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Uncontrolled Electric Vehicle Charging Impacts on Distribution Electric Power Systems with Primarily Residential, Commercial or Industrial Loads

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Abstract: An increase in Electric Vehicles (EV) will result in higher demands on the distribution electric power systems (EPS) which may result in thermal line overloading and low voltage violations. To understand the impact, this work simulates two EV charging scenarios (home- and work-dominant) under potential 2030 EV adoption levels on 10 actual distribution feeders that support residential, commercial, and industrial loads. The simulations include actual driving patterns of existing (non-EV) vehicles taken from global positioning system (GPS) data. The GPS driving behaviors, which explain the spatial and temporal EV charging demands, provide information on each vehicles travel distance, dwell locations, and dwell durations. Then, the EPS simulations incorporate the EV charging demands to calculate the power flow across the feeder. Simulation results show that voltage impacts are modest (less than 0.01 p.u.), likely due to robust feeder designs and the models only represent the high-voltage ("primary") system components. Line loading impacts are more noticeable, with a maximum increase of about 15%. Additionally, the feeder peak load times experience a slight shift for residential and mixed feeders (≈1 h), not at all for the industrial, and 8 h for the commercial feeder.

Keywords: electric vehicle; charging; integration; grid impacts; distribution; profile

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1. Introduction

Adoption of electric vehicles (EV) for personal use is increasing, resulting in higher demands on distribution electric power systems (EPS). Understanding and preparing for changes could prevent disruptions and enable utilities and stakeholders to anticipate options for adaptation. Recent advancements in technology [1] (e.g., lithium ion batteries [2], temperature management [3], etc.) and government incentives are contributing to the increase in the number of EVs charging on distribution EPS today. Growth estimates project that 12 million EVs globally will require EPS power to charge their batteries by 2025 [4]. It is evident that EV battery and powertrain innovations are making widespread electro-mobility a reality, yet much is unknown about how EPS will respond to extreme EV adoption.

Future EV charging scenarios, if uncontrolled, could cause thermal line overloading or voltage violations [5]. And, EVs are expected to account for a significant portion of residential demand and annual energy [6]. To understand the potential impacts of uncontrolled adoption scenarios, this effort considers home- and work-dominant charging situations. The home-dominant case assumes that EV users charge their vehicles primarily at home. In the work-dominant case, sufficient EV infrastructure exists at the work for personal vehicle charging during normal business hours. The home and work charging scenarios result in load profiles that policy makers and grid operators can review when considering EV Supply Equipment (EVSE) incentives and grid infrastructure planning.

Because EV patterns are a function of human activity, the EPS impact is transient but predictable. Simulations that explore the impact of home- and work-dominant charging on different feeders highlight the opportunity for controls. This requires an understanding of the distribution EPS's response at different EV charging levels. This work includes simulations where EVs are added as loads and OpenDSS software performs the power flow calculations.

This distribution system impact study includes a realistic representation of EV charging needs, battery performance, and the grid. The accumulation of the three aspects, under the Department of Energy (DOE) funded RECHARGe project [7], builds upon previous EV and grid research that used the IEEE 34 bus system as a demonstration feeder [8]. This work simulates realistic EV battery charging on the grid using projects from the Electric Power Research Institute (EPRI) 2030 high scenario [9]. To emulate the driving behaviors, and thus the battery charging needs and locations, this work incorporates the EV supply equipment analysis tool, known as EVI-Pro [10], to predict the adoption levels and driving patterns of individuals within ten real world distribution EPSs in an urban U.S. city. Then, an EV battery simulation software determines the power draw for each vehicle. Finally, an EPS models use the EV data to simulate power flows. The results from the study compare the profiles and system performance (i.e., voltage and current loading) of distribution systems supporting different load types accounting for various EV impacts.

Past literature documents the effects of EVs on similar systems by examining costs and carbon emissions impacts on the German power grid [11], reviewing potential EV demand profiles in different locations [12], or assessing changes on residential EPSs caused by different EV adoption levels [13] and the impact of controls on the IEEE 34 bus system [14]. Other work assesses EV integration impacts using a probabilistic model to define EV integration [15] and stochastic integration methods to identify voltage control needs [16]. Past literature also uses probabilistic models to estimate EV load profiles; Zhang et al. estimated and compares EV load profiles for various driver demographics [17]. Another research project describes a Monte Carlo methodology to simulate the EV charging profiles and then assess the change in the bulk systems electrical load [18]. However, none of the past work provide a detailed assessment of multiple distribution systems supporting different load types. This study builds on previous research and fills gaps by modeling the impact of EVs on EPS comprised of specific load types (i.e., residential, commercial, and industrial), accounting for their daily patterns. Much of the past work does not stipulate or compare different integration types nor do they examine the EV and feeder demand profiles in significant detail. The findings of this study refine predictive impacts to the EPS and can inform and enable strategies for mitigating grid issues.

The primary contribution of this work is to describe the potential impact, based on a co-simulation effort, of two uncontrolled EV charging scenarios (home- and work-dominant) on different types of distribution EPSs. This work advances beyond previous works by:

1. Combining realistic EV adoption levels, driving patterns, battery charging time series, and electric power flow simulations to evaluate grid impacts.
2. Illustrating the difference between home- and work-dominant EV charging types.
3. Showing the impact of home vs. work charging scenarios on feeders with different mixes of residential, commercial, and industrial loads to highlight differences.

This paper is organized into two main sections: Methodology and Results. The Methodology section describes the overall approach using a block diagram of the different elements and provides details on the EPS characteristics and types; it describes the method for defining the EV adoption levels and driving behaviors; and defines the co-simulation environment. The Results section defines each feeder's classification, reviews the feeder and EV load profiles, and describes how the profiles combine on average for each feeder subjected to home- and work-dominant charging scenarios. The results also provide insight into how the EV charging changes spatially at the respective EV peak power demand. Finally, the results section concludes with a summary of each feeder's voltage and line overloading performance.

2. Methodology

The electric grid assessment focused on 10 real-world distribution feeders from a major metropolitan area in order to evaluate a diverse but relatable cross-section of feeders. The analysis included power flow simulations for each feeder using OpenDSS software, the simulation process is depicted in Figure 1. It included the pre-processing of grid data to understand feeder characteristics and support grid simulations. The EV charging simulations were based on EV adoption projections coupled with GPS-based driving patterns. This resulted in EV charging demand estimates at 5-min intervals (described in Section 2.2). The EV charging projections (location and power consumption inputs) were then added to the OpenDSS simulations at specific nodes on the feeder. The simulation results provided evidence as to how EPS demand profiles will change, and the impact EVs have on the feeder's voltage and line loading.

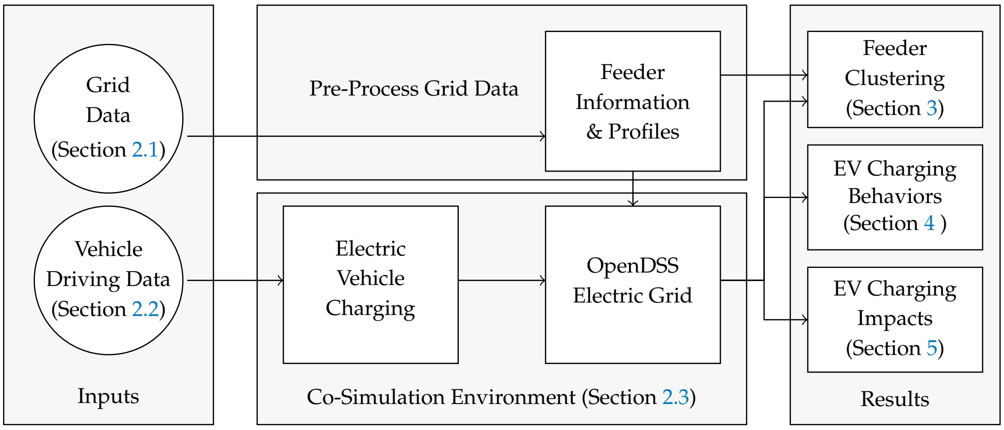


Figure 1. The block diagram describes the experimental process that began with grouping the feeders based on load data. A co-simulation environment emulated electric vehicle (EV) charging and EPS power flows. The simulations used grid and vehicle driving data as inputs. The grid data and simulation results output demand profiles and feeder performance for distribution EPS supporting various types of loads and EV adoption levels.

