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Research paper

Impact of Electric Vehicle customer response to Time-of-Use rates on distribution power grids

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ABSTRACT

Electric Vehicles (EV) present a unique challenge to electric power system (EPS) operations because of the potential magnitude and timing of load increases due to EV charging. Time-of-Use (TOU) electricity pricing is an established way to reduce peak system loads. It is effective at shifting the timing of some customer-activated residential loads – such as dishwashers, washing machines, or HVAC systems – to off-peak periods. EV charging, though, can be larger than typical residential loads (up to 19.2 kW) and may have on-board controls that automatically begin charging according to a pre-set schedule, such as when off-peak periods begin. To understand and quantify the potential impact of EV charging's response to TOU pricing, this paper simulates 10 distribution feeders with predicted 2030 EV adoption levels. The simulation results show that distribution EPS experience an increase in peak demand as high as 20% when a majority of the charging begins immediately after on-peak times end, as might occur if EV charging is automatically scheduled. However, if charging start times are randomized within the off-peak period, EV charging is spread out and the simulations showed a decrease in the peak load to be 5% lower than results from simulations that did not implement TOU rates.

1. Introduction

Electric Vehicles (EV) are estimated to be 31% of the overall share of cars on the road by 2040 (BloombergNEF, 2020). Such a penetration of EVs will significantly increase demand on distribution Electric Power Systems (EPS). To estimate the temporal impacts on the electric grid caused by EV charging demands, this work simulates actual distribution EPSs and connected EV charging loads. One simulation scenario emulates EV charging without intervention or incentives ("no TOU"). A second scenario considers the impact caused by EV customers' response to Time-of-Use (TOU) rate schedules — rates intended to incentivize EV charging during off-peak demand hours using variable cost structures.

TOU rate schedules are simple and effective in shifting controllable loads away from peak periods, as customers are incentivized to recognize the time of day and, during peak hours, actively turn off or not use large energy consuming devices in order to save money. However, customer willingness to adjust varies (Nicolson et al., 2017) and an optimal result is not always achieved (Yan et al., 2018). Customers are more likely to participate in TOU programs when energy consuming devices (e.g. thermostats, dryers, etc.) are controlled automatically using internal settings (Bao and Chung, 2018) or remote connections with an aggregator for demand response with novel (Zehir et al., 2017) or coupon (Ming et al., 2020) incentives. EVs are capable of both of these control capabilities. Literature has demonstrated examples of how battery charging demands are controlled to minimize cost and maintain user convenience (Chung et al., 2019). Previous work has shown that EV owners who voluntarily select TOU rate structures reliably charge their vehicles during the off-peak period as shown in a demonstration project in Los Angeles California (Schey et al., 2012) and a case study in California and Portland (Biviji et al., 2014). Therefore, EV participation in TOU load shifting is likely to be high.

All EVs on the market today include on-board computers that allow for a charging program to match a known TOU schedule. Additionally, EVs consume considerably more electrical power than most residential loads. For example, a level 2 charger consumes between 3 kW and 19.2 kW whereas conventional household equipment, typically leveraged in existing demand response programs, rarely exceeds 2.4 kW (e.g. microwave, dishwasher

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heater, air conditioner compressor and fan running all at once) (Parker et al., 2006). The large magnitude of EV loads and their possible synchronization (e.g., nearly all EVs start charging immediately when the lowest price TOU period begins) could lead to significant EPS impacts, even during "off-peak" periods when non-EVs loads are smaller.

Quantifying the impact of typical TOU schedules for controlling EV charging involves a realistic simulation environment to emulate both the electric grid and EV charging demands. This work uses 10 actual distribution EPS models that power residential, commercial, mixed-use, and industrial loads within a metropolitan area. The projected EV adoption in 2030 on each EPS is derived from the Electric Power Research Institute (EPRI) EV adoption projections (Alexander, 2017). EVI-Pro (Wood et al., 2018a), an EV supply equipment analysis tool, defines the dwell location and energy needs of each vehicle. Finally, high fidelity battery models provide realistic charge demands that depend on the battery type, size and state of charge (Yi and Scoffield, 2018). When combined, these models provide a simulation environment that adequately estimates EV charging impacts on the electric grid.

This paper's structure considers past work, explains the overall methodology, and reports on the simulation results. Literature Review describes past research papers that document EV impacts on the electric grid and how the present work differs from existing literature. Electric Grid & Battery Simulation Methodology defines the simulation environment, the TOU schedules, and the analysis of the simulation outputs. The Results write up provides an overview of the TOU impacts on 10 distribution EPS by describing the change in the power profiles, voltages, and line loading.

2. Literature review

Studies show that EV charging will impact electric grid power demands and performance. Demand profiles will increase considerably with the addition of EV charging (Muratori, 2018) and result in an overall rise in energy consumption (Delgado et al., 2018). In some cases, the increase in EV charging will not impact voltage significantly on primary (medium voltage) distribution system lines (Jones et al., 2020). Other analysis show that the extra load will impact the grid load capacity and power quality (Rizvi et al., 2018). For example, a simulation effort using the IEEE 34 bus model describes a potential change in system voltage (Clement-Nyns et al., 2010).

A recent study provides a review of the same 10 distribution EPS, used in this work, with EVs charging without any control or incentives (Jones et al., 2021). The previous analysis found no significant grid performance issues due to EV charging. This work uses the same simulation methodology as Jones et al. (2021) to emulate the EV charging with TOU rates.

TOU schedules act as a passive mechanism for shifting load by imposing higher energy costs during certain times in the day. An initial study found that charging EV batteries using level 2 equipment results in a profile high point just after the utility TOU peak rate ends (Shao et al., 2010). Another study considered how utility pricing impacts EV adoptions and charging behavior (Wolbertus et al., 2018). Dubey et al. studied the voltage impacts of EV charging under various TOU rate schedules using a Monte Carlo simulation. The study found that the time when the off-peak rate begins can substantially mitigate adverse impacts of EV charging (Dubey et al., 2015). This paper adds to current work by evaluating the impact of realistic charging patterns of EVs under TOU rates on 10 distribution EPS in a metropolitan area.

Other existing papers consider the impacts of EV charging. For example, one study examined power quality on the grid when subject to high power charging (Wang et al., 2021). Another examined power electronics high frequency switching impacts associated with EV charging (Khalid et al., 2019) Other studies consider general trends that could be expected with EV charging and tariffs. von Bonin et al. (2022), is one example, that studies the implications and economic effects of tariffs for EV charging.

