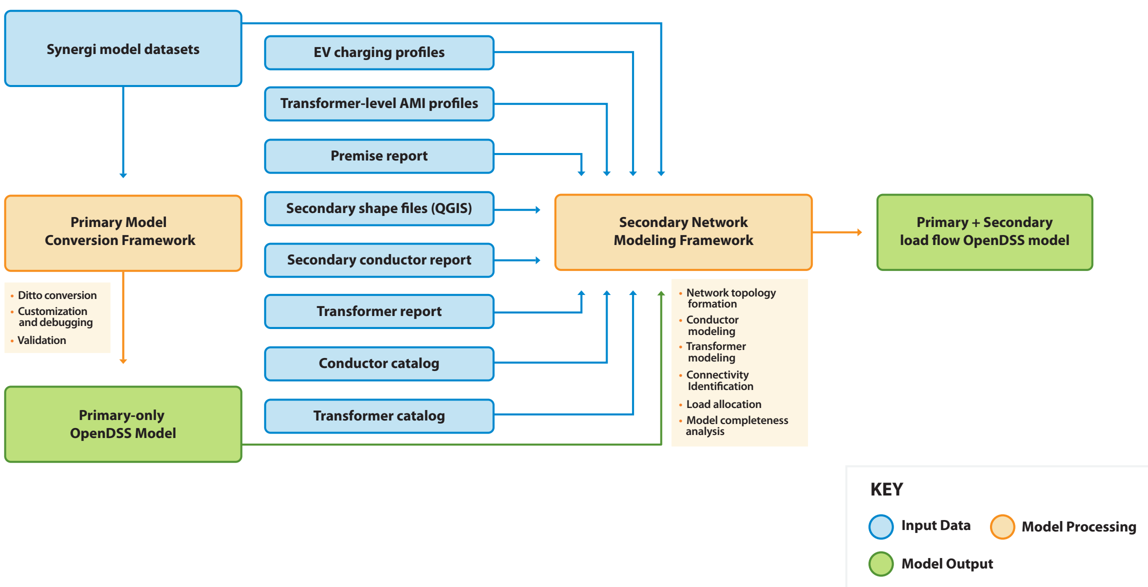


Figure 13. Overall feeder modeling approach.

To model the impacts of EVs on secondary networks, we developed methods to integrate additional datasets (e.g., GIS representations of secondary topologies, customer-to-transformer mappings, conductor and transformer specifications) to the best of our ability. The datasets were extensive, but conflicting and/or missing information required us to make many simplifications and/or assumptions, yielding somewhat imperfect or incomplete primary-plus-secondary load flow models. Nonetheless, this approach sufficiently provided a useful test feeder set to run our analyses on. Additionally, the percentages of the original premises that are included in the final models are provided in Table 8 for reference and as a measure of final model completeness. Furthermore, the assumptions we made within this process were largely based on engineering judgment or guidance from the Xcel Energy team (following documented design standards) and were made regarding several characteristics of the grid model, like customer-transformer groupings, transformer locations within secondary networks, secondary conductors used, transformer and conductor impedances, and any additional missing or inconsistent data points.

While this model build was an extensive process, there are still opportunities to improve these methods in future studies. For example, these models have no direct representation of centralized control schemes used in Volt-VAR optimization programs at Xcel Energy; premise-level load unbalance; load diversity across customers on the same transformer; secondary-system capacitors or VAR compensators; or existing behind-the-meter assets like solar, storage, or existing EVs. AMI data used in these load flow models represents aggregated load profiles at the service transformer level, which we allocated evenly across all customers served by the transformer. NREL also synthesized missing AMI data to approximate total loading on a given service transformer with incomplete AMI coverage. All said, the results of this exercise should be taken with the appropriate level of discretion. Nonetheless, we believe they contain very valuable insights, particularly on the relative grid impacts of managed charging strategies.

For brevity, some of the following results represent a selection of 4 feeders of the total 9[2]. We selected the four feeders as we believe they best represent the key findings from this modeling exercise. While the results of each feeder are unique, there are many commonalities across our broader 9-model set. The high-level statistics of the four models discussed in this report are presented in Table 8. Two feeders are from the Boulder region, and the other two are from Aurora. Key differences in the feeders can be seen regarding feeder length, overhead (OH)-to-underground (UG) ratio, customer counts, and data completeness.

Table 8. Characteristics of the Selected Utility Feeder Models.

Metric	Feeder 1	Feeder 3	Feeder 7	Feeder 9
Single/three-phase customers	3397 / 47	3611 / 1208	3176 / 0	5501 / 0
Total EV count	1638	1497	1138	1488
Percent OH/UG	54.0% / 46.1%	16.3% / 83.7%	0.0% / 100.0%	0.0% / 100.0%
Feeder length	11.5 mi	3.8 mi	4.2 mi	9.6 mi
Percent of premise report loads included in model†	75.9%	83.0%	71.7%	95.6%

† Due to a combination of incomplete secondary data and incomplete AMI data, not all customers in the real-world system are included in this model.

6.2 Feeder-Level Loading

We conducted time-series power flow simulations to assess the impact of a 2030 EV adoption scenario on the modeled feeders. The simulations ran for the first full week of September 2023 (Saturday to Friday) at a 15-minute time step using transformer-level AMI profiles allocated down to the customer level. Figure 14 illustrates the total feeder demand for the selected four feeders both with and without EVs, under various SCM scenarios. Note that the on-board EV chargers are assumed to operate at unity power factor, resulting in relatively minor changes in reactive power loading across scenarios. The exception to this is for very long feeders, where increased line currents from EV charging results in increased reactive losses. Additionally, loads were modeled as constant power loads, meaning that for lower system voltages (resulting from increased EV charging), current would further increase, resulting in additional losses.

