Impact of Electric Tariffs on Medium- and Heavy-Duty Vehicle Charging Costs and Loads

Beia Spiller, Ruolin Zhang, Elizabeth B. Stein, Eleftheria Kontou, and Alexander Yoshizumi

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About the Authors

Beia Spiller is a fellow and the director for RFF's Transportation Program. Prior to joining RFF, she was Lead Senior Economist at Environmental Defense Fund (EDF), where she worked for almost a decade. She was also a Board member for the Association of Environmental and Resource Economists through 2024. Spiller is an energy economist, with experience working on electricity and transportation issues. During her time at EDF, she participated in many electric utility proceedings in New York and California, with a goal of ushering in a cleaner, more efficient and equitable energy system.

Ruolin Zhang is a Transportation Analyst at Kittelson & Associates and a PhD candidate in Transportation Engineering at the University of Illinois at Urbana-Champaign. She specializes in sustainable transportation systems planning and operations, with research focused on electric vehicle (EV) infrastructure planning, charging management, and policy analysis. Her work integrates data-driven modeling, optimization, and spatial analysis to support equitable and sustainable EV adoption in both urban and regional contexts. At Kittelson, Zhang applies her academic expertise to real-world transportation planning projects, bridging research and practice to advance sustainable mobility solutions.

Elizabeth B. Stein is the State Policy Director at the Institute for Policy Integrity at New York University School of Law. Her work centers on state utility commission advocacy relating to electric and gas system decarbonization, electrification of end uses, sustainable rate design for the energy transition, and accurate accounting for energy transition-related emissions impacts. Before Policy Integrity, Stein was Lead Counsel, Energy Transition, at Environmental Defense Fund.

Eleftheria Kontou is an assistant professor of Civil and Environmental Engineering at the University of Illinois Urbana-Champaign. Her research focuses on sustainable and electrified transportation systems planning and management. Kontou was a postdoctoral research associate at the Transportation and Hydrogen Systems Center of the National Renewable Energy Laboratory and the City and Regional Planning Department of the University of North Carolina at Chapel Hill.

Alexander Yoshizumi leads the Systems Planning & Analysis program at the Institute for Transportation Research and Education (ITRE) at NC State University, where he oversees the Triangle Regional Model: the travel demand model serving North Carolina's Triangle region. He also serves as Executive Director of the Applied Data Research Institute, a nonprofit organization that applies data science and systems modeling to address complex, real-world challenges. His expertise spans transportation, energy, and land change systems modeling. He has led and contributed to a wide range of modeling efforts, including travel demand forecasting, process-based land change, regional growth allocation, agent-based evacuation travel, and energy systems operations.

About RFF

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Sharing Our Work

Abstract

This paper employs an economics-engineering model to simulate the impact of various electric tariff structures and rate levels on the charging economics of six hypothetical medium- and heavy-duty vehicle fleets, including their total bills and peak demand without managed charging as well as their opportunity to save money and lower their peak demand by managing their charging. It uses real fleet data from a set of fossil-fueled fleets as the basis for modeling the duty cycle of hypothetical electric fleets; employs heuristics for how an operator would respond to a price signal; models charging behavior in the context of several thousand rates described in the National Renewable Energy Laboratory's Utility Rate Database; compares charging behavior depending on tariff features, including reliance on demand-based versus volumetric determinants, and the extent to which they are time-variant; and evaluates the potential for cost savings, peak demand mitigation, and the alignment between those outcomes. We find that managed charging can provide substantial cost savings for electric vehicle fleets while alleviating peak demand pressures on the grid. Among the tariff structures analyzed, those with time-of-use demand and volumetric components deliver the highest cost-saving opportunities compared with other tariffs, especially for fleets with adaptable charging schedules and significant daily mileage requirements. In contrast, tariffs with flat volumetric rates, or that do not include a demand component, may be straightforward but offer little incentive for cost optimization through load shifting.

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1. Introduction

Medium- and heavy-duty vehicles (MHDVs; i.e., trucks and buses) produce 23 percent of the transportation sector's greenhouse gas (GHG) emissions and over half of all local air emissions; however, they represent only about 10 percent of the vehicle miles traveled (EPA 2025; American Lung Association 2022; BTS, n.d., 2020 data). Electrification of these vehicles could thus help mitigate pollution externalities. The technology to electrify these vehicles has been commercialized, and existing ranges currently allow for many existing diesel fleets to successfully conduct their operations using electric vehicles.

The benefits of vehicle electrification extend beyond emissions reductions; besides providing the driver with improved comfort, health, and driving experience, electric vehicles have often been touted for their lower-cost refueling. Because electric trucks and buses cost significantly more up front than their diesel counterparts,[1] and switching to them will require learning and impose transition costs on the fleet (Spiller et al. 2023b; Danielis et al. 2025), rapid fleet adoption will require unlocking opportunities for operational savings through favorable fueling costs (Konstantinou and Gkritza 2023; Hensher and Wei 2024).

Though keeping operational costs low is essential to advance truck and bus electrification, it is also important to mitigate the costs that these vehicles place on the system. Given the large size of these vehicles' batteries, their individual and aggregate grid impact could be significant (National Grid et al. 2022). Thus, managing their charging will be necessary to ensure that the transition to electric trucks and buses is done in a socially cost-effective manner.

The challenge therefore is to lower the cost of charging for electric-vehicle customers while still incentivizing socially optimal charging behavior. The electric tariff, a price schedule established by electric utilities with regulatory oversight that sets the prices levied on customers for their use of the electric grid and consumption of power, has implications for both sides of this coin.[2] It is a key driver of customers' cost of charging and their charging behavior. If structured carefully, electric tariffs can provide the opportunity for fleet operators to manage charging in a way that reduces both the fleet's electric bill (in comparison with what it would be if fleet operators did not intentionally manage their charging) and the impact on the grid.[3] Essentially, the

[1] See Spiller (2023) for an analysis of the cost differential between electric and diesel trucks.
[2] In some states, the price of the electric commodity delivered by electric utilities may be set competitively, although the pricing for the use of the utility's grid is still set by tariff. See generally Dormady et al (2025).
[3] Notably, charging management could also have important benefits to emissions, by shifting demands into cleaner hours (Lu et al 2023); however, estimating the environmental impacts of these tariffs is beyond the scope of this study.

ability to manage charging can provide large social and private benefits, and electric tariffs can create the price incentive to enable this.

In this paper, we explore the extent to which existing electric tariffs can support the achievement of both goals. Because tariff structures and levels vary by geographic location and each fleet has its own operational needs, understanding the ability of tariffs to reduce customers' peak demand over various measurement periods while reducing the operational costs of adoption requires an exploration of both a variety of tariffs and a variety of fleets. To that end, we simulate the effect of electric tariffs on customer bills and demand levels, by analyzing the impact of thousands of current electric tariffs across the country on four different fleet types—school buses, transit buses, refuse trucks, and delivery vehicles—given an assumed fleet size of 50 vehicles.