Past studies, to the best of the authors' knowledge, did not consider specific TOU impacts on distribution grids using detailed EV charging simulations. Instead, the focus has been on economical (Sharma et al., 2018) or optimal (Suyono et al., 2019) TOU schedules, and the expected changes in the load shape. However, little is known about the potential contribution of EV charging subject to TOU rates on specific distribution systems powering mostly residential, commercial, industrial, and mixed-use buildings. The primary contribution of this work is to simulate different EV charging behaviors on distribution EPS with EVs at 2030 adoption levels to:

- Highlight the impact of the potential response to TOU rate schedules for light-duty EV charging by modeling multiple EPSs to define their power profiles, voltages, and line loading.
- Define the impacts of TOUs on future integration scenarios where EVs primarily plug-in at home or have opportunities at work to charge.
- Quantify EV charging impacts on distribution EPS serving different load types, such as systems that are primarily powering residential, commercial, industrial, or mixed-use loads.

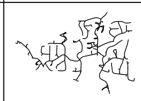
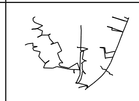
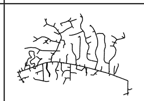
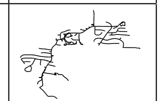
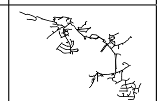
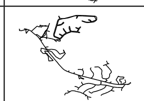
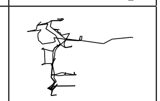
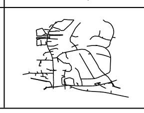
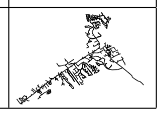
3. Electric grid & battery simulation methodology

This investigation simulated 10 distribution EPS and the EV charging needs within the boundaries of each EPS. The simulation effort, also implemented in Jones et al. (2021), compares power flow estimates without EVs, with EV charging, and with EV charging influenced by TOU rates. The grid and EV models were administered in a co-simulation environment where outputs from one simulation provided the inputs to another.

The EV battery models replicated the driving behaviors and battery charging demands. The EVI-Pro tool, described in Wood et al. (2018b), estimated the vehicle parking locations and dwell periods based on actual INRIX travel patterns (INRIX, 2020). INRIX data represented actual driving patterns and was used recently to evaluate the impact of rain on traffic incidents (Elhenawy et al., 2021). The charge session energy demands, which depended on the battery type, state of charge, and other factors, were emulated using an Idaho National Laboratory (INL) tool known as Caldera (Yi and Scoffield, 2018). The outputs from these two models included EV location and the power draw at each simulation time instance. These outputs were provided as inputs into the EPS simulations.

Grid simulations of the 10 EPS were performed using OpenDSS (OpenDSS, 2020). OpenDSS used the topology and load information for each EPS to run 24-h quasi-static timeseries simulations (Broderick, 2019). A load profile was generated using the entire EPS measured demand. The profile was then divided by the maximum observed annual load to create a load allocation scaling factor for each timestamp. Then, at each timestamp the rated loads were multiplied by the factor to generate each individual load. The new loads were used by OpenDSS to calculate the overall power flow to ultimately output voltages and line loading results.

Table 1
Electric power system topologies.

	Type	Topology		Type	Topology
1	Residential		6	Industrial	
2	Residential		7	Residential	
3	Mixed		8	Mixed	
4	Residential		9	Commercial	
5	Mixed		10	Residential	

3.1. Electric power system

Table 1 describes the topology for each feeder. EPS 1, 2, 3, 4, 7, and 10 had a high percentage of residential customers, while feeders 5, 6 and 8 had higher numbers of commercial and mixed-use loads. Jones et al. (2021) provides a detailed overview of the load type numbers and quantities for each EPS. The EPS types were also defined in Jones et al. (2021) based on a clustering analysis of the load numbers and quantities. EPS 6 and 9 were mostly comprised of larger commercial and industrial loads. Each of the EPS had a base voltage of 19.8 kV except for feeder 10 which was at 25 kV. The OpenDSS models did not include secondary (low voltage) lines which connect service transformers to customer loads. Therefore, the simulations only evaluated the primary line operations.

3.2. Electric vehicle adoptions & driving behavior

This simulation effort emulated realistic EV adoptions and driving behaviors. Understanding EV adoption is important in determining the penetration of EV in and around each EPS. The estimated EV adoptions used in this work incorporated conclusions from the EPRI study (Alexander, 2017) as well as other projections provided by Bloomberg Electric Vehicle Output (BloombergNEF, 2020) and NREL's ADOPT (Brooker et al., 2015). The projections assumed that EVs will account for 13% of the national stock of light duty vehicles by 2030 in the United States.

In addition to EV adoption, driving behaviors were used to determine vehicle energy requirements and dwell periods for charging. Driving behaviors were determined using travel data generated through a tool developed by the National Renewable Energy Lab (NREL) named ZEP or Zone Entity Probabilities. This is a stochastic simulation framework that takes real world independent origin and destination trips and chains them together. The algorithm targets generating vehicle itineraries while also preserving the real-life energy use of the vehicle, and the density of vehicles in given locations at specific times. The utilization of the tool generated 8.6 million trips for the expected EV adoptions in this particular metro area.

Once travel patterns were known, NREL's EVI-Pro tool estimated energy consumption of the EVs. EVI Pro has been used in various projects at NREL for vehicle energy needs estimations (Wood et al., 2018b). EVI-Pro takes vehicle travel data and determines charging demand at different locations and times. In this study there was a specific distribution of vehicles being adopted, which is shown in Table 2. Table 2 provides a breakdown of the different PEVs, which includes all electric and plug-in hybrid electric vehicles (PHEV). Most of the all-electric vehicles had extreme fast charging capabilities (XFC) but charging rates above AC charging power described in Table 2 were not implemented in this simulation. Also, the simulation assumed, based on market projections, that the share of vehicles would be primarily generation 1 (Gen 1) technologies, which typically have lower EV range, charging rate capabilities, and rated battery capacities compared to the second generation PEVs (labeled as Gen 2 in Table 2). Table 2 also characterizes the different PEVs as long-range (LR) or short-range (SR), which is relative to the vehicle type (e.g., truck or car) and the maximum range for PEVs.

The expected distribution of vehicles was assigned to driving itineraries. As the vehicles traveled through the day on their set itineraries EVI-Pro would check to see their need for charge and record the location and energy desired as well as arrival and departure times.