From Fig. 14, it is clear that uncontrolled EV charging significantly increases the peak demand, as shown by the orange lines in the four charts. Peak power increases range from 8% to over 50% compared to the basecase for all 4 feeders. Our modeled TOU-ASAP SCM leads to even larger spikes in demand, due to the high coincidence of EV charging in the evening hours, resulting in peak demand increases ranging from 21% to over 140%. Other TOU-based controls are effective in reducing peak demand by strategically shifting charging to off-peak hours. Across all four feeders, TOU-ALAP and TOU-Random show significantly smaller peak load increases than uncontrolled charging. In one case, on Feeder 7, we actually see a very slight *reduction* in peak load. This was due to a switched capacitor bank switching on during these EV scenarios, significantly reducing feeder VAR demand.

Overall, these results reinforce the conclusions we had in Section 4 and Section 5. SCMs that encourage higher load coincidence will lead to higher peak demand and may increase infrastructure costs, while those that effectively spread out the charging loads to off-peak hours can substantially reduce peak demand compared to uncontrolled charging. Our simulations also highlight the significant variance in EV impacts from one circuit to another as well as the variance in EV charging loads from one day of the week to another.

6.3 All-Feeder Aggregated Point of Common Coupling (PCC) Voltage

In addition to loading levels, we assessed the power quality across EV adoption and SCM strategies. We plotted distributions of point of common coupling (PCC) voltages across customers, and as such, can easily aggregate results

[2] One of the 10 selected feeders, Feeder 2, was not modeled due to incomplete AMI datasets

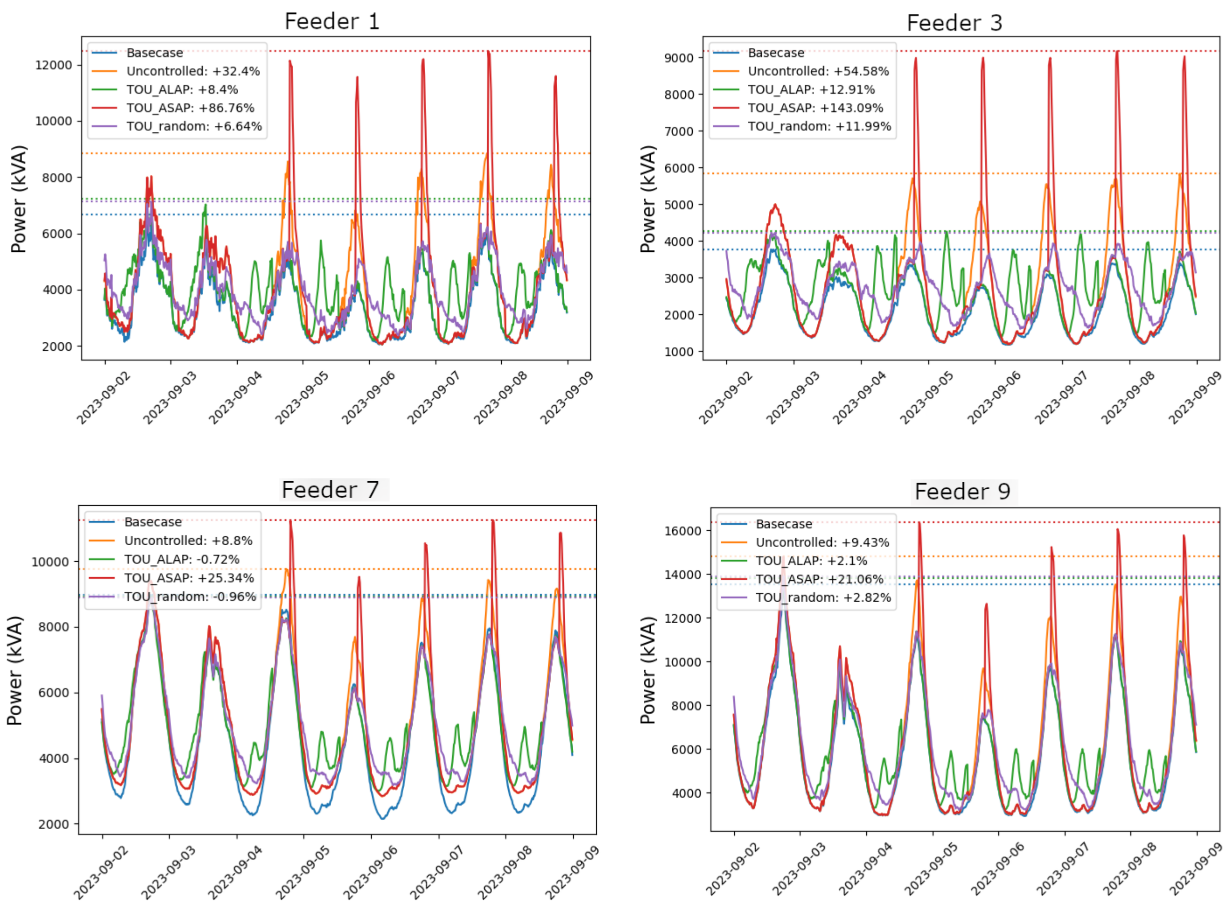


Figure 14. Apparent power loading across selected four feeders.

across our wider sample of nine feeder models. The PCC is defined as the bus in the load flow model to which a load object is connected to, corresponding with the point at which the customer meter connects to the distribution system in the real world. We assessed all customers for which there was sufficient data to fully resolve the secondary conductors in our load flow model (about 16,000 customers in total[3]). Across our modeling timeframe, we measured the lowest voltage experienced by each customer at the PCC. Note that the lowest voltage for each customer may not occur at the same time, and the durations of these under-voltage events are not considered. Nonetheless, to be conservative in our grid impact assessment, we consider the worst-case timestep for each customer independently. In addition to PCC voltages, we also calculated secondary voltage drop, that is, the difference in voltage measured at the transformer's high-side bushings and the PCC at the same timestep of the lowest PCC voltage experienced. This illustrates the extent to which secondary systems contribute to overall system voltage drop and where mitigations may be most needed.