Using telematics data from existing fossil-fueled (FF) fleets across the country, we first simulate unmanaged charging loads.[4] In this simulation, each time a fleet returns to its depot, it promptly charges all vehicles simultaneously until fully charged. The magnitudes and patterns of these unmanaged charging loads depend on the vehicles' and charging infrastructure's characteristics and operations. Given these unmanaged charging loads, we calculate the cost the fleet would face under a variety of electric tariffs, assuming no responsiveness to price.

We then simulate a managed charging scenario in which fleets adjust their patterns of charging—with their flexibility to make such adjustments being limited by vehicle miles traveled (VMT) needs and dwell periods revealed by the telematics data—to minimize their electric bills under the same set of electric tariffs. These managed charging loads, and the resulting bills, thus represent approximately what could be achieved through pricing incentives in terms of reduced peaks and electric bill savings.

The paper proceeds as follows: In Section 2, we provide more detail on electric tariffs for fleets; in Section 3, we describe the methodology; and in Section 4, we present our data. We discuss our results in Section 5, including the impacts on both loads and electric bills. We conclude in Section 6 with a discussion of our findings and suggestions for future research.

[4] Most of the fossil-fueled fleets in our sample are diesel-based, though there is one compressed natural gas fleet.

2. Electric Tariffs for Commercial Customers

In much of the United States, large commercial and industrial customers, which are generally commercial entities with fairly high-capacity electricity service, are often subject to tariffs that have multiple billing determinants. These include both demand-based components, which depend on the customer's peak demand, whether overall or at specific times, and volumetric components, which depend on total energy consumption (see NARUC 2016, 100). Demand charges essentially levy fees on customers for their maximum demand or consumption during one or more prespecified time intervals, such as an hour or 15 minutes.[5] These demand charges are generally fixed throughout the month, which means that whether the customer hits a peak demand only once or sustains that peak demand consistently, they will be charged the same amount.[6] (For a more in-depth description of demand and electricity prices in the framework of utility cost recovery, see Appendix A). Optimizing demand in the face of different price signals emerging from different billing determinants may be challenging for some customers (Stikvoort et al. 2024), though tools such as managed charging software exist to help fleets manage their demand (see, e.g., DOE, n.d.).

Demand charges have proven highly problematic for commercial electric vehicle (EV)-charging customers, particularly public charging stations (Lee et al. 2020; Borlaug and Bennett 2022). Because they are commercial customers with high-capacity electricity service, public EV charging stations are generally subject by default to demand charges (Muratori et al. 2019). For most commercial or industrial customers with any given high level of peak demand, the expectation would be that they would also have a similarly high level of total consumption—the high peak demand would be sustained, or at least frequent, and not all that far off from their typical demand. But this is not true for public EV charging stations—their peak demand might be quite anomalous, bearing little resemblance to average energy consumption for their ongoing operations (Tong et al. 2021). If several chargers are in use simultaneously, just once, a demand charge might get set at a level comparable to that of a sizable commercial facility—but after that one good day, the EV chargers may receive little use. The result is that a public EV charging station with low utilization might incur electric bills that are comparable to that of a sizable commercial facility, while in fact charging only a small number of cars (Muratori et al. 2019).

This is an entirely predictable result during the transition to EVs—low utilization is inevitably the norm early in the transition. The challenge is exacerbated by the fact

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[5] These time intervals are determined by the utility, with regulatory oversight, based on a number of factors.
[6] If the customer is also subject to volumetric charges, then a sustained high level of consumption would be more expensive.

that to be successful, public charging stations must, for the most part, be available on demand to charge EVs at a price that individual car owners can tolerate, whenever EVs in need of a charge happen to show up. The high utility costs associated with demand comparable to that of a sizable commercial facility could not possibly be passed on to a very small number of car-charging customers; if they were, the resulting cost of charging EVs could be orders of magnitude higher than the cost of filling up gas-fueled cars. In short, without some kind of mitigation, demand charges could make public chargers with low utilization impossible for commercial entities to build or operate, posing an insurmountable barrier to early deployment of public charging (or deployment of public chargers in remote locations, where charger usage may always be infrequent).[7]

People who own electric vehicles and charge them using their residential electricity service generally do not encounter this issue on their home electric service, as they do not typically pay demand-based rates at all. And time-of-use (TOU) volumetric tariffs have proven highly effective in helping such residential customers save money on charging relative to a non-time-variant tariff, while also mitigating the impact of incremental electricity demand arising from home charging (see, e.g., Qiu et al. 2022). But the ability to charge quickly while on long trips—in a manner that customers perceive as roughly comparable to refueling an internal combustion engine vehicle—is widely understood as essential for electric cars to compete with gas cars. Because commercial fast charging of cars was one of the earliest commercial charging applications to begin to scale up, the incompatibility between demand charges and early-stage proliferation of public fast charging has been widely understood as a fundamental mismatch between commercial tariffs and vehicle electrification. In response, advocates for vehicle electrification have worked to develop, and sometimes mandate, alternative commercial electric tariff structures for use on a temporary or permanent basis (see, e.g., Alliance for Transportation Electrification 2022; NARUC 2022). In New York, this effort culminated in the passage of a statute that required the establishment of alternatives to traditional demand-based tariff structures to facilitate faster charging.[8]

However, while demand charges may be a demonstrably poor fit for an important early commercial EV-charging use case, not all commercial charging resembles the early public-charging use case. In fact, there may be some EV-charging use cases for which conventional commercial tariffs, including those that result in bills that are driven

[7] Mitigation could occur either through changes in the tariff applicable to the public charging stations or through action taken by the operator, such as investment in battery storage to smooth out peak demand.
[8] The legislation can be found at **https://legislation.nysenate.gov/pdf/bills/2021/S3929**. An amended version of that law (see **https://legislation.nysenate.gov/pdf/bills/2021/A8797**) directed the utility regulator to undertake a process to examine a range of options, including—without limitation—alternatives to traditional demand-based tariff structures; the resulting proceeding remains ongoing at the New York Public Service Commission. For more information on the proceeding, see **https://documents.dps.ny.gov/public/MatterManagement/CaseMaster.aspx?Mattercaseno=22-E-0236**.

primarily by demand-based billing determinants, might be a reasonably good fit. Consider, for example, whether there are EV-charging use cases that may strongly resemble the commercial and industrial facilities that have been able to flourish under conventional electric tariffs. Can commercial EV-charging loads ever have high consumption that is reasonably proportional to their high demand? Are there commercial EV charging entities that have the capability of managing the timing of their charging and its resulting load shape, much as other commercial and industrial customers manage their electric load to avoid the highest prices and optimize their energy procurement?

These types of questions have been explored in large part for electric transit buses and the ability of these fleets to reduce their electric bills in response to time-of-use rates and demand charges. Within the engineering literature, research has demonstrated that transit buses could optimize their charging patterns in response to time-of-use rates (Qin et al. 2016; He et al. 2022, who focus on on-route fast charging; Zhan et al. 2025; Xiao et al. 2024) and demand charges (Qin et al. 2016; He et al. 2020; Al-Hanahi 2022; Xiao et al. 2024) to achieve bill savings. Gallo et al. (2014) calculate the bill impacts for electric transit buses under a demand charge tariff and compare it with alternative tariffs, such as volumetric time-of-use, but do not simulate any price responsiveness.[9] Accounting for price responsiveness is key, however, as Qin et al. (2016) find that by optimizing charging in response to demand charges, a fleet of five electric buses could save over $160,000 in electricity costs over a 12-year vehicle lifetime. While there is evidence from the literature that electric transit buses can benefit from time-of-use rates and demand charges, these papers are limited in that they look primarily at transit bus fleets and generally just one or two specific tariffs. The broader question of how tariff structure and price differences can affect managed charging patterns across a variety of fleet types is still unanswered.