EVI-Pro has various run options, one is the concept of dominance. For example, in a home-dominant scenario all charging occurs at home with two exceptions. The first exception being if the vehicle cannot make it home without charging enroute, then the vehicle will charge at one of the places it would have normally stopped. The second exception is one of charge neutrality, which means that the state of charge (SOC) must be the same each morning of departure if this is not possible after an overnight charge the vehicle will DC fast charge to meet that condition before arriving home to get its remaining required charge. These two exceptions are the reason while in a home-dominant scenario you will still see workplace and public charging.

This study also considered work-dominant EV charging where EV workplace chargers were a priority and residential charging supplemented. EVI-Pro assumes infinite infrastructure capacity, this means that in the home dominant scenario every home location has a charger, the same is true of workplaces. Upon charging vehicles will charge to full or until the time of departure, whichever comes first. The result of different dominance scenarios is apparent in Fig. 1. In the work-dominant scenario, the coincident load through the city decreases in the evening as compared to the home-dominant due to the energy offset by workplace charging

Table 2
Electric vehicle adoptions & battery specifications for 2030 projections.

Vehicle model	Fleet share	EV range (miles)	Rated battery capacity (kWh)	AC charging power (kW)
XFC LR Truck (Gen 1)	24%	200	100	9.6
XFC LR Car (Gen 1)	23%	275	86.8	9.6
PHEV LR Truck	11%	50	25	9.6
PHEV LR Car	9%	50	19.4	3.3
BEV SR Car (Gen 1)	7%	150	47.4	9.6
XFC LR Truck (Gen 2)	7%	250	124.7	11.5
PHEV SR Car	5%	20	6.3	3.3
XFC SR Car (Gen 2)	5%	150	47.4	9.6
BEV LR Car	4%	250	78.9	9.6
XFC LR Car (Gen 2)	4%	300	102.4	11.5
XFC Sports Car	1%	250	92.1	11.5

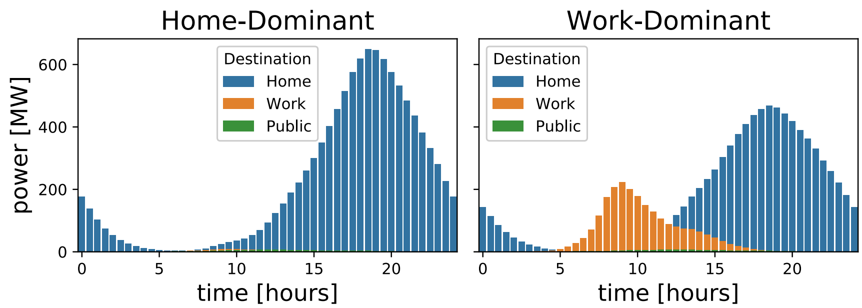


Fig. 1. Charging locations under the home- and work-dominant scenarios. The home-dominant case had very little charging outside of the home which was used only when the EV did not dwell at a residential location. And the work-dominant scenario assumed that any EV that dwelled in an area deemed to be a place of work charged until it left or reached a full state of charge.

3.3. Time-of-use rate schedule

A TOU rate schedule that matches well with existing utility programs across the US today was implemented in this simulation effort. The simulated rate schedule, shown in Fig. 2, did include a specific off- and on-peak rate. However, the rate difference was assumed to be significant enough to influence customer charging behavior. As a result, it was assumed that customers with EVs would actively avoid on-peak rates by shifting vehicle charging to when off-peak rates coincided with their vehicle dwell period. The TOU simulation did not include other loads inside residential or commercial buildings. Fig. 2 shows that the on-peak time began at simulation hour 12 and ended at hour 19 (noon to 7 PM). All other times of the day were considered off-peak utility rate times.

Typically, vehicle dwell period lengths far exceeded the necessary charge session duration, resulting in more flexible charging options. In order to account for these options, two implementations of TOU rate responses were simulated in this work. The options could be self-selected or controls-driven, either way resulting in the same grid impact. One simulation represented a customer response with an immediate reaction to off-peak rates. The other method assumed a more dispersed customer response where off-peak rates were still preferred, but the reaction to lower rates was more randomly distributed. Under both scenarios, the top priority for charge scheduling was to ensure sufficient time was allotted to deliver the desired energy before accounting for TOU rate responses. The first scenario represents what one study indicated as a likely outcome as a result of customer charge scheduling, while the second scenario distributes the demand and limits the customer reaction to the sudden change in the cost of electricity immediately after hour 19. The two TOU responses were defined as:

1. TOU Immediate: EV customers avoided the highest electricity costs and began charging immediately after the on-peak charging ended at hour 19.

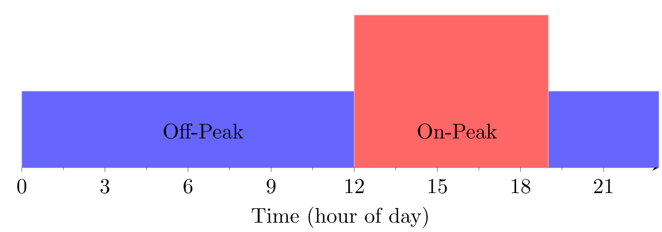


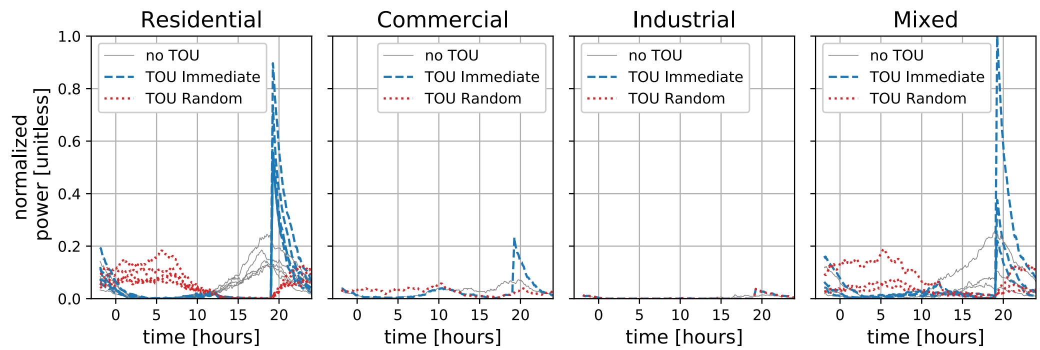
Fig. 2. Time-of-Use on-peak rates occurred between hour 12 and hour 19. All other times of the day were considered off-peak.