Figure 15a first shows a cumulative distribution of secondary lengths, that is, the distance from the transformer to the PCC, for each of the more than 16,000 customers modeled. For all subfigures in Fig. 15, the y-axis is plotted on a log scale to emphasize the edge cases, or those with exceptionally long secondary distances or exceptionally low voltages. Figure 15a shows that the large majority of customers in our models are served by secondaries less than 400 feet. However, even relatively short secondaries may still see significant voltage drop should there be very large loading or smaller conductors. Figure 15b shows a similar cumulative distribution of minimum PCC voltages for each customer. The addition of EVs produces a notable leftward shift in the distribution (towards lower voltages),

[3] A small number of additional customers are modeled as connected directly to the load-side bushing of a service transformer and thus not considered in this voltage analysis.

and reductions in the global minimum and mean PCC voltages as listed in the legend entries. Also listed in the legend are the percentages of customers who experience an undervoltage violation (i.e., below 0.95 pu).

In our Basecase scenario, we see about 4.55% of customers below this threshold at least once during the simulation[4]. Under uncontrolled charging, this number jumps to 6.55% while also showing decreases in the global minimum and global mean voltages. Unsurprisingly, these effects are most pronounced for TOU-ASAP, with 11.53% of customers seeing undervoltages and further decreases in the mean and minimum voltages. TOU-ALAP and TOU-Random both show notable improvements over uncontrolled charging at 5.12% and 5.13%, respectively, only slightly higher than our Basecase. Figure 15c shows similar trends with increasing secondary voltage drop with increasing load from EVs. Within the legend entries, the global max voltage drop, mean voltage drop, and percent of customers seeing a greater than 3% voltage drop are listed.

In a voltage assessment like this, we tend to focus on the edge cases, where customers see exceptionally low voltages and are likely to experience power quality issues like flickering lights or equipment malfuction. It is also important to show the impacts on mean voltages, as decreases in mean voltages may impede a circuit's tolerance for large motor loads, lessen the potential for implementing conservation voltage reduction programs, or lead to a higher reliance on distributed devices like capacitor banks and voltage regulators for voltage support. While these results are aggregated across 9 feeders and more than 16,000 customers, the effects of EV adoption on system voltages are still highly circuit- and location-dependent (i.e., where EVs interconnect on a given circuit). In our analysis, EV loads were randomly allocated across each feeder model, and while not shown in the aggregated plot here, there was notable variance in PCC voltage distributions and subsequent impacts of EV loads from one feeder to another. In reality, there may be more clustered adoptions of EVSEs, different circuit characteristics, adaptive voltage management systems, or differing customer behaviors that lead to more or less severe voltage impacts than what are shown here. Nonetheless, the potential value proposition for SCMs as a means of mitigating voltage impacts are well illustrated by these findings.

It is important to note that the results obtained from this simulation analysis help us understand the potential extent of voltage issues. However, such low voltage levels would not typically occur in real-world operation. In practice, distribution systems are equipped with protection mechanisms that intervene before voltages drop too far. Additionally, system equipment has defined operating limits. Violations such as excessive voltage drops can trigger protective actions, including automatic shutdown or disconnection. Therefore, these results should be interpreted as a theoretical analysis intended to provide insights into system vulnerabilities and to highlight the need for voltage support, infrastructure upgrades, or SCM strategies.

6.4 Feeder-Level Voltage Unbalance

In this study, all residential charging loads are single-phase. As such, depending on the location to which they interconnect and pre-existing grid conditions, this has the potential to exacerbate or alleviate voltage unbalance. Voltage unbalance is defined as the maximum phase voltage deviation from the average phase voltage divided by the average phase voltage:

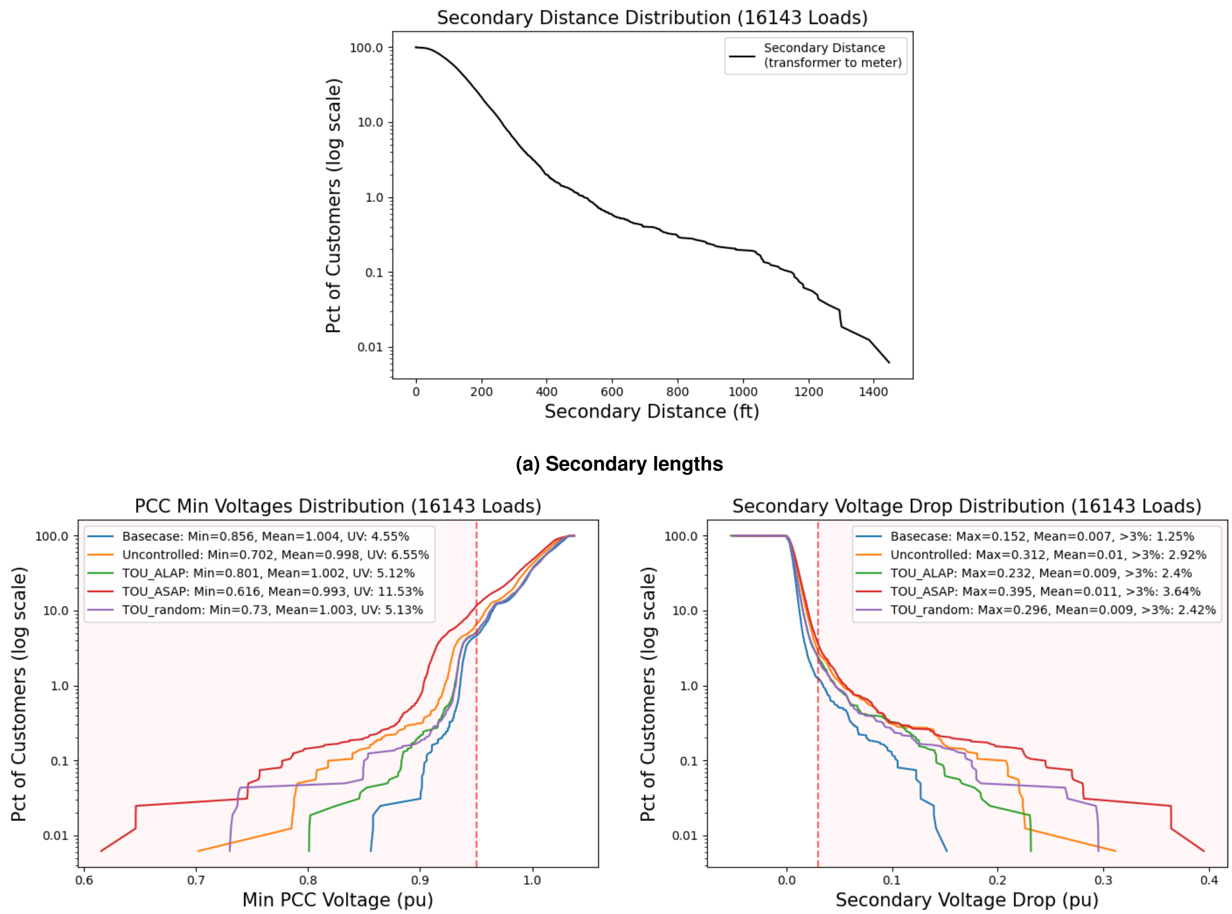
$$\%\text{Voltage Unbalance} = 100 \times \frac{\text{Maximum Deviation from Average } V}{\text{Average } V} \tag{6.1}$$