Thus, our review of the literature suggests that the answers to these questions are, for the most part, unknown. Solutions to the demand charge problem applicable to the low-utilization public-charging use case have sometimes been adopted as generally applicable commercial charging tariff solutions (see Silverman 2023). Yet no rigorous analysis has considered how a variety of commercial-charging use cases might interact with the types of electric rates that would be applicable to them across the United States. We seek to fill that gap with this paper.

3. Methodology

In this paper, we use an economics-engineering model to simulate the impact of various tariff structures and rate levels on electric bills (under both managed and

[9] Similarly, Phadke et al. (2019) estimate the cost of charging a heavy-duty truck under demand charges and time-of-use rates but do not simulate responsiveness. They find that time-of-use rates would result in cheaper charging rates, though it is unclear whether incorporating fleet responsiveness to pricing would change this result.

unmanaged charging loads), maximum loads, and managed charging for four different types of fleets: school buses, transit buses, refuse trucks, and class 6 delivery vehicles. The ideal approach to estimating this impact would be to have a controlled experiment in which we impose a range of tariffs on several fleets and observe how these tariffs affect our outcomes of interest. However, this ideal experiment is impossible, as any fleet would be subject to a limited number of different tariffs (that is, those that are available from the utility that serves the fleet's premises); this means that conducting this type of experiment at a large scale, using tariffs from across the country, would be infeasible. Furthermore, adoption has been slow, with heavy-duty electric vehicles not surpassing 1 percent of new vehicle sales (IEA 2024), making it hard to access observed outcome data that reflect a wide variety of use cases.

However, internal combustion engine vehicle characteristic benchmarking, where electric and internal combustion engine vehicles are treated as equivalent for the purpose of simulating electric vehicle behavior (Zhan et al. 2025), provides a feasible alternative for examining the impact of tariffs. Using duty cycles inferred from available medium- and heavy-duty vehicle telematics data (described in more detail in Section 4), we simulate responses of a model electric fleet to price signals arising from electric tariffs.[10] Freight and logistics companies typically employ centralized management strategies and operations research techniques to optimize their outcomes under different constraints, including varying tariffs. Techniques such as routing and scheduling offer a basis for how tariffs can be managed effectively (Bartolacci et al. 2012). Thus, while a controlled experiment is infeasible, our methodology reflects the approach often taken by fleets looking to optimize either their operations or their charging schedules.

Our first step is to identify the patterns of use for the different FF fleets, including total daily VMT and dwell and operational times of day. To do so, we created a package of Python functions that can be used to estimate the times at which fleet vehicles are in depot by applying user-specified rules to the processing of vehicle telematics time-location data. We processed the data to one-hour intervals that specify whether vehicles are active or dwelling. All telematics data are from the Livewire database.[11] Furthermore, we acknowledge that fleets operate their vehicles heterogeneously, meaning some vehicles within a fleet may have different patterns of use than others. Therefore, we employ a clustering methodology to identify different patterns of use within each fleet. We describe the clustering approach in more detail in Appendix F.

Once we identify each FF fleet's operational patterns, we simulate the unmanaged charging load of a 50-vehicle fleet of EVs that has comparable shares of vehicles with duty cycles identical to those of our observed FF fleet (that is, a model electric fleet), with unmanaged charging consisting of vehicles returning to the depot at the end of their shifts and charging at maximum speed until the batteries are fully charged. This

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[10] To differentiate from the observed FF fleets, we use the term "model electric fleet" to describe the electric fleets modeled after these FF fleets.
[11] We obtained the data from **https://livewire.energy.gov/** in September 2024.

requires an assumption about the charging speed employed; we determine this exogenously based on the total required power (given daily VMT) and the number of hours available for charging.[12]

By simulating the unmanaged charging loads at this stage, we can identify which tariffs would apply to the model electric fleet. As we describe further in Section **4**, we leverage a nationwide database of electric tariffs to identify the subset of commercial tariffs each model electric fleet would be subject to if they were located in a particular service territory.

Once we have identified these tariffs, we estimate the costs the fleet would face under each of these tariffs for their unmanaged charging load profiles, assuming no price-responsiveness. Of course, fleets may be able to respond to pricing by smoothing loads (staggered charging) or shifting the timing of the load, depending on their operational requirements and the structure of the tariff. Thus we next simulate price-responsiveness and identify the managed charging profiles for each tariff. In this setting, the model electric fleet responds to the underlying electric tariff and moderates the total demand levels across all vehicles to achieve the lowest electric bill. Essentially, the model electric fleet responds by shifting its charging patterns in a way that reduces its charging cost, while still being able to maintain its operations (including not changing daily VMT or hours of operations). We model two possible fleet responses to price signals in a tariff: shifting charging operations into lower-cost times and staggering the charging of vehicles such that the total demand across all vehicles is lower. These responses vary by fleet, given the length and timing of the fleet's dwell hours and the speed of the chargers.

How an electric fleet responds to the tariffs depends on the characteristics of each tariff. Characteristics include whether the tariff includes a demand charge, whether there is a time variation in either the demand or the volumetric portion of the tariff, and the magnitude in \$/kWh or \$/kW of the volumetric and demand charge components, respectively. Based on these characteristics, we assign tariff types as described in Table 1. We define each combination of demand and volumetric rate as a tariff type (column 1). Note that while some tariffs have no demand charge, all have volumetric charges.

[12] Importantly, to reduce our optimization complexity, we employ a simplifying assumption that unmanaged charging charges at full speed until the batteries are full. In reality, charging slows at 80 percent charge.

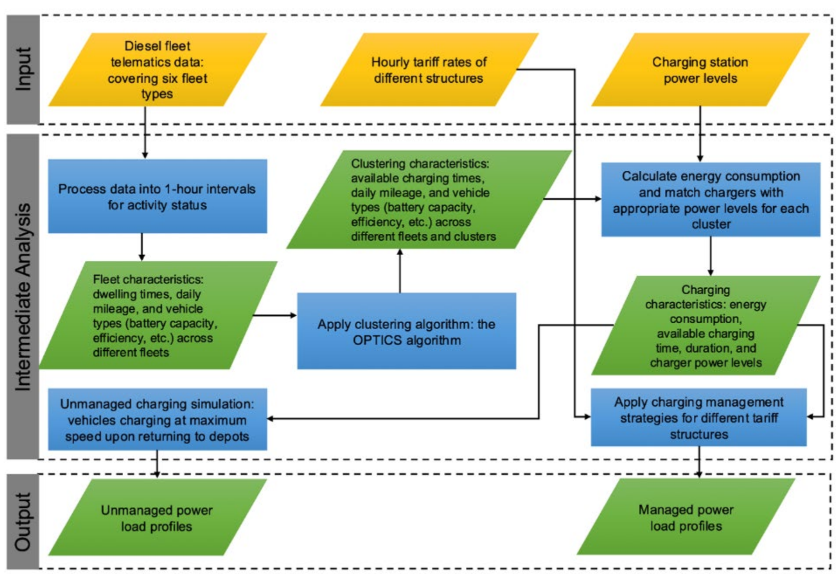
Table 1. Electric Tariff Types

Tariff type	Demand charge	Volumetric charge
No demand & flat vol. (NDFV)	None	Flat
No demand & TOU vol. (NDTV)	None	TOU
Flat demand & flat vol. (FDFV)	Flat	Flat
Flat demand & TOU vol. (FDTV)	Flat	TOU
TOU demand & flat vol. (TDFV)	TOU	Flat
TOU demand & TOU vol. (TDTV)	TOU	TOU