2. TOU Random: EV customers stopped charging during on-peak hours and began charging again at random times once off-peak rates returned.

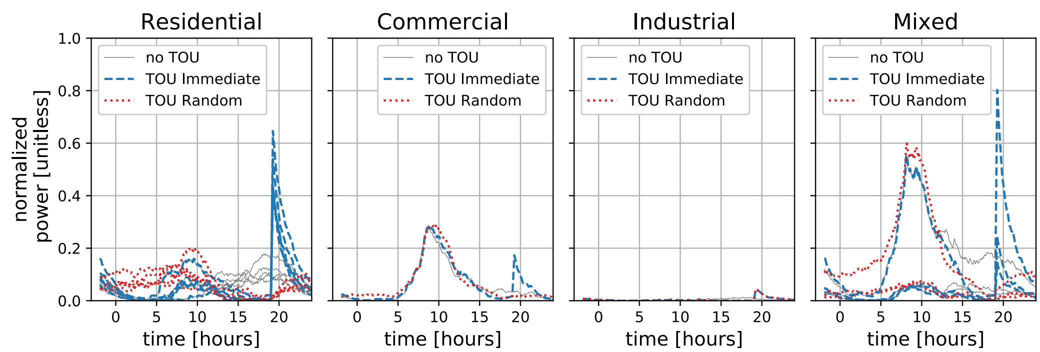
Compliance with the two TOU approaches was assumed to be high (i.e., close to 100%) since all EV have on-board computers and control infrastructure that allow a TOU Immediate to be executed reliably. TOU Random is not currently included in existing systems but could be implemented with no additional control infrastructure. However, implementation of an on-vehicle controller that randomizes start times would require software modifications by vehicle or charger manufacturers.

3.4. Electric vehicle battery simulations

Simulation of the EV battery charging demands used the Idaho National Laboratory (INL) tool called Caldera. Caldera is an EV charging infrastructure simulation platform designed to study the impact of EV charging on the grid and develop strategies to manage charging. Its foundation is a library of high-fidelity EV charging models derived from extensive charging and battery testing data that INL has collected over the past decade. Caldera's charging models accurately estimate charge power profiles, efficiency, and power factors for a wide variety of EVs and charging



(a) Home-Dominant EV charging scenario



(b) Work-Dominant EV charging scenario

Fig. 3. EV battery charging under the home- and work-dominant scenarios were influenced by the TOU Immediate and TOU Random. TOU Immediate caused significant increases in demand as soon as on-peak rates ended. And, TOU Random distributed the charging throughout the night and morning to avoid a significant spike in power demand. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

technologies under varying grid conditions. These charging models are implemented through an agent-based modeling approach representing each EV as an individual load on the distribution system.

4. Results

It was apparent the TOU rates influenced the charging demands that were used as inputs into each of the 10 EPS. The additional EV loads increased the overall feeder profiles and, in most cases, the TOU Immediate increased the peak demand of the EPS. The change in load profiles under the TOU scenarios caused the maximum line loading and minimum voltage to change in comparison to the with EV baseline for both home- and work-dominant cases.

4.1. Electric vehicle charging demands

EV battery charging demands influenced by TOU pricing were significantly different than the with baseline. The EV demands for each of the EPS within their designated categories (i.e., Residential, Commercial, Industrial, or Mixed) in the no TOU, TOU Immediate, and TOU Random for the home- and work-dominant scenarios are plotted in Fig. 3. EV battery charging without TOU rates is represented by the gray lines in Fig. 3(a). This group typically followed a pattern where limited charging occurred in the morning, slowly increased to a peak around hour 19, and then decreased during the night. The EV charging without TOU under the work-dominant scenarios, depicted in 3(b) followed a similar pattern with the home-dominant case for residential EPS, but the commercial and mixed EPS showed that significantly more charging occurred during the day.

The TOU Immediate response influenced the EV battery charging for both the home- and work-dominant scenarios. Customers in each of the EPS in the four categories avoided charging between hours 12 and 19, as depicted in Fig. 3(a) with the blue lines. In each EPS category, except for industrial, the immediate customer response to lower rates significantly increased EV charging demand as soon as off-peak energy prices were available. This caused a significant spike in power to occur right after hour 19 in the home-dominant case. This spike in power was slightly reduced in the work-dominant scenario depicted in Fig. 3(b) since more EV batteries were charged during the daytime off-peak hours. Under the work-dominant scenario EV battery charging on the commercial and mixed EPS increased during on-peak work hours relative to the home-dominant case. This occurred because the simulation assumed that each EV must be fully charged by the end of the day, which for some vehicles with a low charging flexibility required the use of on-peak charging. These EPS also saw an increase in total energy delivered to EVs, relative to the home dominant scenario, due to the influx of vehicles commuting to places of work.

The TOU Random approach shifted EV battery charging away from the on-peak times without creating a large increase in power demand when off-peak rates began. Under the home-dominant scenario, Fig. 3(a), charging during on-peak hours was avoided in all of the feeders in each of the four categories. To avoid on-peak power rates, the battery charging was distributed almost evenly throughout the night and morning hours. In contrast, the work-dominant scenario results, depicted in Fig. 3(b),

Table 3
Home-dominant electric vehicle charging locations & demands at peak.