Given that residential chargers may be added to existing services, there may be less flexibility for the utility to designate the phase to which they interconnect and there may require additional phase balancing elsewhere on the feeder. The results shown in Fig. 16 represent, at each time step, the *feeder-wide worst* voltage unbalance. The approach goes beyond simply measuring unbalance at the feeder head, and looks at all nodes of the feeder. This comprehensive approach can aid in addressing power quality complaints, inform load transfers from one feeder to another, or even help to improve the sensitivity of certain protective devices[5].

Recommendations from C84.1 (*ANSI*) explain voltage unbalance should remain below 3% to ensure adequate power quality for customers. From the figure, it is seen that Feeder 1 experiences substantial voltage unbalance even in the basecase, and the addition of EVs greatly exacerbates this. This suggests that single-phase, residential EV charging

[4] Feeder 9 strongly skews this percentage due to about 20% of customers on that feeder being below 0.95 pu in the basecase simulation. When this feeder is excluded from the plot, the remaining 12,656 customers have only 0.29% below this threshold.

[5] For protective devices with a neutral element (e.g., 50N/51N), the pickup value must be low enough to detect high-impedance faults but high enough to not trip on neutral current from typical load imbalance.



(a) Secondary lengths

(b) PCC voltages **(c) Secondary voltage drops**

Figure 15. Secondary voltage assessment

has the potential to cause unacceptable voltage unbalance, and the risk is even higher when there is limited flexibility in where EV chargers are distributed across a given feeder. In contrast, feeders like Feeder 7 show a lesser increase in voltage unbalance, well under 3%, illustrating, once again, the circuit-by-circuit variance in EV grid impacts.

6.5 Considerations for SCM Implementation

Across our analyses, we see similar results regarding the effectiveness of passive TOU-based SCMs: that TOU-ALAP and TOU-Random generally lessen the grid impacts of new EV charging loads and, as such, present a value proposition for managed charging programs. However, there are additional considerations beyond this modeling exercise regarding which SCM is best-suited for future grid deployment. From an implementation standpoint, an uncontrolled charging strategy is likely the most straightforward, requiring no direct control or advanced programming of EVSEs. Any EVSE model, manufacturer, or vintage can participate in uncontrolled charging and fewer systems or utility programs are needed. Additionally, the condition of the distribution system does not explicitly rely on customer participation in SCM programs to mitigate grid impacts, and as such may be less susceptible to future impacts from customers opting out of a managed charging program or to future revisions of the SCM program. Nonetheless, our modeling results show considerable grid impacts resulting from an uncontrolled charging strategy, and as such the future system upgrade costs may be significant.

Conversely, while the upfront costs to implement a TOU-based SCM program may be higher (e.g., costs associated with program design, program management, customer recruitment) and there may be more specific EVSE requirements (e.g., the ability to delay charging to a random interval or ensure that energy requirements are still met by the morning departure time), our study results show considerable reductions in grid impacts under these passive SCMs.