Managed charging approaches thus vary by tariff structure, as the presence of demand charges or TOU pricing affect an electric fleet's decision to lower its maximum demand or shift its charging into off-peak periods. Depending on the characteristics of the applicable tariff, the optimal approach to manage consumption might involve optimization for two different temporal price signals, which may conflict (Stikvoort et al. 2024).

Figure 1 provides a graphical representation of the methodological framework for simulating charging strategies of our model electric fleets.

Figure 1. Methodological Framework for Simulating Charging Strategies of FF Fleet Vehicles



Note: Blue boxes indicate transformations and analyses; yellow boxes, data inputs; and green boxes, outputs.

No demand and flat volumetric (NDFV) tariffs present a unique case where charging management strategies cannot be leveraged to reduce electric bills. As the tariff imposes a uniform volumetric rate, the only means to lower expenses would be through the reduction of total energy consumption, which for an electric fleet means a decrease in VMT. However, changes in fleet operations other than charging are beyond the scope of this study.[13]

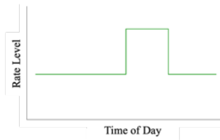
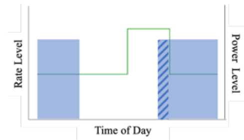
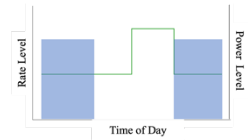
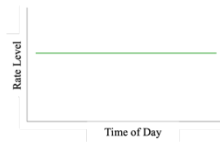
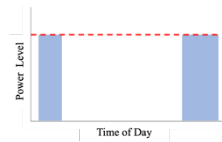
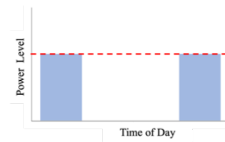
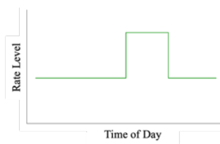
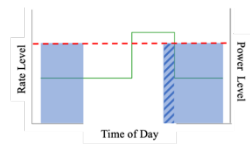
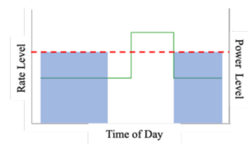
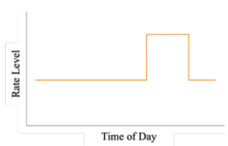
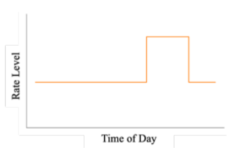
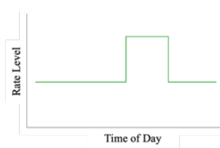
For **no demand and TOU volumetric (NDTV) tariffs**, a heuristic strategy is adopted to align charging with off-peak hours. If off-peak hours are insufficient to meet charging needs, remaining charging spills over into higher-cost periods. Each cluster within the fleet is allocated charging times based on its specific dwell times.

In the scenario of **flat demand and flat volumetric (FDFV) tariffs**, the focus shifts toward minimizing peak power demand by solving an optimization model (as described in equation (1)), as peak power demand is the only variable that can influence the bill without changing VMT. Furthermore, because all FDFV tariffs have the same profile, regardless of the price level, we need to solve the model only once, reducing computational complexity.

We describe our routine for developing managed charging scenarios under each tariff type and provide schematic diagrams of tariff influences on electric fleet charging in Table 2. Parameters and variables for optimization model of FDFV tariffs are given in Table 3.

[13] Changing operations may not be entirely realistic either. Given requirements by the end user (e.g., required bus routes that operate during the day, businesses that want deliveries during the day, and children who need to be taken to school at specific hours of the day), the ability of any fleet to shift hours is likely quite limited (see, e.g., Holguín-Veras et al. 2006 and Holguín-Veras 2008 for discussions of delivery fleets' ability to shift their operational behavior).

Table 2. Managed Charging Strategies Under Varied Tariff Structures

	Demand rate	Volumetric rate	Unmanaged power load profile	Managed power load profile	Description
NDTV	NA				*Heuristic approach:* Charge during the off-peak hours that overlap with the fleet's dwell period.
FDFV					*Optimization model:* Use all available dwell/charging times to reduce peak demand.
FDTV					*Optimization model:* Reduce peak demand as much as possible, while charging during off-peak hours as much as possible.
TDFV			NA	NA	*Enumeration approach:* List the scenarios of charging at different times and identify the one with the lowest cost; as shown in algorithm 1 (see Appendix H)
TDTV			NA	NA	*Enumeration approach:* List the scenarios of charging at different times and identify the one with the lowest cost, as shown in algorithm 1 (see Appendix H)

Note: Columns 1 and 2 illustrate schematic diagrams of demand and volumetric rates; columns 3 and 4 depict schematic diagrams of unmanaged and managed load profiles with highlighted shifts in charging activities and peak demand; column 5 provides brief descriptions of the corresponding strategies.

Table 3. Parameters and Variables for Optimization Model of FDFV Tariffs

	Parameters
$\boldsymbol{T}$	Set of time intervals, where $t \in T$ and $T = \{1,2, \ldots ,24\}$
$\boldsymbol{N}$	Set of medium- and heavy-duty electric vehicles in the fleet, where $n \in N$ and $N = \{1,2, \ldots ,10/50/100\}$
$\boldsymbol{s_{nt}}$	Binary indicator: 1 when vehicle n is available to charge in time interval t; 0 otherwise
$\boldsymbol{c_d}$	Demand rate $(\$/kW)$
$\boldsymbol{p_n}$	Charger power level for vehicle $n(kW)$
$\boldsymbol{b_n}$	Number of charging slots that vehicle n needs
	Variables
$\boldsymbol{x_{nt}}$	Decision variable: 1 if electric vehicle n is charged during time interval t; 0 otherwise
$\boldsymbol{D_{max}}$	Maximum demand level over the charging period