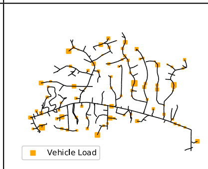
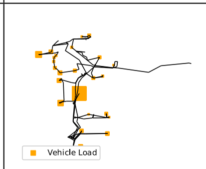
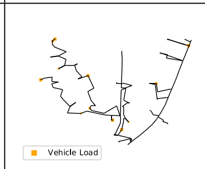
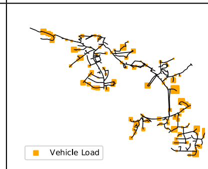
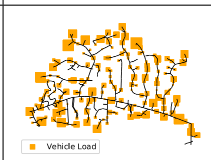
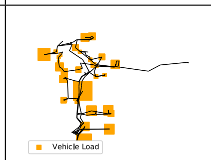
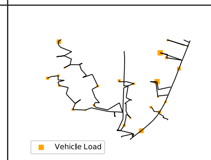
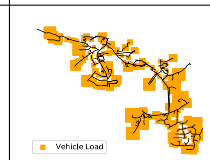
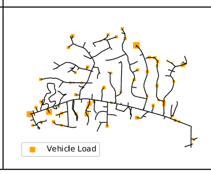
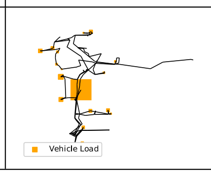
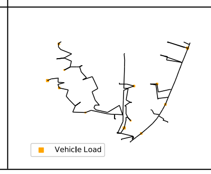
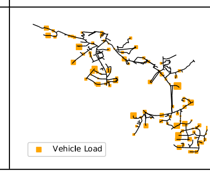
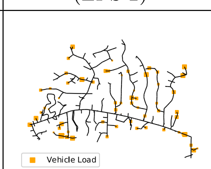
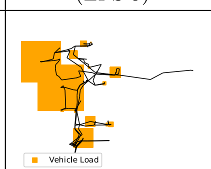
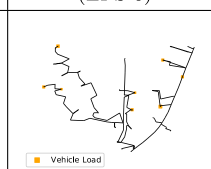
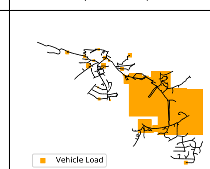
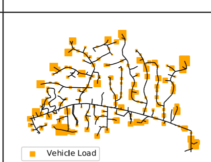
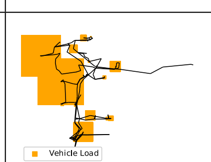
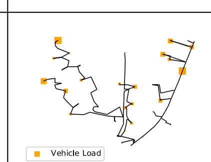
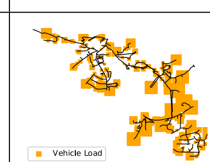
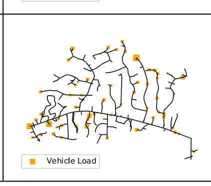
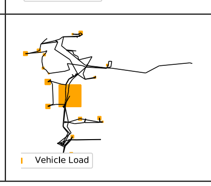
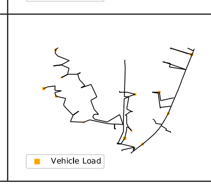
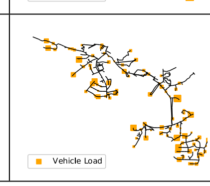
	Residential (EPS 2)	Commercial (EPS 9)	Industrial (EPS 6)	Mixed (EPS 8)
No TOU				
TOU Immediate				
TOU Random				

Table 4
Work-dominant electric vehicle charging locations & demands at peak.

	Residential (EPS 2)	Commercial (EPS 9)	Industrial (EPS 6)	Mixed (EPS 8)
No TOU				
TOU Immediate				
TOU Random				

showed that the on-peak time was not avoided and feeders with more commercial loads (e.g. commercial and mixed-use EPS) experienced a peak in EV battery charging around hour 9.

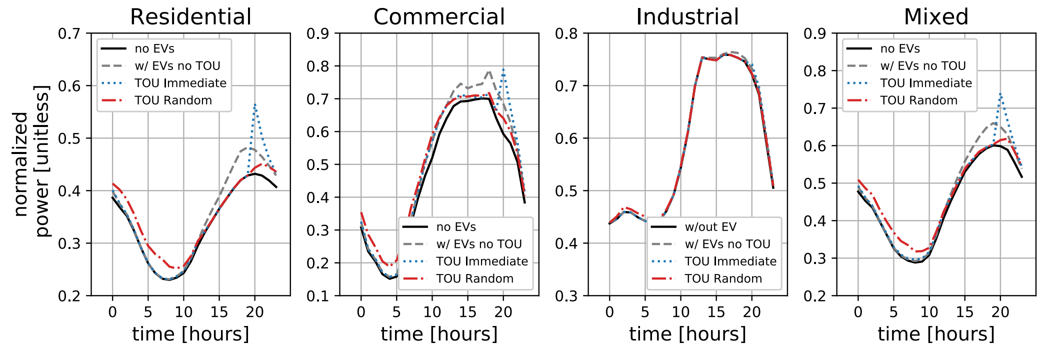
The EV battery charging mapped locations and sizes provided a sense for how each TOU scenario relied on the EPS customer characteristics. Tables 3 and 4 depict the peak charging demands on four EPS that represent residential, commercial, industrial, and mixed systems under the home- and work-dominant scenarios, respectively. In the home-dominant case, shown in Table 3, the EV without TOU and TOU Random had similar charging locations and sizes at the EV charging peak. TOU Immediate was much different and had significant charging at nearly all of the EV stations available with the exception of the industrial EPS. The EV charging of the industrial EPS was not significant in the home-dominant case and therefore did not include very many charging locations of significant size.

The work-dominant scenario primarily influenced EPS with commercial or industrial type loads. Residential EPSs, like EPS 2, did not exhibit significant difference between the home- and work-dominant scenarios as shown in Tables 3 and 4. The commercial and mixed EPS, on the other hand, had considerably more charging at single points on the distribution systems in the no TOU and TOU Immediate cases, as shown in Table 4. The TOU Random response decreased the amount of charging at single points on the systems by distributing the loads throughout the day.

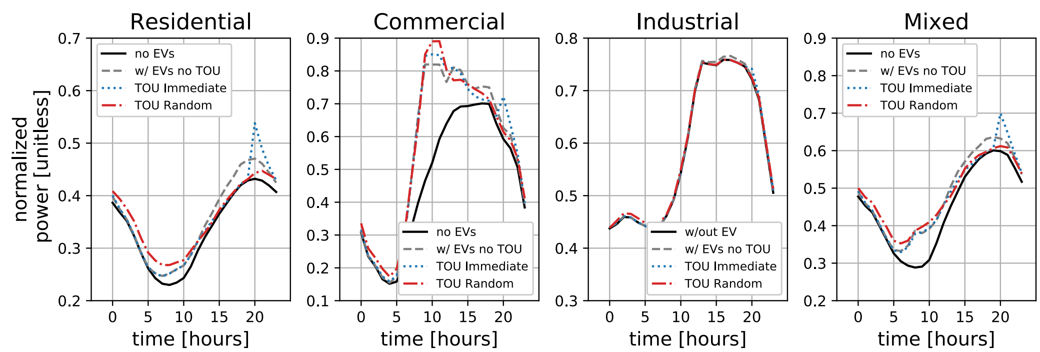
4.2. Electric power system profiles

As expected, the additional EV battery charging loads resulted in noticeably higher overall demand profile for residential, commercial, and mixed EPS as shown in Fig. 4. Fig. 4 plots the average power profiles for the EPS within each of the four categories. The industrial feeder, on the other hand, did not charge many EVs and therefore did not experience a significant change in its power profile.