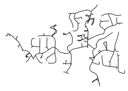
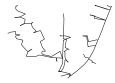
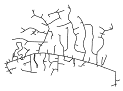
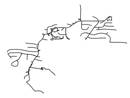
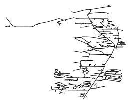
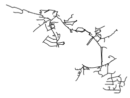
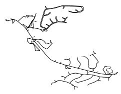
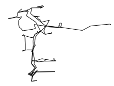
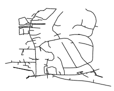
2.1. *Electric Feeder Characteristics & Load Types*

Models for each of the 10 study feeders were implemented in the distribution power flow simulation software OpenDSS. The study feeders operated at a base voltage of 19.8 kV, except feeder 10 which was at 25 kV. The OpenDSS model did not include the secondary (low-voltage) lines which connect service transformers to customer loads. Therefore our simulations only evaluated the primary (high-voltage) distribution systems' operations.

Table 1 provides an overview of each feeder, and the number of customers broken out by load type. Feeders 1, 2, 3, 4, 7, and 10 have a high percentage of residential customers, while feeders 5 and 8 have higher percentages of commercial and mixed-use loads. Feeders 6 and 9 mostly have larger commercial and industrial loads. Together these 10 feeders provide a good proxy for a comprehensive look at EV impacts across different parts of an average American city. Past grid related studies used utility-provided data in a similar manner to understand system performance, such as distributed photovoltaic array hosting capacity evaluation [19] and a EV hosting capacity analysis [16].

The feeders' peak loads ranged between 6 and 17 MW, as shown in Figure 2. Each feeder had a different percentage of load by customer type. Note that the percentage of customers did not equal the percentage of load associated with the particular customer. For example, the number of commercial customers on Feeder 3 was about 16% of the total customers on the feeder, but had close to 47% of the total load. Another example was seen on Feeder 6, where industrial loads accounted for only 12% of the customers, but were around 50% of the total load.

Table 1. Feeder Customer Details.

	Number of Customers						Number of Customers				
	Res.	Comm.	Ind.	Mixed			Res.	Comm.	Ind.	Mixed	
1	887	31	0	75		6	0	44	7	9	
2	555	66	0	41		7	1144	102	0	77	
3	2364	540	4	354		8	1283	183	1	1028	
4	1018	23	0	57		9	0	59	0	3	
5	408	264	0	391		10	3014	429	14	235	

The categorization of the different feeders into four groups involved a clustering analysis that considered the ratio of customer types and the associated aggregated loads. Using the information described in Table 1 and the corresponding total loads depicted in Figure 2, a K-means clustering algorithm [20], implemented in [21], was used to evaluate these features and identify similarities amoung the 10 feeders. The algorithm segmented the feeders into 4 groups in hopes of identifying the primary load (i.e., residential, commercial, industrial, or mixed) supported by each system. The clustering allowed for the feeders to be grouped by load demand similarities so that comparisons of the simulation results would be more thorough and consistent. The K-means algorithm was used for this application because a desired set of clusters could be pre-defined by the user; the methodology desired a total of 4 groups: residential, commercial, industrial, and mixed.

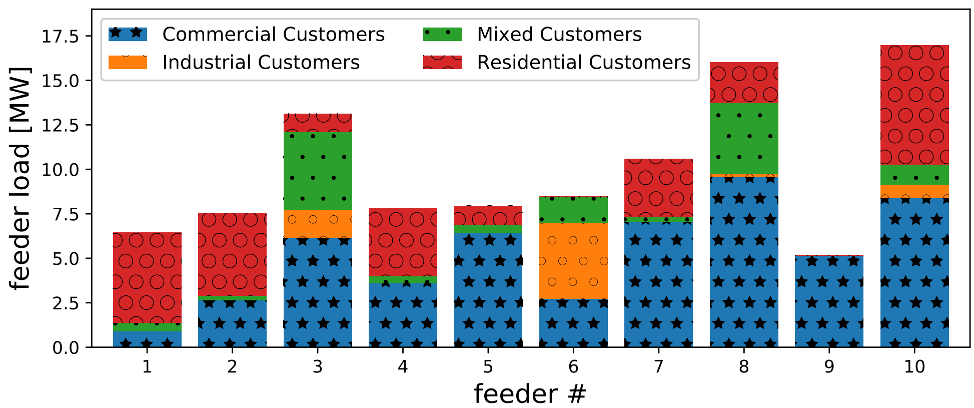


Figure 2. Each feeder had various levels of commercial, industrial, mixed, and residential loads.

The power profiles were normalized to a common mode, which allowed for the comparison of feeders of the same type but different magnitudes, using Equation (1) [22]:

$$z_{\text{i}} = \frac{x_i - min(x)}{max(x) - min(x)} \tag{1}$$

where x_i was the numerical value at instances i, x was the power profile, min(x) and max(x) computed the minimum and maximum values over a full year, and z_i was normalized value at i. The normalization transformed the average profile of each feeder to a value between 0 and 1. This allowed for direct comparison between the feeder loads, EV loads, and feeder plus EV loads.

2.2. Electric Vehicle Adoptions & Driving Behavior

The EV driving data represented realistic patterns of individuals that reside or work within the spatial extent of the 10 study feeders described in Section 2.1. The EVI-Pro tool estimated the driving behavior based on existing EV adoptions and future EV use projections [23]. Similar to the analysis performed for Columbus, Ohio [23], this assessment estimated EV adoptions by considering actual EV and plug-in vehicle registrations. Then, using market analysis that predicts future growth, such as the EPRI study [9] and Bloomberg Electric Vehicle Outlook [24], existing adoptions were scaled to emulate 30% growth projected to occur by 2030. Finally, the new EVs were assigned to locations using spatial growth estimates that considered the existing registration data.

To estimate travel patterns of the EVs, the EVI-Pro tool leveraged INRIX GPS travel trajectories. The travel trajectory data included travel times and the GPS coordinates associated with the start, stop, and intermediate locations. These travel data determined the type and location of EVSE infrastructure, as well as EV battery charging needs based on distance traveled. Using the GPS input data, the EVI-Pro tool defined the EV charge start and departure times, and the location of each charge event. This charge event schedule provided the simulation with the parameters necessary to calculate the charging time series and location for each EV.

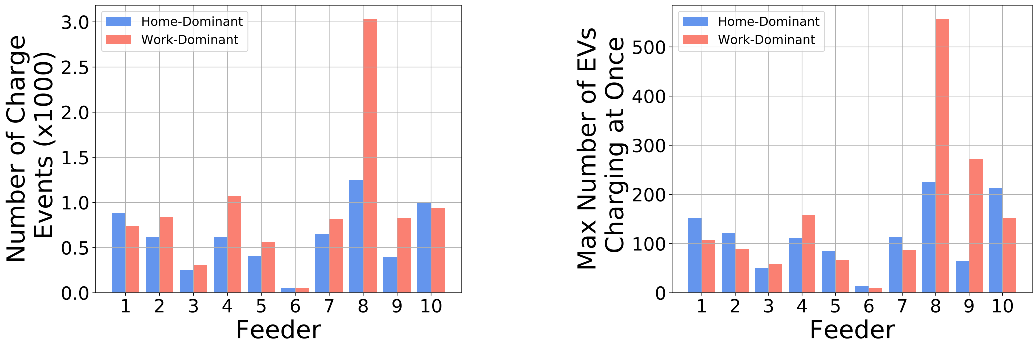
The analysis included two types of charging scenarios:

1. Home-Dominant: Each residential node where an EV parks was assumed to have an EVSE. This scenario includes a small amount of work and public charging, but non-residential charging is only utilized if the EV did not dwell at a residential location (e.g., vehicle owners who live in an apartment complex within an urban downtown area which is not categorized as a residential).
2. Work-Dominant: Any EV that dwelled in an area deemed to be a place of work will charge while parked until it leaves or reaches a full state of charge. The same EV will also charge at home, but the charge acquired at the work will offset much of the home energy needs.