The optimization model for FDFV tariffs is as follows:

$$min\, S = min\{c_d\, D_{max}\} \qquad (1)$$

subject to

$$x_{nt} \leq s_{nt} \qquad \forall\, t \in T, \forall\, n \in N \qquad (1a)$$

$$\sum_{t \in T} x_{nt} = b_n \qquad \forall\, n \;\in N \qquad (1b)$$

$$\sum_{n \in N} x_{nt}\, p_n \leq D_{max} \qquad \forall\, t \in T \qquad (1c)$$

$$x_{nt} \in \{0,1\} \qquad \forall\, t \in T, \forall\, n \in N \qquad (1d)$$

The optimization model for FDFV tariffs aims to minimize the electric bill for a fleet of medium- and heavy-duty electric vehicles by managing charging schedules to reduce peak power demand. The objective of the model is to minimize function S, which is determined solely by the product of the demand rate (c_d) and the peak power demand (D_{max}), reflecting the structure of FDFV tariffs, where reducing peak demand directly lowers the electric bill. The decision variable in the model, x_{nt}, indicates whether vehicle n is charged during time interval t, taking a value of 1 if charging occurs and 0 otherwise. This variable is critical for mapping out the charging schedule of each vehicle in the fleet. For each time (t) and vehicle (n), the model has several constraints: Constraint 1(a) stipulates that charging activities can occur only within the available charging time slots. Constraint 1(b) ensures that the total charging time is equivalent to the dwell hours required by the electric fleet's operation. Constraint 1(c) guarantees that demand does not exceed the maximum, D_{max}. Constraint 1(d) indicates that x_{nt} is a binary variable and thus takes a value of either 0 (not charging) or 1 (charging). This model simplifies the optimization process under FDFV tariffs by focusing on peak demand reduction, making it efficient and effective for operational planning and cost minimization in electric vehicle fleets.

Under the flat demand and TOU volumetric (FDTV) tariffs, the strategy to minimize electric bills involves lowering the peak power demand and ensuring that charging occurs during off-peak hours, when volumetric rates are lower. This approach necessitates an optimization model (as described in equation (2)) similar to the one used for FDFV tariffs, but with modifications to accommodate the TOU volumetric structure. An additional parameter, $c_{v,t}$, is introduced to represent the time-varying energy rates, which affects the model's objective function.

The optimization model for FDTV tariffs is as follows:

$$min\, S = min\{c_d\, D_{max} + 20 \sum_{t \in T} \sum_{n \in N} x_{nt} \cdot p_n \cdot c_{v,t}\} \qquad (2)$$

subject to

$$x_{nt} \leq s_{nt} \qquad \forall t \in T, \forall n \in N \qquad (2a)$$

$$\sum_{t \in T} x_{nt} = b_n \qquad \forall n \in N \qquad (2b)$$

$$\sum_{n \in N} x_{nt}\, p_n \leq D_{max} \qquad \forall t \in T \qquad (2c)$$

$$x_{nt} \in \{0,1\} \qquad \forall t \in T, \forall n \in N \qquad (2d)$$

The modified objective function for FDTV tariffs aims to minimize both the demand charge, based on peak demand, and the energy charge, which is now time-dependent. The optimization seeks to strategically schedule the charging of electric vehicles to leverage lower energy costs during off-peak hours, while also managing the fleet's overall peak demand to minimize the demand charge. This dual-focus optimization under FDTV tariffs enhances the potential for cost savings by leveraging the flexibility in charging times and the variability in volumetric rates throughout the day.

When calculating the TOU demand bill, we use the following formula:

$$\text{demand bill} = L_{\text{peak}} \times P_{\text{peak}} + L_{\text{offpeak}} \times P_{\text{offpeak}},$$

where L_{peak} is the peak load during peak hours, P_{peak} is the price during peak hours, L_{offpeak} is the peak load during off-peak hours, and P_{offpeak} is the price during off-peak hours.

For TOU demand and flat volumetric (TDFV) tariffs, the optimization routine involves carefully assessing the trade-off between minimizing peak demand and ensuring as much charging as possible occurs off peak. In this setting, the optimization is more complex than in a flat demand scenario, because any demand incurred in the off-peak hours is subject to a charge. Thus, the price differences between the tariff's peak and off-peak hours significantly affect the final bill.

For TOU demand and TOU volumetric (TDTV) tariffs, charging management is even more challenging, as the optimization algorithm needs to consider the TOU volumetric charges as well as the TOU demand charge. This results in an intricate optimization routine because the peak hours of the demand charge may not match the peak hours of the volumetric charge. Therefore, for both TDFV and TDTV cases, we adopt a methodology that identifies the charging scenario with the lowest cost. This algorithm strategically balances the trade-off between minimizing demand occurring during peak hours and smoothing demand to reduce off-peak hour peaks. Starting with the minimum required charging time, the algorithm prioritizes off-peak hours to maximize cost savings. It incrementally adds available time slots, extending the charging window until all possible charging times are used. This approach may inevitably lead to charging during peak hours, reflecting the delicate compromise between charging over fewer hours to remain in off-peak hours and charging over a longer time period to diminish peak demand. The specific algorithm is shown in Appendix H.

4. Data

4.1. Fleet Characteristics

As outlined in Section 3, our analysis uncovers patterns of use for several observed FF fleets, focusing on total daily VMT, dwell times, and operational hours. Because of the heterogeneity of vehicle operations, we employ a clustering methodology to capture the diversity of use patterns within each FF fleet. These clusters are characterized by the share of the total fleet that falls within the cluster, dwell times, total dwell hours available for charging, the average daily mileage covered by the vehicles, and the types of vehicles used within each cluster. These attributes are essential for a comprehensive understanding of the FF fleet's operational behaviors and for informing the development of tailored charging strategies.

The analysis of the various FF fleets reveals differences in operational patterns across clusters, particularly in terms of dwell periods, daily mileage, and vehicle types. The FF school bus fleet operates as a single cluster, staying in depots overnight, which aligns with its typical usage during school hours. Each FF transit fleet is divided into two clusters with different dwell times, reflecting varied usage throughout the day. The FF refuse fleet also has two clusters, one primarily dwelling in the afternoon and the other overnight, suggesting different collection schedules or shift patterns. Each FF delivery fleet is split into three clusters with slightly different overnight dwell periods, likely based on delivery schedules.

Despite having multiple clusters, both the FF delivery fleets and the FF refuse fleet exhibit relatively consistent daily mileage across clusters. By contrast, the transit vehicles show a range of mileages, indicative of different route lengths or service frequencies. The FF school buses we identified from Livewire have lower daily mileage, as a result of its short, localized routes for shuttling students.[14] Each FF fleet's daily mileage provides insight into its energy consumption and, for an equivalent electric fleet, sheds light on the charging patterns needed to maintain operations efficiently.

For more information on the clusters within each FF fleet, refer to Appendix Tables B.1 and B.2.

4.2. Charging Characteristics

We next derive the charging characteristics of an electric fleet composed of vehicles with comparable duty cycles to those in each real FF fleet. This process takes into account the type of vehicle (that is, some kind of truck, school bus, or transit fleet), its typical daily travel distance, and the applicable EV's specific energy efficiency (kWh per mile) to ascertain the charging requirements for each vehicle.[15] The total energy required for a day's operation is derived by multiplying the vehicle's average daily mileage by its energy efficiency. Subsequently, to determine the rate at which power must be supplied to fully charge the vehicle within the allotted time frame, the total energy requirement is divided by the time available to charge.[16] Based on this estimated power need, we select an appropriate charger type with a power output that meets or exceeds this rate, ensuring that the vehicle's battery can be fully recharged within the available dwell period.