A closer look found that the EPS demand profiles without EVs and with EVs varied depending on the EPS type. For instance, the residential EPS tended to experience an increase in demand that was noticeably higher starting around hour 12 (shown in Fig. 4) when EVs were not influenced by TOU rates in the home- and



(a) Home-Dominant EV charging scenario



(b) Work-Dominant EV charging scenario

Fig. 4. EVs without TOU, TOU Immediate, and TOU Random caused the existing demand profiles for each category to increase by different mounts. TOU Immediate resulted in the largest peak demands. TOU Random distributed the charging and ultimately produced peak loads that were less than the no TOU scenario except in the commercial system under the work-dominant charging scenario.

work dominate cases. The work-dominant scenario did have a slightly lower power profile with the addition of EVs compared to the home-dominant case because many of the EVs charged during the day at commercial or office locations. Similar behavior was observed in the mixed feeders on average except that the power profile with EVs did not diverge from the no EV profile until around hour 13. Also, the mixed-use EPS experienced more day-time charging in the work-dominant scenario than the residential systems.

The commercial EPS experienced different changes in its profile compared to systems with more residential loads. For commercial systems, the home-dominant scenario was similar to residential in that the profile had a slight increase in demand that began just after 12 and peaked around hour 18. However, the work-dominant simulations found that the peak load of the EPS shifted from hour 18 to around hour 10 and increased by about 18% for commercial systems. In comparison, the residential and mixed EPS only experienced an increase in the peak load of about 12% and 10% respectively. Additionally, the shift in the peak time for commercial systems was more significant than the others that only experienced a change in time of less than an hour on average for the case where EVs were added without TOU.

4.2.1. Time-of-use immediate

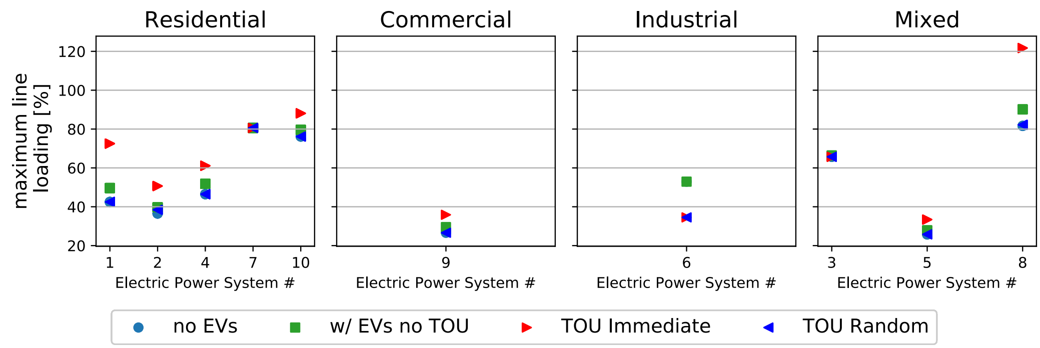
TOU Immediate response caused the overall demand profiles for residential, commercial, and mixed EPS to reach a maximum at hour 20, coinciding closely with the sudden shift in rates. This increase far exceeded the EV with no TOU simulation results and increased the residential overall peak load by 20% and the mixed EPS peak load by 14% for the home-dominant scenario depicted in Fig. 4(a). The commercial EPS did not experience an increase in peak demand but had a shift in the peak demand time from hour 18 to 20. The work-dominant scenario results, shown in Fig. 4(b), were similar for the residential and commercial peak loads. However, the change in the peak power were smaller: 12% for residential and 10% for mixed EPS. The commercial and industrial EPSs showed very little change between the EV with no TOU charging and the TOU Immediate response. The commercial system's peak load increased by only 4% around hour 10.

4.2.2. Time-of-use random

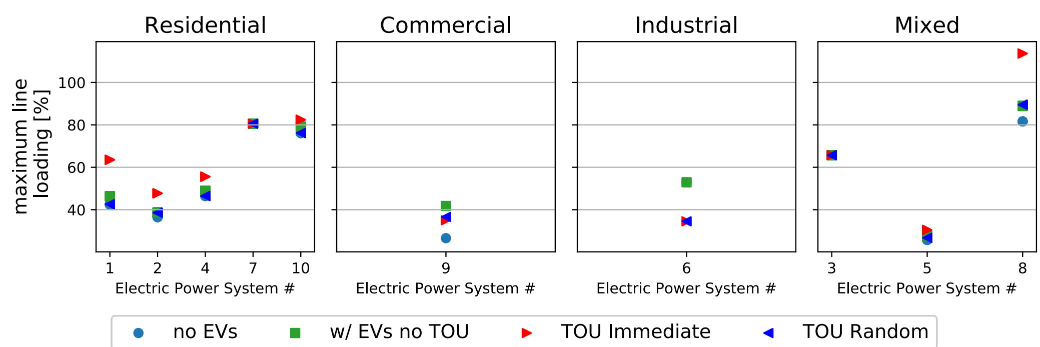
The TOU Random response created a more even distribution of EV charging start time after on-peak hours and eliminated the demand spike by shifting the charging to other parts of the day. The EPS experienced very slight increases in the peak power in the home- and work-dominant cases as shown in Fig. 4. For example, the residential systems showed a decrease in peak power of only 5% compared to the no TOU EV simulation results and the peak time shifted from hour 20 to hour 21. Similarly, the mixed EPS, on average, had a peak power of about 6% less than the profile with EVs. The residential and mixed EPS each had power demand peaks that were less than the no TOU simulation results. The commercial system, on the other hand, exhibited an increase in the peak demand under the TOU random in the work-dominate scenario that went up by 7% compared to the no TOU simulation results.

4.3. Electric power system performance

EV charging on each of the distribution EPS altered the line loading performance of each system at different scales depending on the control and charging approach. For the home-dominant



(a) Home-Dominant EV charging scenario



(b) Work-Dominant EV charging scenario

Fig. 5. The no TOU charging of EVs was found to not alter the maximum line overloading on each of the EPS in the home- and work-dominant cases. Using the TOU Immediate approach caused higher line loading and one EPS exceeded the 100% limit. However, the TOU Random produced results that matched well with the simulations without EVs and was considered the best approach for minimizing the line overloading potential.

charging approach, each EPS experienced an increase in the maximum line loading when EVs were added and not controlled, as shown in Fig. 5. The most significant changes were observed in the residential, industrial and one of the mixed (EPS 8) systems. In the work-dominant charging scenario, the commercial and industrial EPS had the most significant differences between the no EV and with EV cases in line loading.