Five light duty EV charger sizes were considered, ranging from 3.6 kW to 11.5 kW, though the vast majority were either 7.2 kW or 9.6 kW level 2 chargers. Eight different types of EVs were modeled based on the specifications of current and anticipated future EV models: batteries ranged from 5 kWh to 95 kWh. An EV with a 95 kWh battery and charge rate of 9.6 kW was the most common vehicle in the simulation, though large battery vehicles (>50 kWh) were simulated about as often as small battery vehicles (<50 kWh).

EVs were simulated over one 24-h period representing a weekday. A typical vehicle commuted to work in the morning, dwelled at work during the day, and returned home at night, perhaps stopping in a commercial area during the day. However, since all travel information was based on actual GPS measurements, the inventory included many "atypical" vehicles, such that dwelling at any type of charger (residential, work, or public) at any time of day was possible. Every EV with a state of charge less than 100% charged during the 24-h period. All vehicles were returned to their original location by the end of the 24-h period. During the 24-h period, each vehicle charged an equivalent amount to the distance that it traveled during the 24-h. Thus, both the locations of vehicles and the battery states of charge were identical at hour 0 and hour 24.

The EV charging data used as inputs into the grid model varied depending on the feeder. For example, the total number of charge events ranged from around 50 on feeder 6 to about 3000 on feeder 8 as depicted in Figure 3a. Most of the feeders (except for feeders 1 and 10) had a higher number of charge events for the work-dominant scenario. Another explanation of the data, depicted in Figure 3b, highlights the scenario where the most amount of EVs were charging at the same time. Just over half of the feeders experienced higher number of charging events at once under the home-dominant case.



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

Figure 3. The number of electric vehicles (EV) charging on a particular feeder was different for the home- and work-dominant scenarios. (**a**) The number of EVs charge events ranged from 50 to around 3000. (**b**) The maximum number of EVs charging at once was lowest (≈6) for feeder 6 and high above 500 for feeder 8.

2.3. Co-Simulation Environment

Two simulators ran simultaneously, one modeling the behavior of the distribution EPS and one modeling the EV battery charging behavior and rate. EV battery charging depended on driving patterns provided by EVI-Pro and high fidelity EV charging models derived from extensive charging and battery testing conducted at Idaho National Laboratory [25]. The output of the charging simulation was the real and reactive power consumed by each EVSE. These loads were added to an OpenDSS simulation of the EPS that includes true historical load profiles for non-EV loads and the power flow across the feeder is calculated. Voltages at busses with EVSEs were then passed back to the battery charging simulation and used for calculating the power demands at the next time step. The co-simulation used three inputs: vehicle and charger data produced by EVI-Pro, an OpenDSS model of the study feeder, and the load on the study feeder without EVs. The environment then outputs the combined EV and feeder demand.

The simulation depended on a set of assumptions for how the EV charging and electric grid functions. The physical mapping assigned each residential and public EVSE from EVI-Pro to the closest bus on the study feeder with an existing load. Any EVSEs 200 m or further from the feeder were not considered, as the distance from the primary distribution lines (modeled here) to the customer meter is rarely more than 200 m.

To simulate the grid, OpenDSS used the grid topology information and feeder load profiles for a 24-h period. The examination of worst case scenarios used the peak load days extracted from a data set of feeder load over a one year period. The simulation code converted the load data to a percentage of the maximum value; the rated capacity of each (non-EV) load on the feeder was then multiplied by the percentage to define the load magnitudes, allowing for a temporal analysis. At 5-min intervals the non-EV and EV loads were updated and solved in the OpenDSS simulation software. The environment used the *opendssdirect* package in Python to retrieve and then record the systems results at each interval.

3. Feeder Clustering

As a first step, the K-means clustering analysis performed a quantitative characterization of each feeder. The algorithm grouped the 10 feeders into one of four categories based on its dominant load type: residential, commercial, industrial, or mixed, as seen in Figure 4. The feeder clustering depended on the number of loads and the amount of power demanded for each customer type. Therefore, the name of each cluster represents the most significant type of load that each feeder serves. The cluster results illustrated in Figure 4 using the first two Principal Components from a principal component analysis of the eight features (i.e., customers (#) and load (kW) across the four customer types (residential, commercial, industrial, and mixed)). Figure 4 describes the K-means-defined clusters with ellipses to clearly show which feeders fall into the residential, commercial, industrial, and mixed clusters. The groupings based on this clustering analysis were then used in the following sections to identify trends in similar feeders.

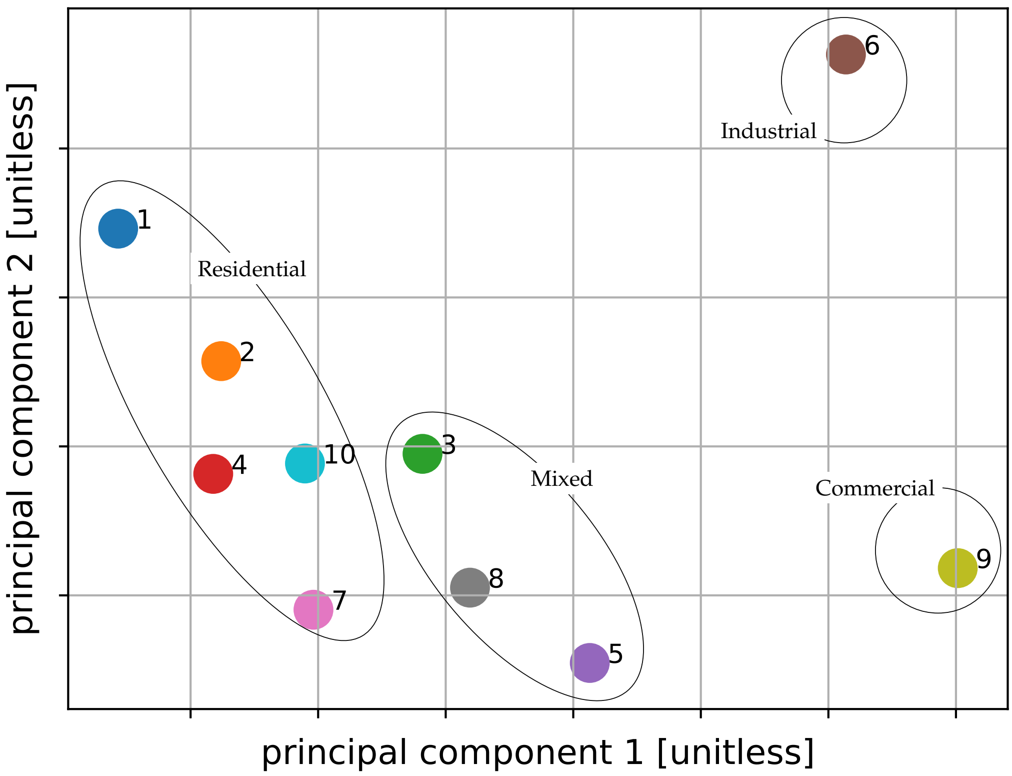
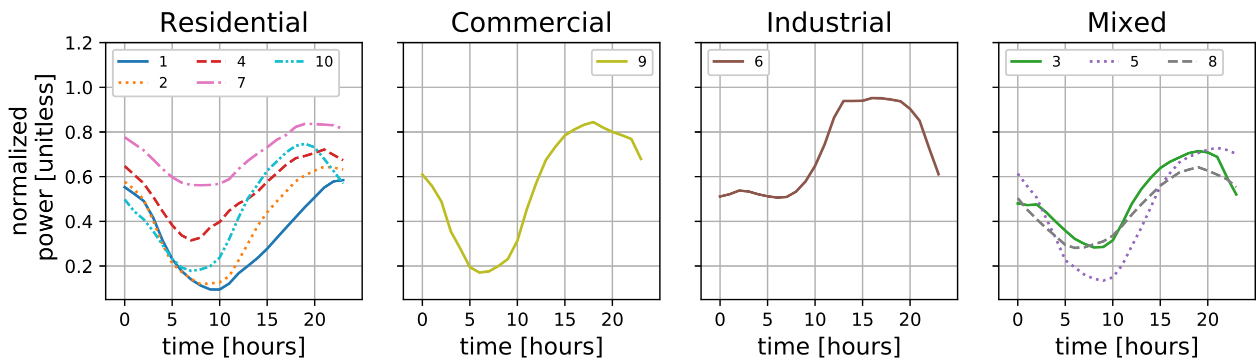