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[14] Low VMT is likely typical for most urban-based school districts; however, rural school districts are more likely to have high VMT. Thus, this analysis is not reflective of those school districts whose buses have long routes to travel.
[15] To identify the vehicle's energy efficiency, we identified MHDVs that were on the market at the time of writing this paper and then chose the vehicle that allows for similar operations, including the use type (e.g., we selected only electric school bus options for the school bus fleets) and those that allowed the fleet to achieve similar VMTs for the routes identified in the Livewire data. See Appendix Table B.2 for a list of the vehicles chosen and their characteristics.
[16] Again, this is based on our simplifying assumption that charging speeds remain fixed for the entire battery refueling.

The differing charging characteristics of the model electric fleets reflect the differing power requirements driven by the operational needs of their FF counterparts. In Appendix Table C.1, we include information about the various model electric fleets we model based on the relevant FF fleet's telematics data (e.g., the fleet name, type, mileage efficiency, assumed charger type, and time available to charge). Model electric versions of the transit fleets, such as the one modeled after compressed natural gas fleet *cngsocal*, with daily mileages ranging from 140 to 247 miles, require both level 2 (19.2 kW) and level 3 (50 kW) chargers. The electric transit fleet modeled after diesel fleet *ornl* has a slightly lower average daily mileage (96 to 159 miles) but follows a similar pattern, with higher-powered level 3 (50 kW) chargers used to support quicker turnaround times, particularly for the clusters with higher daily distances. The model electric delivery fleets (modeled from diesel fleets in San Diego and Texas) have average mileages ranging from 104 to 163 miles and could use mostly level 2 chargers (19.2 kW). These fleets have slightly higher energy demand but can generally recharge overnight or during available downtime. The diesel school bus fleet exhibits more uniform operational patterns, with a daily mileage of around 116 miles and relatively uniform energy requirements. Thus the model electric school bus fleet with similar operational patterns would rely primarily on level 2 (19.2 kW) chargers, as the consistent schedules offer ample opportunity for overnight charging. Finally, the model electric refuse fleet, with lower daily mileages (84 to 96 miles), also depends on level 2 chargers (19.2 kW).

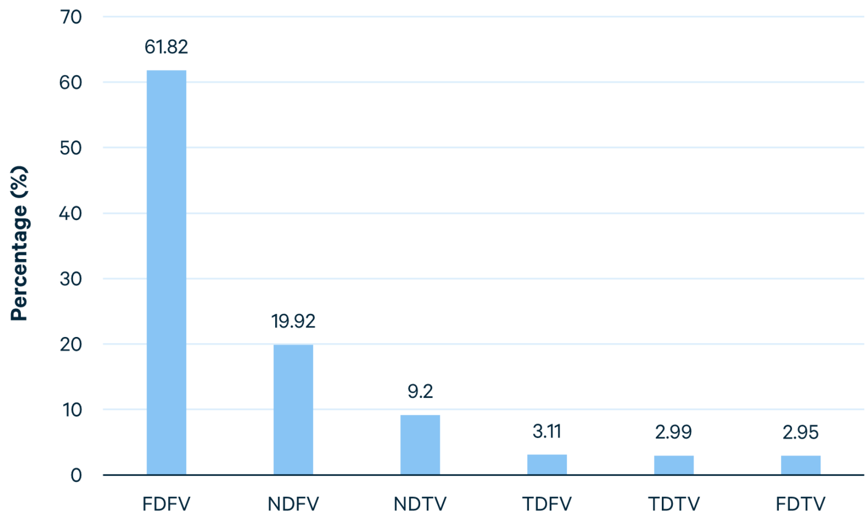
For detailed fleet-specific charging characteristics, including computations of average daily mileage, efficiency, charging needs per vehicle, and charger type, refer to Appendix Table C.1.

4.3. Tariff Data

Our study leverages the National Renewable Energy Laboratory's Utility Rate Database (URDB), selecting commercial sector tariffs in effect as of 2023. From over 13,000 rate entries, we filter out irrelevant rates, such as those specific to irrigation or services unrelated to the fleet operations examined (exclusion criteria are detailed in the Appendix D).

Figure 2 illustrates the percentage distribution of different tariff type combinations using the model electric transit fleet modeled after *cngsocal* as an example. The largest category is FDFV, accounting for almost 62 percent, followed by NDFV at almost 20 percent and NDTV at approximately 9 percent. The other combinations, TDFV, TDTV, and FDTV, have smaller proportions of approximately 3 percent each. Given the similar distribution of tariff type availability observed across all fleets and cases, this illustration of tariffs available for this model electric fleet provides a representative view of how tariff combinations are distributed more broadly.

Figure 2. Percentage Distribution of Tariff Type Combinations for the *cngsocal* Model Electric Fleet (representative of study findings)

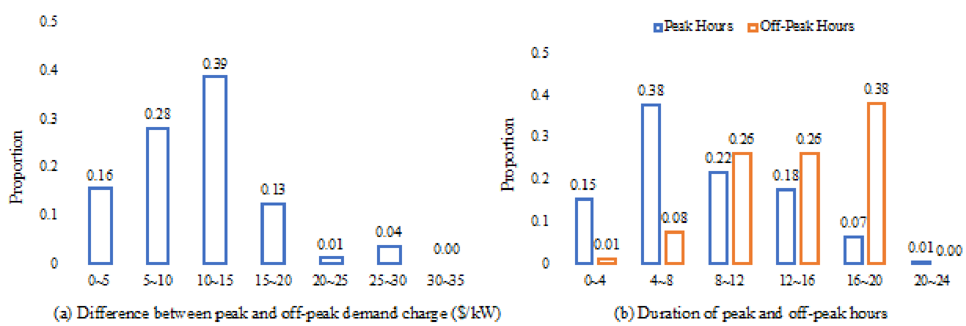


To ensure that our analysis reflects the electricity costs faced by commercial fleet as fully as possible, we filter the URDB dataset to include only those tariffs that bundle the energy commodity with delivery services. This step is essential because in states that have restructured their electric utilities, customers may procure energy separately from delivery; thus the delivery-only rates offered by distribution-only utilities do not represent the full cost of electric service. Customers may procure energy separately from delivery, and thus delivery-only rates do not represent the full cost of electricity. We begin by reviewing the regulatory status of each state, focusing our analysis on utilities operating in states that are fully regulated or only partially restructured. In the latter case, such as California, we retain only those tariffs that are explicitly labeled as “bundled.” Beyond relying solely on the bundled field in the URDB, we cross-check rate metadata and utility names to verify that included rates reflect vertically integrated utility structures. This manual screening helps ensure that major investor-owned utilities in states with vertically integrated electric utilities are appropriately represented, even in cases where labeling inconsistencies might have otherwise excluded valid bundled tariffs. Although this conservative approach may have led to the inadvertent omission of some applicable rates due to mislabeling or ambiguity, it supports consistency in comparing rates that reasonably reflect total energy costs. This filtering step is applied before tariff categorization and thus underpins all downstream modeling and analysis in this study. (For a comprehensive breakdown of rates by season and fleet size, see the details in Appendix Table E.1.)