TOU Immediate simulation results showed a noticeable impact on the maximum line loading for most systems operating under the home- and work-dominant charging scenarios. EPS 8, for example, experienced a line loading that caused it to exceed the maximum threshold and reach just over 120% in the home-dominant case (Fig. 5(a)) and 112% in the work-dominant charging simulations (Fig. 5(b)). The commercial and industrial systems, however, had maximum line loading results in TOU Immediate that were lower than the no TOU case except for the commercial system in the home-dominant scenario.

The TOU Random produced maximum line loading results that matched closely with the simulations that did not include EVs. This was evident in the residential, commercial, and mixed EPS for in the home-dominant charging scenario results. In the work-dominant simulations, the TOU Random was not as close to the no EV case but was lower than the with EV charging case (e.g. commercial work-dominant). Overall, the TOU Random eased the line loading strain on all of the distribution EPS.

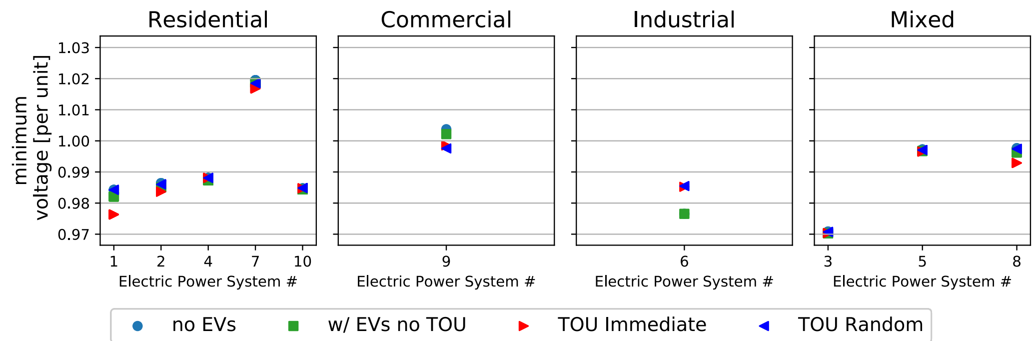
The difference in the minimum voltage between the EPS without EVs and the three cases with EVs followed similar patterns with the line loading outputs, as shown in Fig. 6. The differences in voltage were very small and none exceeded the ANSI standard threshold of 0.95 PU. Similar to the line loading results, it was evident that the TOU Immediate generated the worst minimal voltages while the TOU Random produced results closer to the simulations that did not include EVs. However, there were some exceptions as the commercial system's voltage was slightly better under the TOU Immediate for the home-dominant scenario.

4.4. Time of use schedule impacts

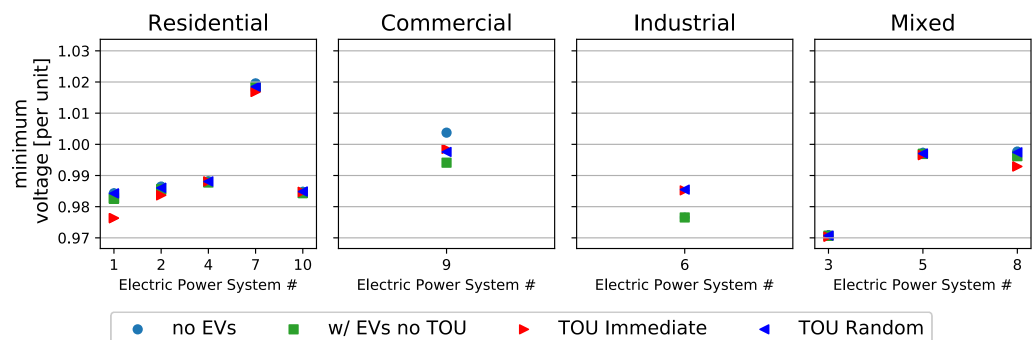
EV charging impacts varied depending on the TOU schedule and customer response. The previous sections describe the results under a common on- and off-peak schedule. As a result, EPS 8 experienced line loading well above the 100% threshold. However, other EV TOU charging schedules produce more favorable results that avoid extensive line loading. To evaluate this hypothesis, the simulation was run with TOU schedules that followed off-peak hours: 00:00 to 08:00; 08:00 to 12:00; 12:00 to 20:00; and 19:00 to 12:00 for TOU Immediate and Random.

The four different TOU schedules caused EPS 8 demand profile to vary depending on the start of the off-peak hours. Fig. 7(a) plots the system's power demand for an entire day under the no EV, with EVs, and the four TOU schedules for the TOU Immediate and Random scenarios. The TOU Immediate response caused the EPS demand to increase dramatically (>2 MW) when off-peak began at hour 0, 8, and 19. The fourth case, where off-peak started at hour 12, the power profile experienced an increase less than 0.5 MW above the EVs with no TOU case. In contrast to the TOU Immediate results, the TOU Random response did not have large spikes in demand and instead the EV charging was distributed within the off-peak hours.

Three of the four new TOU schedules caused the maximum line loading to exceed 100% in the TOU Immediate scenario,



(a) Home-Dominant EV charging scenario



(b) Work-Dominant EV charging scenario

Fig. 6. The minimum voltage changed only slightly for the three EV integration cases in the home- and work-dominant scenarios in comparison to the EPS results without EVs. TOU Immediate and TOU Random had little impact on the voltage, but in most cases the typical implementation produced the worst-case results and the random stat times helped keep the voltage closer to the no EV simulation results.

as shown in Fig. 7(b). The schedule that had off-peak electrical rates between hours 12 and 20 was the only TOU Immediate scenario that did not exceed the line loading limit of 100%. In this case, the demand profile matched the simulation that charged EVs without a TOU schedule except for a small increase in load between hour 12 and 13. The TOU Random simulations resulted in smaller maximum line loading values than the no TOU case with the exception of the scenario that started off-peak at hour 12. The other three TOU approaches also shifted the maximum line loading to around hour 17.

The minimum EPS voltages did not experience a significant change in comparison to the no EV or EVs without TOU simulations as shown in Fig. 7(c). As expected, the TOU Immediate resulted in the most significant change and caused the voltages to drop below 0.99 PU. The TOU Immediate scenarios where the off-peak hours began during the day (e.g., hour 8 and 12) did not have lower voltages because the maximum EPS power demand did exceed the no TOU EV simulation results. In this case, the lowest voltage occurred in the EPS peak that was not influenced significantly by EV charging. The TOU Random simulation results did not experience significant changes in the minimum voltage. However, three of the TOU Random simulations approached had minimum voltages close to the no EV results. The TOU Random was able to improve the system operations under most of the rate schedules scenarios.