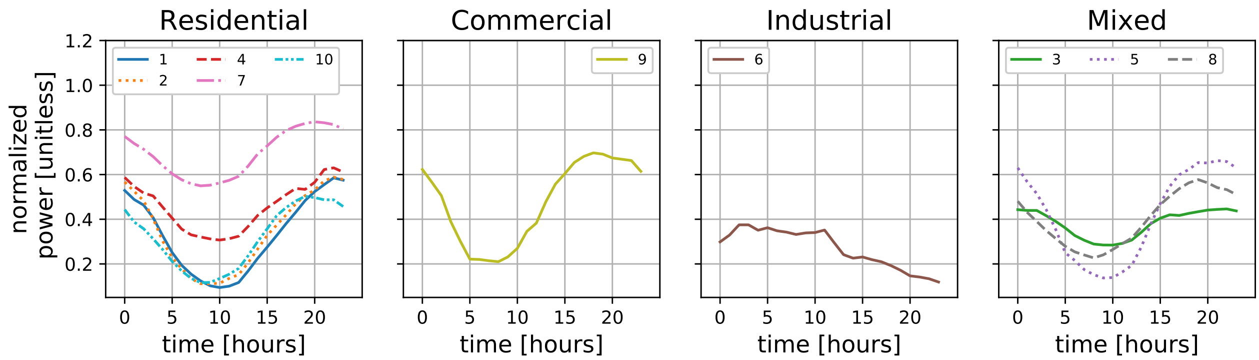
Figure 4. The classification of each feeder (indicated with the numerical label) depended on the the number and amount of demand for each load type. The K-means clustering algorithm grouped them into four categories. The first two principal components for each feeder provided a means to visualize the multidimensional data to describe the K-means algorithm results.

Examination of typical load profiles for weekday (Figure 5a) and weekend (Figure 5b) operations provided supporting evidence to help confirm the clustering results. Feeders labeled as residential experienced a low between hours 8 and 10 in the morning and high around hour 20. The three feeders in the mixed category had a slightly different peak around hour 17 for weekday operations and shifted to around hour 20 during the weekend. It was evident that the feeders within residential and mixed clusters were influenced by both residential and commercial loads.

The weekday and weekend profiles for feeders 6 and 9 show operations not influenced by residential loads. In contrast with feeders supporting primarily residential or commercial loads, the industrial system did not have a significant valley (or low point) in its profile. In addition, the profile experienced a significant drop in power and remained relatively flat throughout the day during the weekend. The commercial feeder's profiles observed during weekday and weekend operations each had a minimum that occurred around hour 6 and peak at hour 17. These trends clearly showed the strong influence of the commercial and industrial loads on these two feeders.



(**a**) Weekday average profiles



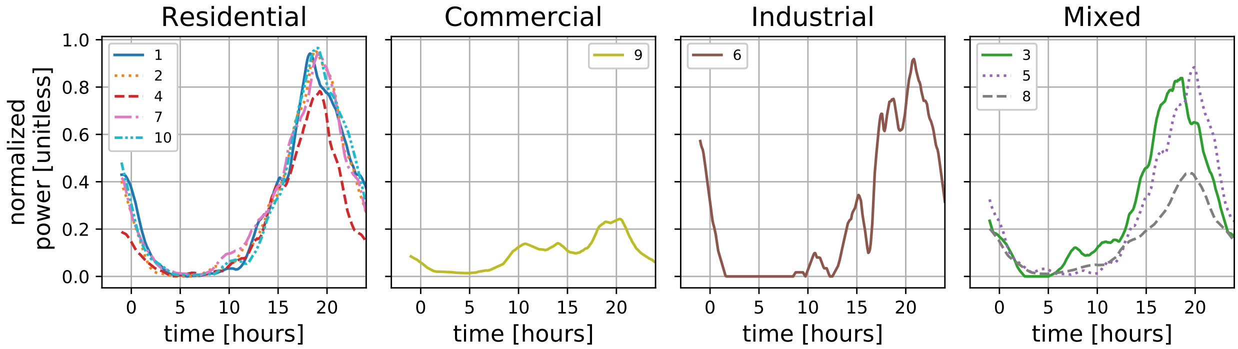
(**b**) Weekend average profiles

Figure 5. The typical (average) profiles for each feeder during the (**a**) the weekdays and (**b**) weekend days. For each feeder type, the overall demand tended to be smaller on weekend days compared to weekdays. Exceptions included systems that supported mostly residential loads (e.g., Feeder 1).

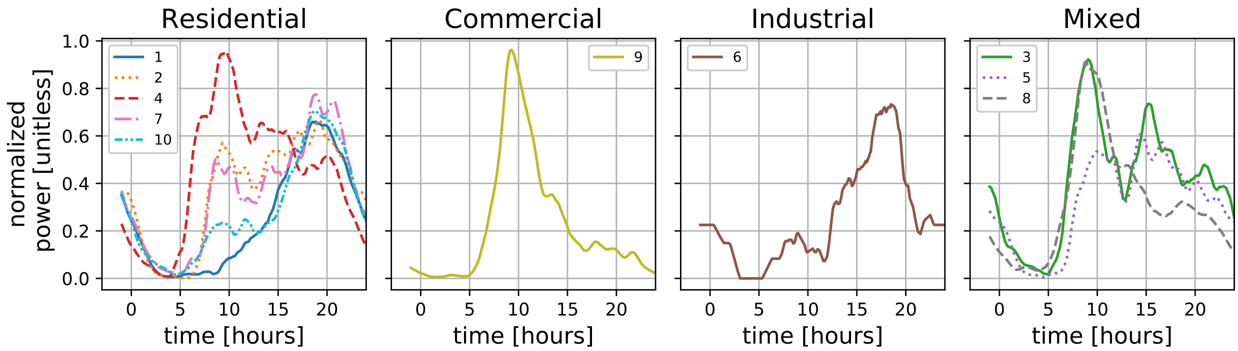
4. Electric Vehicle Charging Behaviors

4.1. Electric Vehicle Charge Profiles

The majority of the EV charge profiles followed two distinct patterns based on the feeder classification and charging scenario. The first pattern type resembled a triangle centered at hour 19 in the home-dominant case for residential and mixed feeders (Figure 6) and at hour 9 in the work-dominant scenario for Feeders 8 and 9 (Figure 6b). The second pattern type can be observed in the home-dominant charge scenario on the commercial feeder, which looks like a chair with a sitting area that starts at hour 10 and ends at hour 16, followed by a sharp spike (Figure 6a). A reversed version of this chair-like pattern can be seen in the work-dominant scenario on most of the residential and mixed feeders (Figure 6b). The charge profiles varied between the home- and work-dominant scenarios: the residential feeders evening magnitudes decreased and some of their peaks shifted to the middle of the day; the commercial feeder peak increased dramatically and shifted to the morning; a slight change in the industrial peak time was observed between the two scenarios; and each of the feeders in the mixed category experienced a shift in the peak time with a slightly higher magnitude in the work-dominant case.