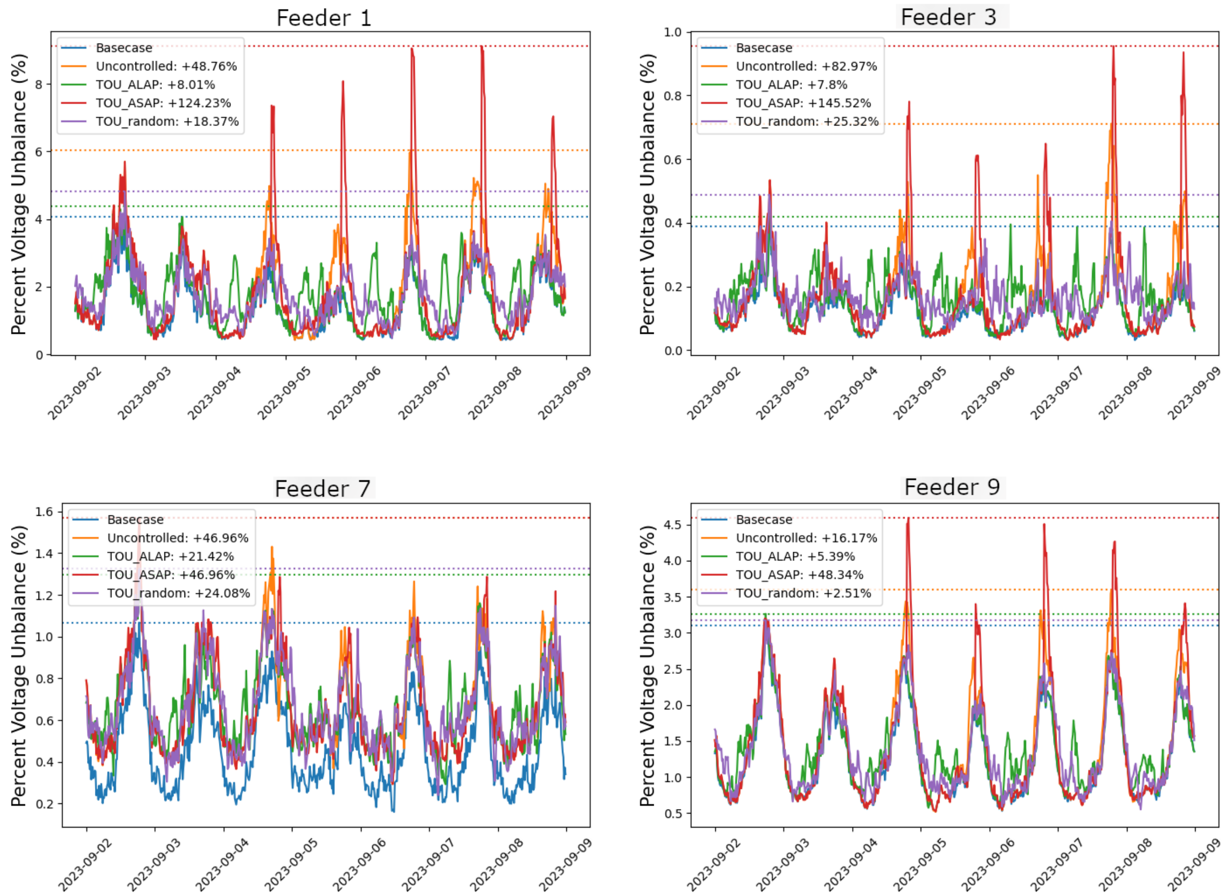


Figure 16. Feeder voltage unbalance

As mentioned, this study assumes a 100% customer participation rate among those customers with EVSEs in our 2030 scenario. Real-world participation rates, or real-world customer adherance to the TOU rate schedule (e.g., not as strict adherence as the least-cost charging behaviors we modeled) under passive SCMs may differ and impact the effectiveness of such a passive strategy.

While not explicitly analyzed in this grid modeling exercise, grid-aware active SCMs like those presented in Chapter 4 may also be of value for utilities seeking system impact mitigation. While possibly the most costly strategy upfront due to the costs associated with the buildout of robust communication, cybersecurity, and control systems, active SCMs have a lower reliance on customer behaviors for impact mitigation, beyond the initial opting in to the program and potential future opting out. With direct EVSE control, transformer overloading may be more effectively managed if sufficient numbers of customers participate in the program, and with sufficient grid data, additional loading or operational constraints may be added to a grid-aware SCM (e.g., feeder-loading, substation-loading, voltage-based) to further prevent system violations.

Regardless of the SCM, should it provide reductions in EV-induced grid impacts at the distribution level, we may extrapolate potential similar benefits at the bulk-system level, reducing or shifting systemwide peak loads and possibly having desirable effects at the transmission- or bulk-generation-scale. A future study may benefit from characterizing these bulk-system value streams from managed charging to further justify the deployment of a managed charging strategy.

7 EVI-DiST Development and Operation

7.1 Framework

Electric Vehicle Integration - Distribution System Integration Tool (EVI-DiST) is a co-simulation software platform for modeling, analyzing, and controlling grid-scale EV charging integration from primary distribution feeders to secondary circuitry levels (*EVI-DiST*; Panossian et al.). NREL developed EVI-DiST to offer a user-friendly interface for accessing the analysis results generated during this project. EVI-DiST allows any utility company to analyze the impact of EV charging on their utility grid's infrastructure using new datasets and different simulation configurations such as charge control types, simulation month, and feeder selection.

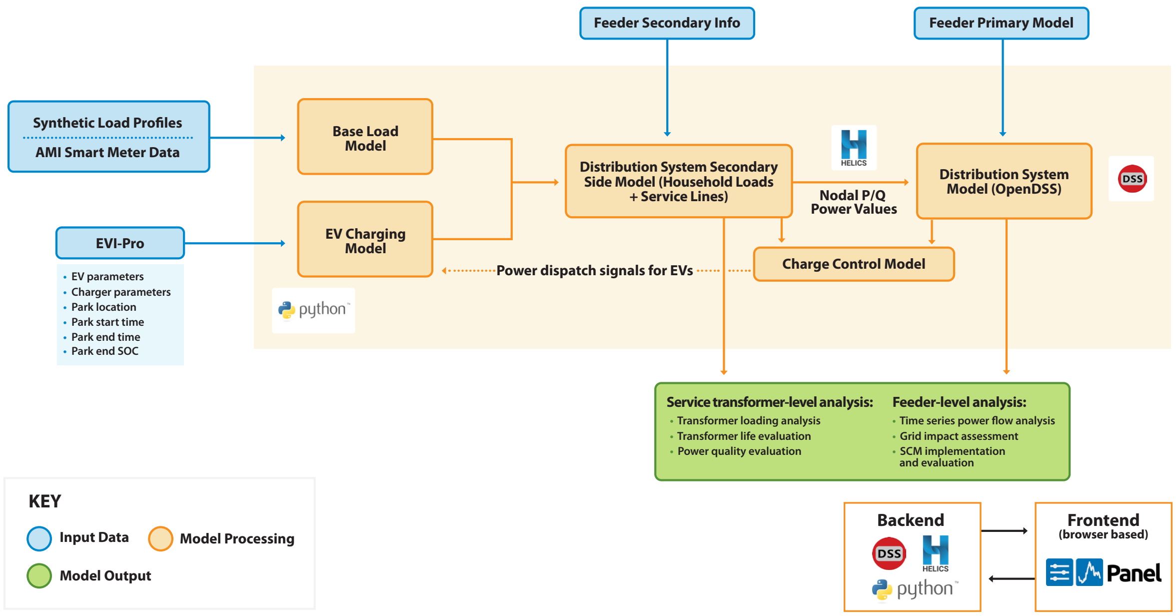


Figure 17. EVI-DiST operation framework.

The framework of EVI-DiST is illustrated in Fig. 17. The tool processes inputs such as EV charging events, building load profiles, and feeder primary and secondary models. Through time-series simulations, it generates EV charging profiles based on a selected charge control method and evaluates their impact on the feeder infrastructure (e.g., transformers and distribution lines).