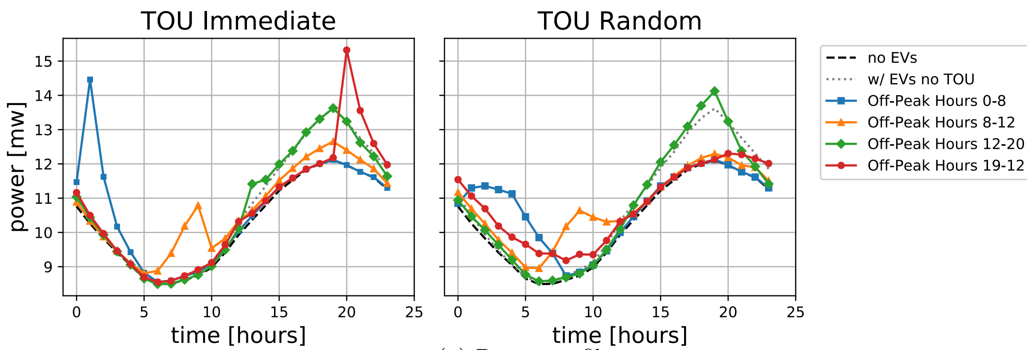
5. Conclusions

This paper describes and reviews the results from a simulation effort that considered the impacts of EV charging on 10 distribution EPS of variable composition. The assessment quantified the load and performance impacts associated with and without TOU pricing and two charging scenarios. The two charging scenarios were home- and work-dominant, which were found to impact residential, commercial, industrial, and mixed-use EPS differently. For example, under the work-dominant charging scenario, the commercial EPS's peak load increased and was shifted dramatically from the evening (hour 18) to the morning hours (around hour 10). This was in contrast to the home-dominant scenario that did not shift the peak on the commercial EPS and was only slightly higher in magnitude.

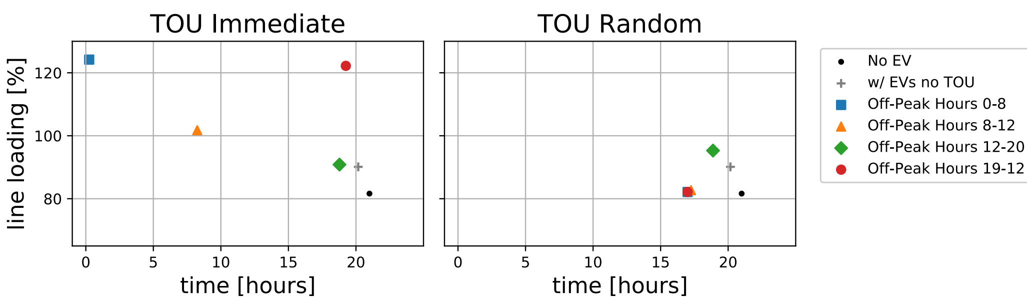
The analysis considered potential EV charging responses to TOU rates. Without TOU rates the overall system load and line loading increased while the minimum system voltage on all of the EPSs decreased within acceptable limitations. One mixed-use feeder's line limit, however, did exceed 100% and reached 120% in the home-dominate scenario and 112% in the work-dominate case. The high line loading was attributed to the extra EV loads, but the system was also already heavily loaded.

Its also worth noting that the peak load increased dramatically for residential (20%) and mixed (14%) EPS in both the home- and work-dominant cases compared to the simulations without TOU. But this load growth under the TOU Random response significantly reduced the peak load below the TOU immediate and the no TOU charging results. This suggests that EV load growth has the potential to cause significant impacts to the grid under certain scenarios, but incentive structures and charging preferences that result in a more distributed EV charging load will greatly mitigate these effects.

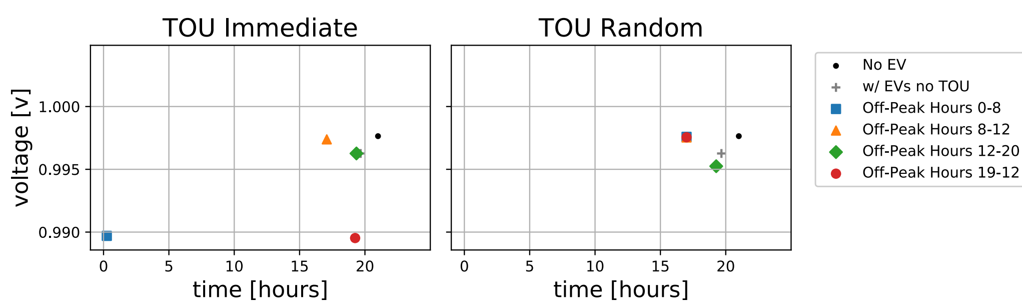
Questions still remain concerning how EPS will respond to increased EV charging loads. For example, it is unclear what will happen with a combination of high PV penetration and EV



(a) Power profiles



(b) Maximum line loading



(c) Minimum voltage

Fig. 7. The TOU impacts on EV charging varied depending on the off-peak start times. (a) The demand profiles in the TOU Immediate experienced significant spikes while the TOU Random distributed the charging evenly of the off-peak times. The TOU Random scenario improve the line loading (b) and minimum voltage (c) compared to the no TOU scenario while the TOU Immediate often caused the system performance to be below the no TOU case.

charging. Also, what will happen if commercial and residential loads have different TOU rates and schedules. Future work is also necessary to understand how TOU can coincide or coexist with other EV charging ancillary services. However, it is clear that customer charging preferences between home and work locations, as well as the response to incentives can result in varying grid impacts with the lowest impacts resulting from behaviors with a more distributed EV charging load.

CRediT authorship contribution statement

C. Birk Jones: Conceptualization, Methodology, Formal analysis, Drafting manuscript. **William Vining:** Data curation, Formal analysis, Editing. **Matthew Lave:** Formal analysis, Supervision, Writing – review & editing. **Thad Haines:** Formal analysis, Writing – review & editing. **Christopher Neuman:** Methodology, Software, Writing – review & editing. **Jesse Bennett:** Formal analysis, interpretation of data, Writing – review & editing. **Don R. Scoffield:** Methodology, Software, Formal analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Matthew Lave reports financial support was provided by US Department of Energy.

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