(**a**) Home-dominant scenario charge profiles



(**b**) Work-dominant scenario charge profiles

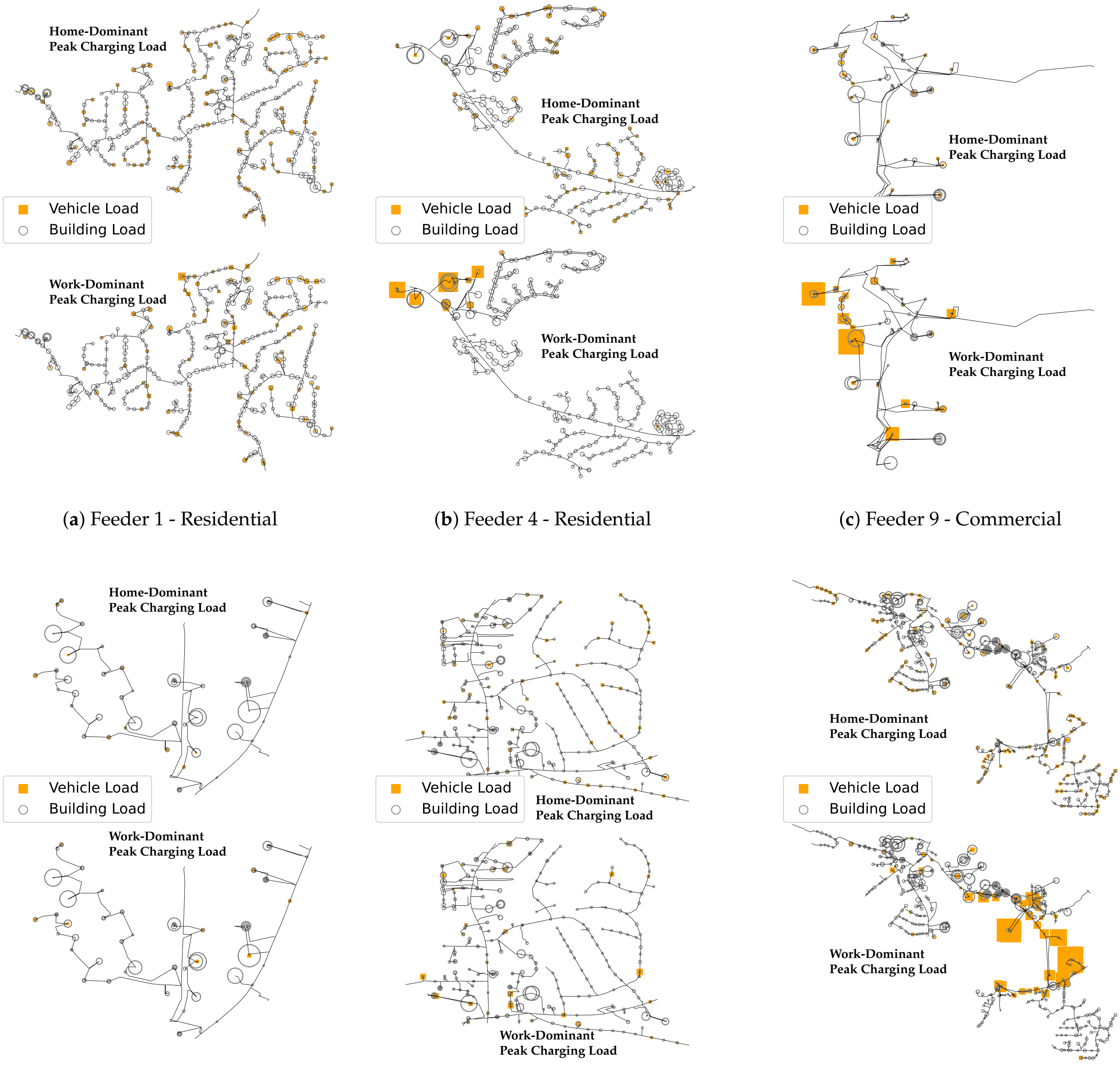
Figure 6. The EV charging demand profile changed dramatically from the home to the work-dominant scenarios when the feeder supported commercial loads. (**a**) The home-dominant scenario produced similar profiles for feeders designated as residential, industrial, and mixed. The commercial feeder had a significant amount of charging that occurred during the day. (**b**). In the work-dominant charging case, some profiles did not change, but others with substantial commercial loads had a shift in the peak which moved from the evening to the middle of the day.

4.2. Electric Vehicle Peak Charging Locations

Figure 7 depicts the building and EV loads spatially during peak EV loading under the home- and work-dominant scenarios for Feeders 1, 4, 9, 6, 5, and 8; the two load types—EV and building loads—in Figure 7 have markers that correspond with the size of their loads. Both EV and building loads have the same scale in the plots to allow for direct comparison. The subfigures include both home- and work-dominant results delineated by labels. The feeder maps highlight the differences among the feeders within similar classifications defined earlier in Section 3 and compares the home- and work-dominant scenarios.

There was relatively little difference between the home-dominant and work-dominant scenarios for Feeder 1 (Figure 7a), as it is almost entirely a residential feeder so there are few work chargers. In contrast, residential feeder number 4 had significant amounts of charging distributed throughout the feeder under the home-dominant scenario, but transitioned to very little charging at homes and a large amount at commercial centers at the feeder peak as shown in Figure 7b. Comparing differences between feeders 1 and 4 showed how home- and work-dominant charging locations may differ even on Feeders with primarily residential loads.

Commercial Feeder 9, shown in Figure 7c, had significantly more EV demand in the work versus the home-dominant scenario, as expected due to the significant amount of commercial loads that existed on the feeder. Industrial Feeder 6 did not have much EV loading in either the home-dominant or work-dominant scenarios (Figure 7d). Mixed use Feeder 5 resembled the residential feeders, which relatively little change between home-dominant and work-dominant scenarios (Figure 7e). Mixed use Feeder 8 (Figure 7f), on the other hand, had a notable difference between home-dominant and work-dominant EV charging, which resembled the commercial feeder's behavior.



(**a**) Feeder 1 - Residential (**b**) Feeder 4 - Residential (**c**) Feeder 9 - Commercial

(**d**) Feeder 6 - Industrial (**e**) Feeder 5 - Mixed (**f**) Feeder 8 - Mixed

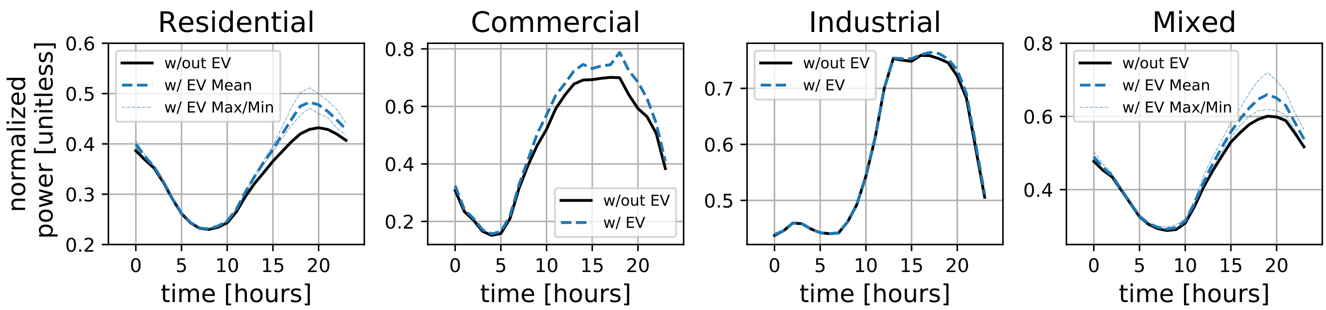
Figure 7. The feeder maps depict the Electric Vehicle (EV) charging locations at the home- and work-dominant peaks for the respective feeders. Notable findings include the following: the two residential feeders, Feeders 1 (**a**) and 4 (**b**), experienced different EV charging behaviors; the commercial feeder (**c**) had a significant increase in the amount of charging at commercial loads; (**d**) Industrial Feeder 6; the mixed use feeders also had varied spatial results where Feeder 8 (**f**) had a significant number of EV charging at one location and Feeder 5 (**e**) did not have as significant of a change between the two cases.