EVI-DiST is built entirely in Python within a Conda environment (*Anaconda*). Its frontend uses the Panel framework that provides a web-based interface for the user dashboard (*Panel*). Simulations and analysis are performed on the backend. EVI-DiST also relies on open-source Helics and OpenDSS platforms for grid-wide power flow simulations (*OpenDSS*; *Helics*). Backend and frontend contents are also shown in Fig. 17[6].

EVI-DiST offers two operating modes, Lite and Plus, depending on functions needed for the analysis. The Lite mode is designed to perform weeklong simulations with various EV charging controller options, without including a power flow solver, for quick assesment of EV-grid impact. It delivers time-series and histogram load profile results at both the feeder and transformer levels, accompanied by key descriptive and statistical insights into transformer overloading for the selected transformer. The Plus mode performs a daylong simulation solving power flow equations and producing voltage and current profiles for feeder nodes and lines. EVI-DiST Lite is the best option for quick service trasnformer loading analysis and evaluating impact of SCM algorithms on transformer loading. EVI-DiST Plus, on the other hand, provides deeper analysis into feeder-level operation and understanding voltage impacts in addition to service transformer loading.

[6]Detailed documentation, including installation instructions and user guidelines, is available in the tool's GitHub repository (*EVI-DiST*). This documentation can also be accessed locally after installation.

EVI-DiST is designed to simulate EV charging behavior for a specified EV adoption scenario, charging control algorithm, and feeder model. To operate, it requires several input files. A feeder is primarily characterized by its unique transformers, premises, distribution lines, and their geographical locations. The input file containing this information is referred to as the *premise report*. The premise report is a CSV file that is used to extract the mappings between transformers, feeders, and premises. Another essential input is the *EV adoption scenario file*, which includes columns detailing EV charging events, such as parking durations, energy demands, charging power levels, and EV types. The adoption file also includes vehicle IDs for each charging event, generated by the travel analysis and mapped to specific premises and transformers within a given feeder.

Both Lite and Plus modes use the premise report and adoption scenario files as inputs, but also require additional files for running a new simulation, which are detailed in their respective sections below.

7.2 Lite Mode

In the *Configurations* page shown in Fig. 18, the user can select the feeder from a dropdown list, which is populated directly from the premise report. EVI-DiST currently offers seven different EV charge control options, reflecting the SCM algorithms we discussed earlier in this report.

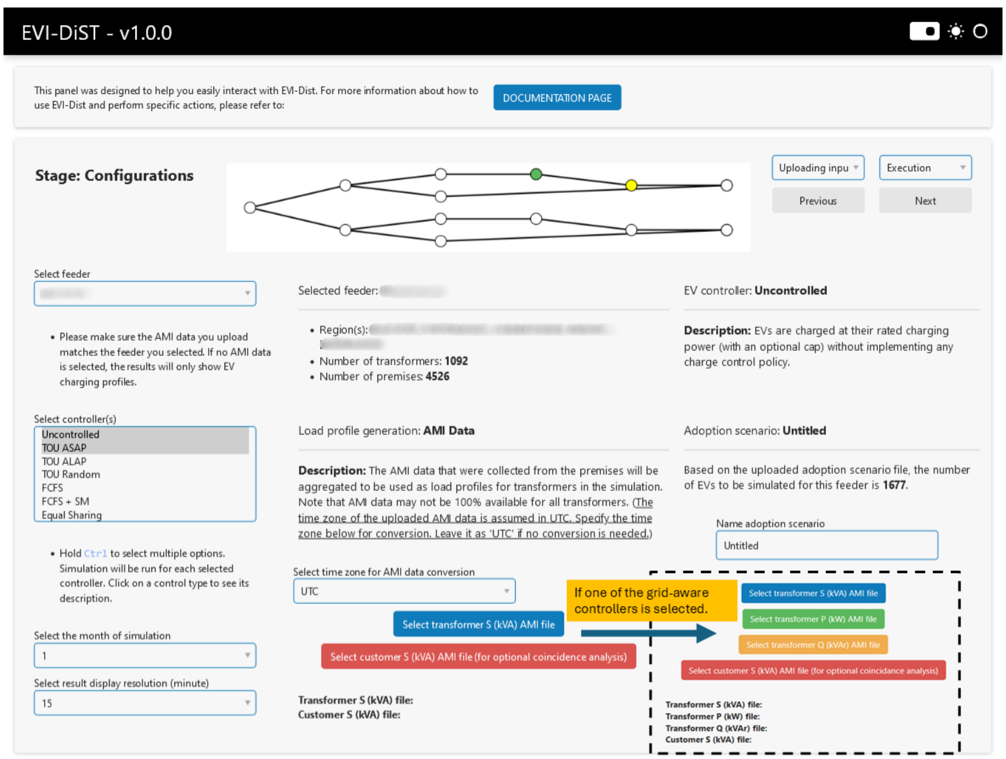


Figure 18. EVI-DiST Lite configurations page.

All simulations are run at a 1-minute resolution but can be displayed at different resolutions. By default, the display resolution is set to 15 minutes to optimize rendering performance, but it can be adjusted to a finer resolution for more detailed analysis.

EVI-DiST Lite also requires the *AMI data* for the selected feeder. The AMI data includes the aggregated baseload profiles for the transformers (represented as column names) within a specific feeder, covering a defined time period. Therefore, the user must ensure that the uploaded AMI data file corresponds to the selected feeder and that the profiles' time period includes the chosen month.

The Uncontrolled and TOU-based controllers (ASAP, ALAP, and Random) only require transformer apparent power data, while the grid-aware controllers (FCFS, FCFS+SM, and Equal Sharing) also require active and reactive power profile files. Therefore, if at least one grid-aware controller is selected, two additional buttons will appear to allow the user to upload these necessary readings. The FCFS+SM (supply minimum) controller is an additional option not described earlier. While this controller follows the FCFS principle, it also ensures that all EVs connected to the same transformer receive a guaranteed minimum share, which is adjustable by the user.

EVI-DiST Lite includes an optional coincidence analysis feature, which requires selecting customer-level AMI data using the corresponding button. This analysis is performed for each selected controller after the simulations are completed.