We also explore the characteristics of demand charges and volumetric charges, as illustrated in Figures 3 and 4. The figures provide the proportion of peak and off-peak hours and their price differences. For demand charges, panel (a) of Figure 3 reveals that 39 percent of the intervals show a difference between peak and off-peak hours ranging from \$10 to \$15 per kW, with the average difference across all intervals being

$10.59 per kW. Panel (b) of Figure 3 provides insights into the duration of peak and off-peak hours over a 24-hour period. The chart shows that peak hours for demand charges most commonly span 4–8 hours. In contrast, off-peak hours are typically longer, with the most common off-peak period duration lasting 16–20 hours. This indicates that there are extended periods during the day where lower demand charges apply, offering opportunities for fleets to shift their charging and energy-intensive operations to these off-peak hours to achieve cost savings compared to unmanaged charging.

Figure 3. Peak and Off-Peak Hour Price Differences and Duration Distribution for Demand Charge



For volumetric charges, panel (a) of Figure 4 shows that 33 percent of the cases have a small price difference between peak and off-peak hours, ranging from $0.0005 to $0.05 per kWh. Another 20 percent of the cases fall above $0.05 and below $0.10 per kWh, while 28 percent fall between $0.10 and $0.15 per kWh. Because a volumetric charge is applied separately for every kWh consumed, even seemingly small differences in volumetric charges based on time of consumption can provide substantial room for cost optimization through careful management of energy usage. Panel (b) of Figure 4 depicts the distribution of peak and off-peak hours. For peak hours, the most common duration is 4–8 hours. Tariffs with longer peaks (8–12 hours and 12–16 hours) are somewhat less common, and only a handful of tariffs have an extremely long peak (16–20 hours). For off-peak hours, the most common duration is 8–12 hours, while the least common duration is the shortest (4–8 hours).[17] Unlike for demand charges, where off-peak windows skew toward longer periods of time, volumetric off-peak windows tend to be shorter, indicating a narrower window for customers facing time-variant volumetric charges to achieve cost savings.

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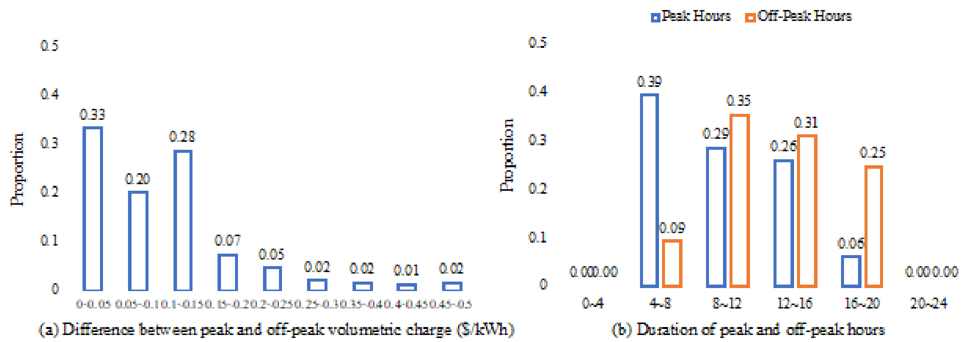
[17] Note that some tariffs have three periods: a peak period, an off-peak period, and a shoulder period. In this case, we do not aggregate the shoulder period into either the peak or off-peak period; thus the summation of peak and off-peak period windows do not necessarily add up to 24 hours.

Figure 4. Peak and Off-Peak Hour Price Differences and Duration Distribution for Volumetric Charge

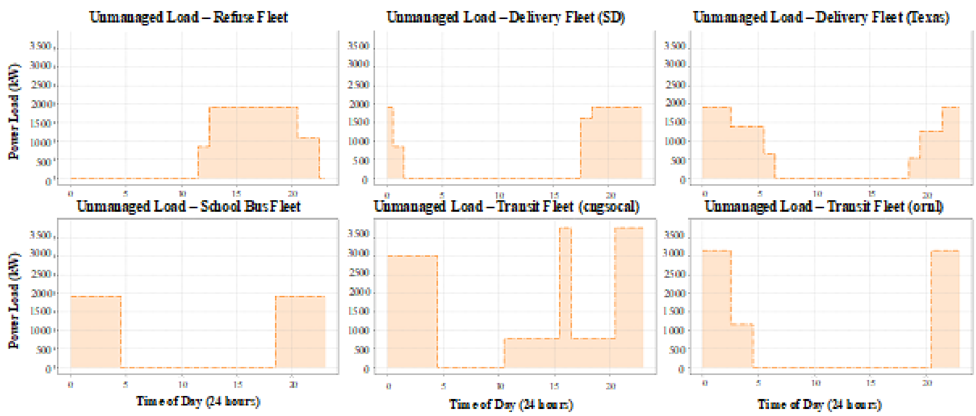


In conclusion, where both demand and volumetric charges are applicable, fleet operators must consider both when planning energy usage and optimizing costs, as their combined impact can significantly influence overall charging cost.