5. Electric Vehicle Charging Impacts

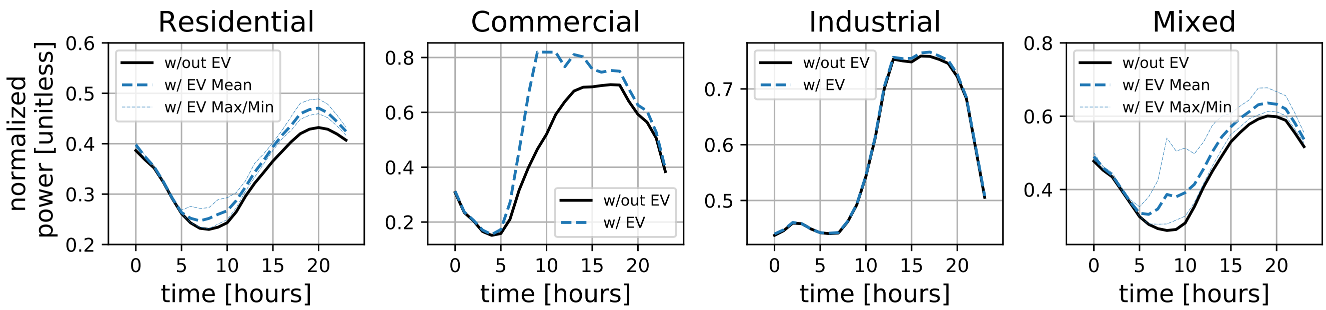
5.1. Feeder plus Electric Vehicle Charging Profiles

On average, the load profile changes depended on the feeder's classification. Figure 8 describes the observed changes by plotting the average normalized power with and without EVs added to the existing loads. The boundary around the profile with EVs added describes the minimum and maximum of the feeder within the cluster; the commercial and industrial feeder classes only had one feeder in each and therefore did not produce a minimum and maximum profile.

The home-dominant case added very little load during the middle of the day, but increased the load by a notable amount in the evening when the residential, commercial, and mixed use feeders were already at peak load without EVs, as shown in Figure 8a. This peak load, which often occurred around hour 20, increased by 11.7% and 9.8% on average for the residential and mixed feeders respectively. The commercial feeder experienced a larger increase 12.4% beyond the original peak. The industrial feeder had little change, with an increase of only 0.7%, since there were no residences and limited public charging opportunities on the industrial feeder.



(**a**) Feeder profiles with and without home-dominant EV charging.



(**b**) Feeder profiles with and without work-dominant EV charging.

Figure 8. The impact of the Electric Vehicle (EV) charging profiles on the overall demand varied between the home- and work-dominant scenarios. The plots in subfigures (**a**,**b**) describe a potential change in the average feeder profile for the residential, commercial, industrial, and mixed systems. The figures highlight the average change for each group using the dashed line and the minimum/maximum potential change with the small dotted line. (**a**) The home-dominant case tended to increase each feeder type's peak, which usually occurred between hours 17 and 20. (**b**) The work-dominant EV adoption strategy showed an increase in charging throughout the day for the residential feeders, a significant increase in the daytime charging for the commercial and mixed feeders, and no change in the industrial feeder.

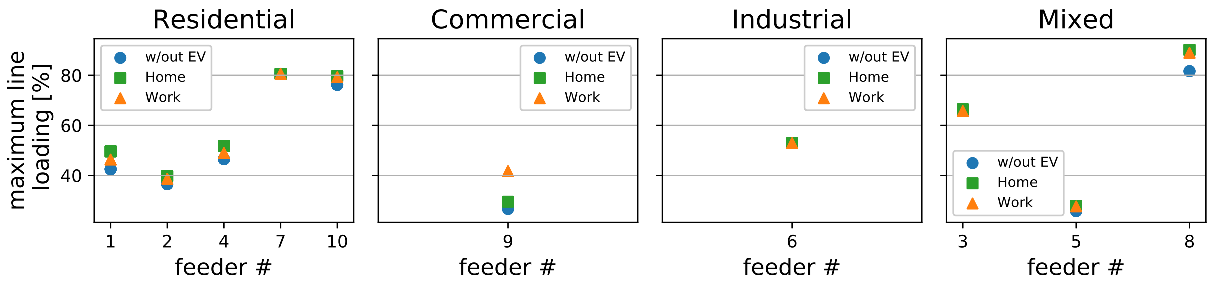
Under the work-dominant charging scenario, each of the feeders experienced an increase in EV loads both during the middle of the day and during the evening peak (Figure 8b). Due to the proliferation of midday workplace charging, each feeder type had a smaller amount of EV demand during the evening peak. On average, the residential feeders increased the evening peak by only 8.9%, and mixed use feeders increased by only

5.8%—both of these were smaller than the increase in peak load seen in the home-dominant charging. The commercial feeder, conversely, had a larger increase in peak load, as the large amount of work charging created a new midday peak-peak load increased by 16.9% and shifted to around 10AM. The industrial feeder again had little change in load profile (0.95%), since there were no residences and few public or workplace charging opportunities.

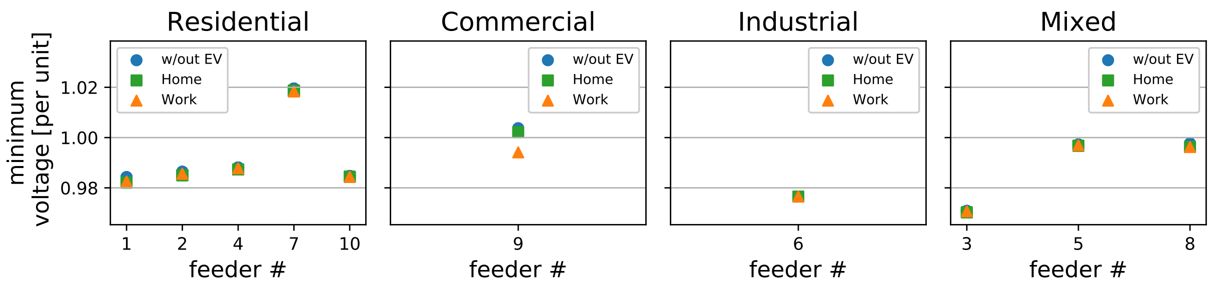
5.2. Feeder Performance

The 10 study feeders exhibited robust characteristics, meaning that they typically had significant available capacity and were far from voltage or thermal limits prior to the incorporation of EV loads. The percent line loading relative to the line's thermal limit (Figure 9a), and the minimum system voltages (Figure 9b) described the impact of EVs on each distribution EPS.

The change in the distribution system performance when adding EVs varied depending on the feeder classification and the EV charging scenario, Figure 9a provides an illustration of this. Simulations of residential and mixed feeders all had home-dominant EV adoption power demands that caused the line loading values to be greater than the work-dominant case or did not show a notable change (i.e., Feeder 7). The commercial feeder's greatest line loading value occurred under the work-dominant scenario. The industrial feeder experienced a small increase in EV load that resulted in an insignificant change in the line loading.



(**a**) Maximum line loading percentage for each system by feeder type.