7.3 Plus Mode

This mode runs powerflow simulations of feeders using co-simulation with the controller and EV charging model. Running powerflow with grid-aware active control is more computationally heavy, but it provides insights into feeder loading and node voltage impacts (Panossian et al.).

The co-simulation is run within a HELICS framework (*Helics*). HELICS manages message passing and simulation execution such that different simulation tools can run, communicate with each other, and operate in a time-synchronized manner. Within HELICS, there are three modules: the powerflow module, which runs the OpenDSS model of the feeder; the controller module, which sets power limits on the EVSE within the simulation; and the EV charging module, which sets the power draw of the EV (Fig. 17). The OpenDSS module accepts power setpoints from the EV charging module and can provide data such as bus voltage, transformer loading, line currents, and net-load measurements at interconnection points. The modular framework also maintains flexibility, allowing for future work to leverage different software for any of the modules, so long as they have the HELICS wrapper and can be configured for the same inputs and outputs as the original modules. Example result pages are shown in Fig. 19. This display results page is organized into multiple sections as explained below.

7.3.1 Transformer Loading Summary

This section provides a summary of the transformer kVA loading within the feeder network as shown in Fig. 19a. A bar graph displays the total number of transformers within the feeder network (in blue) and the total number of overloaded transfomers (in red), catagorized by their kVA rating. A list of the overloaded transformer names and ratings is displayed to the right of the bar graph.

A user can configure how the transformer loading should be analyzed using the buttons and sliders above the bar graph in Fig. 19a. There are two options for the analysis to be conducted:

- *Consecutive overloading duration* will consider a transformer overloaded if the transformer was consistently and consecutively loaded above the loading cut-off value for the minimum duration time.
- *Total overloading duration* will consider a transformer overloaded if the transformer is loaded for a total combined time throughout the simulation above the loading cut-off value for the minimum duration time.

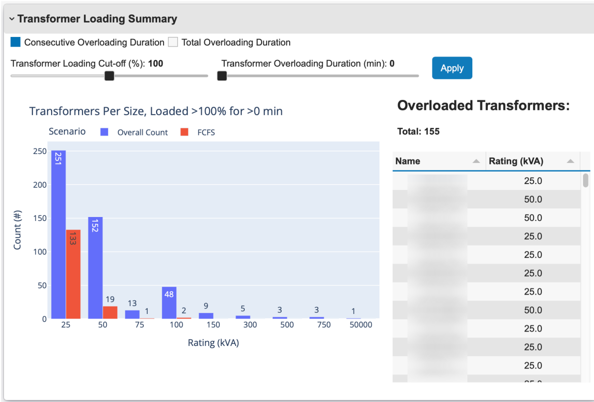
Then, the analysis presents the following:

- *Transformer loading cut-off* determines what loading level a transformer must exceed to be considered as overloaded. The value is defined as the percentage of a transformer's kVA rating.
- *Total overloading duration* sets the minimum time required that a transformer must remain loaded beyond the cut-off value to be considered as overloaded.

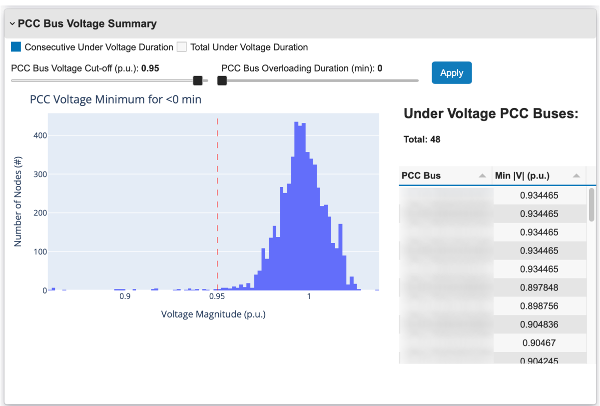
7.3.2 Line Loading Summary

This section provides a summary of the distribution line loading within the feeder network, shown in Fig. 19c. A bar graph displays the total length (in miles) of lines within the feeder network (in blue) and the total length (in miles) of overloaded lines (in red), catagorized by their line codes. A list of the overloaded line names and ratings is displayed to the right of the bar graph. Primary and secondary lines are summarized separately.

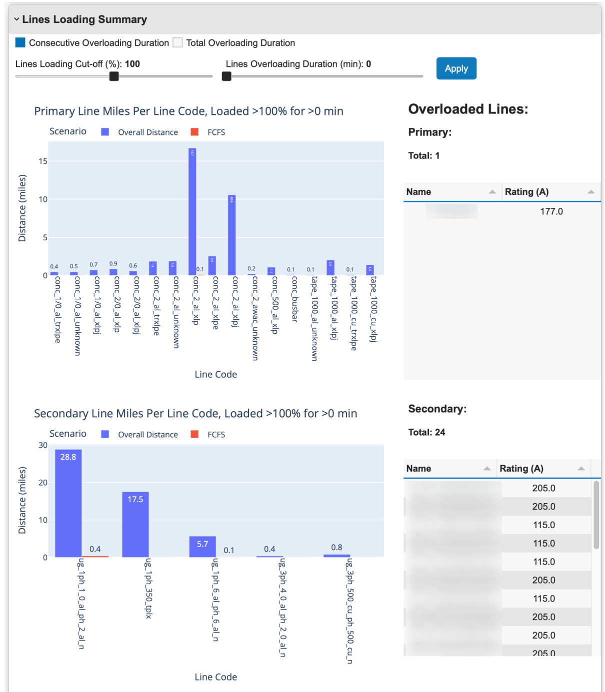
The user can configure how the line overloads should be analyzed and presented similar to the previous case. However, line loading considers the load in Ampere during the simulation and the Ampere rating of the conductors.



(a) Transformer apparent power overloading result with a bar graph, table, and customizable overloading criteria.



(b) The PCC bus per-unit voltage result with a histogram, table, and customizable overloading criteria.



(c) The distribution line current overloading result with a bar graph, table, and customizable overloading criteria.

Figure 19. An example set of results page for EVI-DiST Plus simulation.