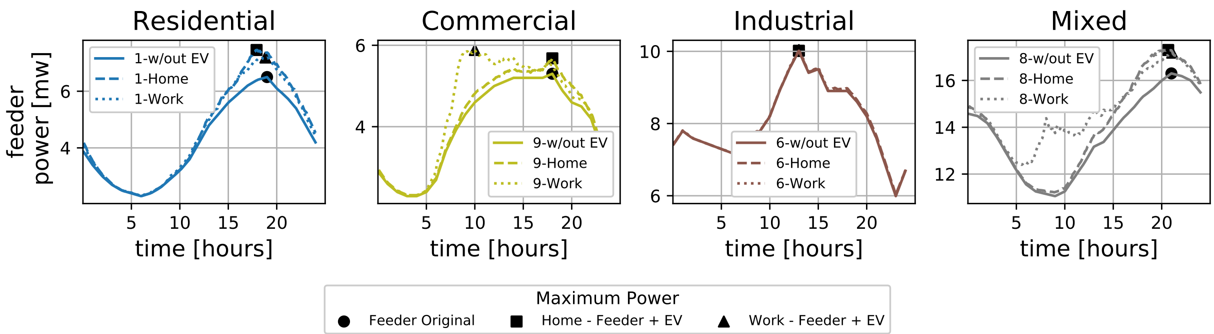


(**b**) Minimum voltage for each system by feeder type.

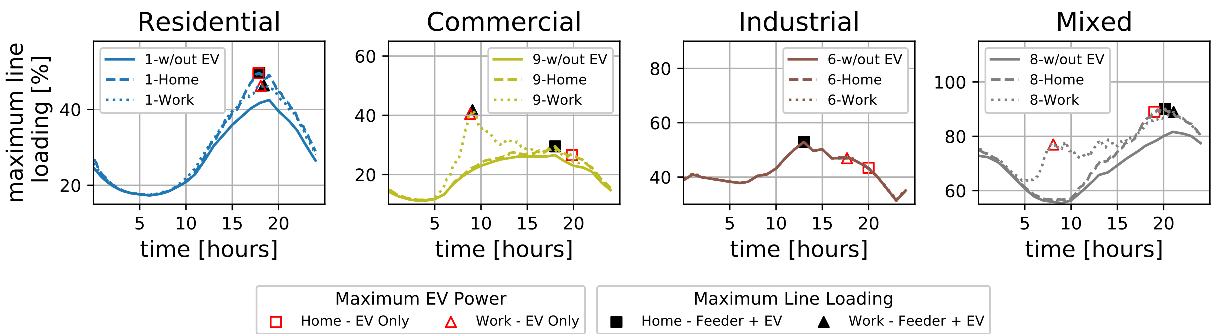
Figure 9. Each feeders' performance varied slightly when subjected to the home and work-dominant Electric Vehicle (EV) charging scenarios. (**a**) increases in the maximum line loading tended to be largest in the home-dominant case for residential and mixed use feeders, and the work-dominant impacted the commercial feeder the most. (**b**) The EV chagrining had very little impact on each of the feeders' voltage; The most significant change occurred in the commercial feeder under the work-dominant charging scenario.

Since EVs increase load, they can lower the voltage on the feeder, especially at nodes with many EVs. Figure 9b shows the minimum voltage on each study feeder. Feeders within the same classification tended to have a similar response in voltage with the addition of EV charging. Residential and mixed feeders experienced a slightly lower minimum voltage in the home-dominant compared to the work charging case with the exception of Feeder 7 which had a slightly lower work charging result. The simulation results for the commercial feeder revealed an obvious decrease in voltage compared to the no EV case. Similar to the line loading results, the work-dominant charging scenario caused the minimum voltage to be the lowest on the commercial feeder.

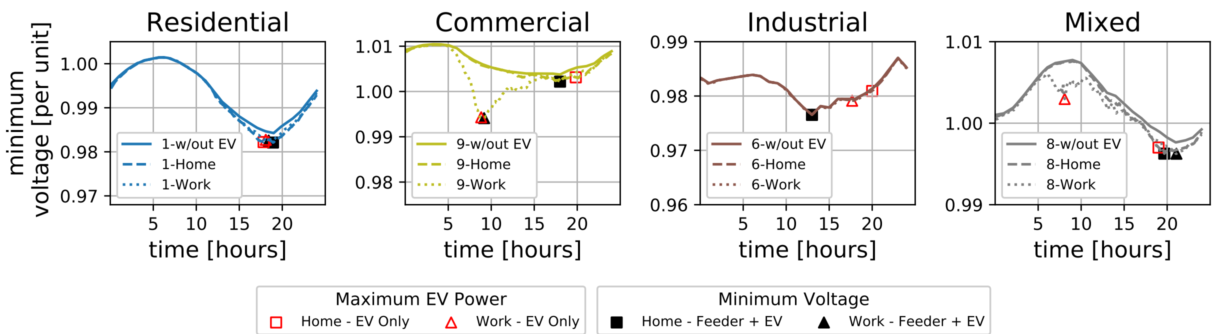
Figure 10a describes the power demand profile over a 24-h period for Feeders 1, 9, 6, and 8 (one feeder from each cluster). In this case, the scatter points describe the point at which the feeder, home-dominant feeder plus EV, and the work-dominant feeder plus EV maximum power occurred. The additional EV load due to the home-dominant or work-dominant charging scenarios caused the feeder peak load to increase in magnitude but remained at or close to the original hour of occurrence for Feeders 1, 6, and 8. Feeder 9 (the commercial feeder) experienced an increase in peak load magnitude that remained at the original time for the home-dominant case but shifted to hour 10 in the work-dominant EV scenario.



(**a**) Feeder load profiles for 1, 9, 6, and 8.



(**b**) Feeder maximum line loading percentage profiles for Feeders 1, 9, 6, and 8.



(**c**) Minimum voltage profile for Feeders 1, 9, 6, and 8.

Figure 10. Sample feeders from each cluster type described the potential cause for the worst case line loading and voltage. (**a**) Describes the four feeders (1, 9, 6, and 8) power demand for a 24 h period under the three different EV loading conditions. (**b**) Highlights the line loading percentages throughout the day for each scenario and markers that describe the EV and overall power peak times. And, (**c**) describes the minimum feeder voltage profiles define the time and extent of the worst case voltage; the markers identify how the lowest voltage corresponds to the EV and overall feeder peaks.

The maximum line loading and minimum voltage measurements on the four feeders depicted in Figure 10b,c most often corresponded with the feeder peaks and not the highest EV demand. This implies that EV charging in concentrated areas may not necessarily cause the worst case performance on the primary system. For example, the mixed use feeder (Feeder 8) experienced the worst line loading and voltage around hour 20 for the home- and work-dominant cases which was around the overall peak and not when EV demand was at its highest. Figure 10c shows the lowest voltage over the course of a 24-h period and the scatter points describe the maximum power peak (or high point) and the point at which the voltage reached a minimum. And in Feeder 8's case, the EV peak was slightly different in two integration scenarios and did alter the voltage and line loading by a noticeable amount, but it did not result in the worst case.

6. Discussion & Conclusions

The two EV adoption scenarios considered (home-dominant and work-dominant), caused residential, commercial, industrial, and mixed use feeders' load profiles to change in different ways. The integration of EVs under the home-dominant scenario increased the peak load for each feeder, as the EV load was well correlated with non-EV feeder load. However, the magnitude of the increase and the resulting impact on feeder line loading and voltage was most significant in feeders with residential loads. In the work-dominant case, on the other hand, more daytime charging occurred, which was generally during "off peak" times for the non-EV feeder loads. The change in line loading and voltage was smaller for residential and mixed use feeders, but larger for the commercial feeder (where non-EV loads were large in the middle of the day). Additionally, much of the charging on the commercial feeder occurred in concentrated areas, leading to a larger impact on line loading than on other feeders where EVs were more spread out. However, the concentration of EVs did not result in the worst case performance.

Assessment of only ten feeders limits our ability to make widespread conclusions concerning how residential, commercial, industrial, and mixed feeders will respond. The results do, however, provide reasonable examples for how feeders with different load types will react to an increase in EV loads. For the 2030 scenario considered, the impact of EV charging on the study feeders' primary lines was found to be small and would not require significant intervention through controls or infrastructure upgrades. However, higher EV adoption scenarios (e.g., 2050) would be expected to amplify the line loading and voltage impacts and may require mitigation. Similarly, distribution networks with less excess capacity could experience line loading failures sooner rather than later.

Questions associated with the integration of EVs on the grid still remain. This work did not consider the types of controls useful for mitigating line loading or voltage issues associated with integrating EVs. Controls can range from simple (e.g., randomized charging start time) to complex (e.g., centralized aggregator), and could also look at the interplay between Distributed Energy Resources (DER) and EVs. The methodology presented in this paper can be directly applied to such controls analysis and ultimately understand the value of each control strategy. Using this methodology to test controls and the integration of generation resources could answer such questions as:

1. What is the impact of time of use (TOU) controls on demand profiles?
2. Does the utilization of DERs on distribution systems help mitigate changes in voltage?
3. How does the integration of DERs impact the line loading?

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Abbreviations

The following abbreviations are used in this manuscript:

DER	Distributed Energy Resources
EPS	Electric Power System
EV	Electric Vehicle
GPS	Global Positioning System
TOU	Time of Use

References

1. Zakaria, H.; Hamid, M.; Abdellatif, E.M.; Imane, A. Recent Advancements and Developments for Electric Vehicle Technology. In Proceedings of the 2019 International Conference of Computer Science and Renewable Energies (ICCSRE), Agadir, Morocco, 22–24 July 2019; pp. 1–6. [CrossRef]
2. Morello, R.; Di Rienzo, R.; Roncella, R.; Saletti, R.; Schwarz, R.; Lorentz, V.; Hoedemaekers, E.; Rosca, B.; Baronti, F. Advances in Li-Ion Battery Management for Electric Vehicles. In Proceedings of the IECON 2018—44th Annual Conference of the IEEE Industrial Electronics Society, Washington, DC, USA, 21–23 October 2018; pp. 4949–4955. doi:10.1109/IECON.2018.8591185. [CrossRef]
3. Hu, X.; Zheng, Y.; Howey, D.A.; Perez, H.; Foley, A.; Pecht, M. Battery warm-up methodologies at subzero temperatures for automotive applications: Recent advances and perspectives. *Prog. Energy Combust. Sci.* **2020**, *77*, 100806. [CrossRef]
4. Cohen, A. Manufacturers Are Struggling to Supply Electric Vehicles with Batteries. Section: Business. 2020. Section: Business. Available online: https://www.forbes.com/sites/arielcohen/2020/03/25/manufacturers-are-struggling-to-supply-electric-vehicles-with-batteries/ (accessed on 15 November 2020).
5. Quiros-Tortos, J.; Ochoa, L.; Butler, T. How Electric Vehicles and the Grid Work Together: Lessons Learned from One of the Largest Electric Vehicle Trials in the World. *IEEE Power Energy Mag.* **2018**, *16*, 64–76. [CrossRef]
6. Gerossier, A.; Girard, R.; Kariniotakis, G. Modeling and Forecasting Electric Vehicle Consumption Profiles. *Energies* **2019**, *12*, 1341. [CrossRef]
7. Walkowicz, K.A.O.; Lave, M.; Scofield, D. *Smart Electric Vehicle Charging for a Reliable and Resilient Grid (RECHARGE)*; Technical Report NREL/PR-5400-73712; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2019.
8. Scoffield, D.; Yi, Z.; Medam, A.; Harper, J.; Jun, M.; Pratt, R.; Coignard, J. *Systems Research Supporting Standards and Interoperability (GM0085) Final Report*; Technical Report INL/EXT-19-53792; Idaho National Laboratory (INL): Idaho Falls, ID, USA, 2019.
9. Alexander, M. *Plug-In Electric Vehicle Market Projections: Scenarios and Impacts*; Technical Report 3002011613; Electric Power Research Institute: Palo Alto, CA, USA, December 2017.
10. Wood, E.W.; Rames, C.L.; Muratori, M. *New EVSE Analytical Tools/Models: Electric Vehicle Infrastructure Projection Tool (EVI-Pro)*; Technical Report NREL/PR-5400-70831; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2018.
11. Hanemann, P.; Behnert, M.; Bruckner, T. Effects of electric vehicle charging strategies on the German power system. *Appl. Energy* **2017**, *203*, 608–622. [CrossRef]
12. Schey, S.; Scoffield, D.; Smart, J. A First Look at the Impact of Electric Vehicle Charging on the Electric Grid in The EV Project. *World Electr. Veh. J.* **2012**, *5*, 667–678. [CrossRef]
13. Muratori, M. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. *Nat. Energy* **2018**, *3*, 193–201. [CrossRef]
14. Dias, F.G.; Mohanpurkar, M.; Medam, A.; Scoffield, D.; Hovsapian, R. Impact of controlled and uncontrolled charging of electrical vehicles on a residential distribution grid. In Proceedings of the 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Boise, ID, USA, 24–28 June 2018; pp. 1–5. [CrossRef]
15. Wang, S.; Li, C.; Pan, Z.; Wang, J. Probabilistic Method for Distribution Network Electric Vehicle Hosting Capacity Assessment based on Combined Cumulants and Gram-Charlier Expansion. *Energy Procedia* **2019**, *158*, 5067–5072. [CrossRef]
16. Jones, C.B.; Lave, M.J.; Darbali-Zamora, R. Overall Capacity Assessment of Distribution Feeders with Different Electric Vehicle Adoptions. In Proceedings of the IEEE Power & Energy Society General Meeting, Montreal, QC, Canada, 2–6 August 2020.

17. Zhang, J.; Yan, J.; Liu, Y.; Zhang, H.; Lv, G. Daily electric vehicle charging load profiles considering demographics of vehicle users. *Appl. Energy* **2020**, *274*, 115063. [CrossRef]
18. Harris, C.B.; Webber, M.E. An empirically-validated methodology to simulate electricity demand for electric vehicle charging. *Appl. Energy* **2014**, *126*, 172–181. [CrossRef]
19. Reno, M.J.; Broderick, R.J. Statistical analysis of feeder and locational PV hosting capacity for 216 feeders. In Proceedings of the 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, USA, 17–21 July 2016; pp. 1–5. [CrossRef]
20. Parsian, M. *Data Algorithms*; O'Reilly Media, Inc.: Newton, MA, USA, 2015.
21. Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Prettenhofer, P.; Weiss, R.; Dubourg, V.; et al. Scikit-learn: Machine Learning in Python. *J. Mach. Learn. Res.* **2011**, *12*, 2825–2830.
22. Han, J.; Pei, J.; Kamber, M. *Data Mining: Concepts and Techniques*; Elsevier: Amsterdam, The Netherlands, 2011.
23. Wood, E.W.; Rames, C.L.; Muratori, M.; Srinivasa Raghavan, S.; Young, S.E. *Charging Electric Vehicles in Smart Cities: An EVI-Pro Analysis of Columbus, Ohio*; Technical Report NREL/TP-5400-70367; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2018. [CrossRef]
24. BNEF EVO Report 2020 | BloombergNEF | Bloomberg Finance LP. 2020. Available online: https://about.bnef.com/electric-vehicle-outlook/ (accessed on 15 November 2020).
25. Yi, Z.; Scoffield, D. A Data-Driven Framework for Residential Electric Vehicle Charging Load Profile Generation. In Proceedings of the 2018 IEEE Transportation Electrification Conference and Expo (ITEC), Long Beach, CA, USA, 13–15 June 2018; pp. 519–524.