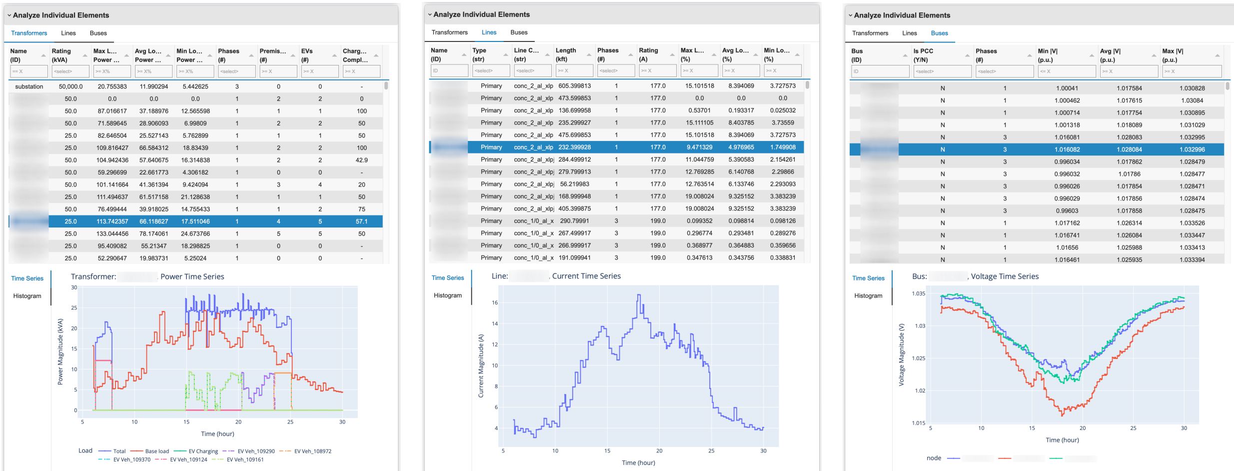
7.3.3 PCC Voltage Summary

This section provides a summary of the voltage minimums of the PCC buses within the feeder network, shown in Fig. 19b. A histogram displays the distribution of the minimum voltage of all PCC nodes within feeder. If the PCC bus has more than one phase, the lowest voltage among the phases is considered. A list of PCC buses that had a voltage below the user-defined minimum for a user-defined duration is displayed to the right of the histogram. These limits can be configured similar to the previous sections.

7.3.4 Analyzing Individual Elements

Every element within the feeder network (such as transformers, lines, and distribution buses) can be further analyzed. We can select a specific element (e.g., a single transformer) to view a time-series or histogram plot of its respective loading value. The results are shown in Fig. 20.

The *Transformers* tab lists the details of each transformer as shown in Fig. 20a. Details include the name assigned to the transformer, kVA rating, maximum load power, average load power, minimum load power, number of low-voltage-side phases, number of premises fed by the transformer, number of EVs charged by the transformer, and the EV energy satisfaction ratio. Note that the maximum, average, and minimum load powers displayed in the table are a percentage of the kVA rating. The time series plot shows total load, base load (e.g., house lighting and appliances), and the EV charging loads. Both the combined EV charging profile and individual charging profiles are shown as traces. A histogram showing the time-weighted distribution of the transformer's total load can be viewed by switching from the *Time Series* tab to the *Histogram* tab.



(a) **(b)** **(c)**

Figure 20. Viewing simulation results in detail for each category: (a) Transformers, (b) Lines, (c) Buses.

The *Lines* tab lists the details of each transformer as shown in Fig. 20b. Details include the name assigned to the distribution line, whether the line is part of the primary or secondary distribution network, line code, line length, number of phases, ampere rating, maximum load current, average load current, and minimum load current. The time series plot shows the total load current magnitudes for each phase of the line. A histogram showing the time-weighted distribution of the line's total load can be viewed by switching from the *Time Series* tab to the *Histogram* tab.

The *Buses* tab lists the details of each bus as shown in Fig. 20c. Details include the name assigned to the bus, whether the bus is a PCC, number of phases of the bus connection, minimum voltage magnitude, average voltage magnitude, and maximum voltage magnitude. The time series plot displays the voltage magnitudes of each phase of the selected bus. A histogram showing the time-weighted distribution of the bus voltage magnitudes can be viewed by switching from the *Time Series* tab to the *Histogram* tab.

8 Conclusions and Future Study

In this report, we performed a data-driven transportation energy and power demand analysis for light-duty EVs within two regions in Colorado to investigate reliable pathways to integrate the mobility demand into a residential distribution network. We explored possible effects on distribution transformer loading and identified potential wider grid impacts of increased EV adoption using data for selected Colorado feeders.

This study illustrates that SCM methods may significantly affect how utilities adapt to increasing EV loads—some SCM strategies may in fact exacerbate negative grid impacts, relative to uncontrolled EV charging, while others may alleviate grid impacts. Utilities can carefully use SCM methods to reduce load coincidence across both EV and non-EV loads. Our results show that both uncontrolled and TOU-based SCM strategies notably increase the number of overloaded service transformers and total duration of overloads. In contrast, grid-aware active SCMs manage EV charging load in a manner that considerably reduces transformer overload events. However, due to transformer capacity limits, some EV owners may not fully meet their energy needs. For one of the investigated feeders, our results show that both grid-aware active SCMs (FCFS, ES) can satisfy over 94.5% of charging events.

Ultimately, a detailed cost-benefit analysis would be warranted to determine if implementing a particular SCM strategy is a worthwhile investment, considering its field practicality, implementation costs, and user enrollment success. Future evaluations should also consider more coordinated controls with load forecasting capabilities.

This study also introduced a new NREL-developed tool, called EVI-DiST, which enables grid impact evaluation of EV charging and SCM at both the transformer and feeder levels. EVI-DiST provides an open environment to utility engineers and researchers to integrate various data inputs and perform quick and detailed EV grid integration analysis. With EVI-DiST, utilities can conduct similar studies and can take advantage of the tool to understand their systems' capabilities and future needs and reassess frequently as system forecasts evolve. This project shows that the tool has been applied in real-world conditions and is a valuable resource for any utility in the country.

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