5. Results

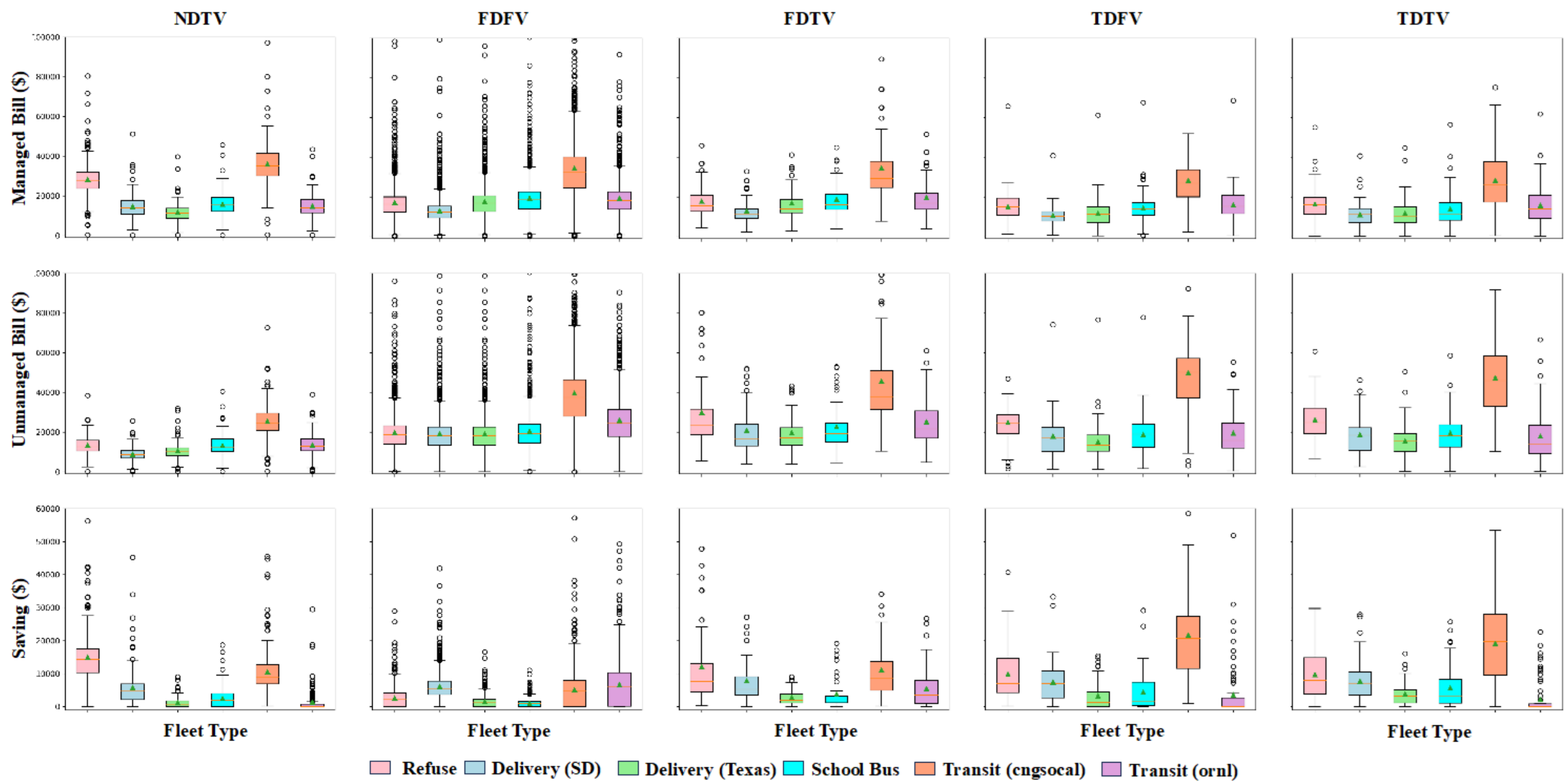
Figure 5 illustrates the unmanaged charging load profiles for the six fleets across a typical weekday 24-hour period, from the hour beginning at 12 a.m. to the hour beginning at 11 p.m. Each subplot corresponds to a different fleet. One of the transit fleets (*cngsocal*) exhibits the highest peak demand, exceeding 1,800 kW with a sharp load increase around midday. The other transit fleet (*ornl*) also shows a high peak demand, surpassing 1,500 kW, with a significant portion of charging spread across late-night hours. For the school bus fleet, the charging profile aligns with the typical school schedule. Charging occurs predominantly after school hours, with peak demand reaching 800 kW. Little to no charging occurs during the day, when the buses are in operation. The refuse fleet charges predominantly in the late morning to afternoon, after its typical early-morning operations. Both delivery fleets (San Diego and Texas) begin charging around 6–7 p.m., with peak demand of 2,000 kW and load gradually increasing after the evening hours.

Figure 5. Unmanaged Charging Load Profiles for Various Fleet Types



Managed charging practices allow electric fleet operators to respond to time-variant electric tariffs, either by shifting their consumption to a different time or by spreading their consumption over their dwell time to minimize their electric bill, or both. Following the optimization models described in Section 3, our analysis results in managed charging load profiles as shown in Figure 6. These optimizations can achieve significant electric bill savings, depending on the fleet and the tariff. In Figure 6, we show the distribution of managed and unmanaged bills and savings; for simplicity, our bills do not include any fixed charges, and thus, depending on the tariff, the variable portion of the bill (as shown in Figure 6) can be zero (or even negative in the case of negative off-peak pricing, which happens infrequently; an example is shown in Appendix Figure D.1).

Figure 6. Distributions of Managed and Unmanaged Electric Bills (Excluding Fixed Charges) and Savings Achieved for Six Fleet Types Under Five Tariff Types



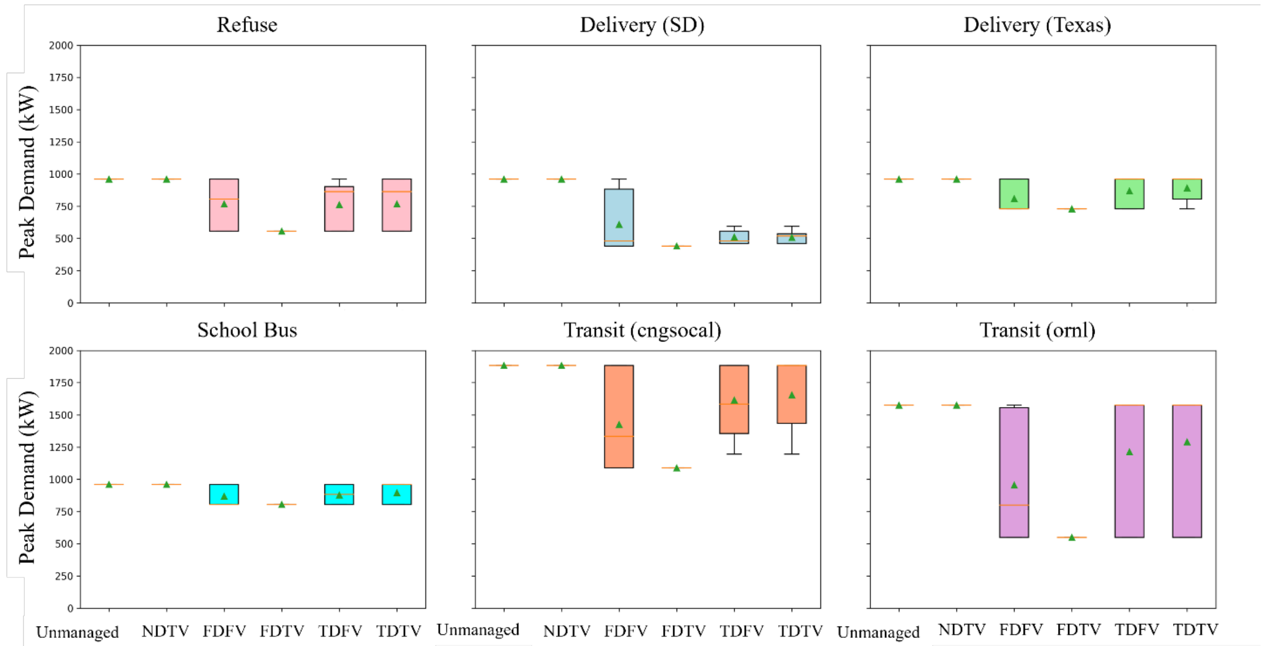
Note: The top row shows distributions of managed electric bills; the middle row, distributions of unmanaged electric bills; and the bottom row, distributions of bill savings from managed charging. The colored boxes represent different fleet types.

Figure 6 highlights key differences in savings potential from managed charging across both fleet types and tariff structures. The transit fleets in our sample tend to benefit the most from managed charging under most tariff types, as reflected by the substantial savings observed, especially under time-variant tariffs. Similarly, our model electric refuse fleet consistently shows significant savings potential, with time-variant tariffs enabling higher savings in comparison with flat demand-based rates. The delivery fleets also see considerable savings under managed charging, although their results are more varied across tariff types. On the other hand, the school bus fleet generally experiences lower savings, likely because its operational hours typically align well with peak tariff hours (which means that its unmanaged charging will align naturally with cheaper, off-peak hours, providing fewer opportunities for shifts in charging to reduce costs), thus providing fewer opportunities for shifts in charging to reduce costs.

In terms of tariff types, the results indicate that compared with flat-demand tariffs, time-of-use demand tariffs offer greater opportunities for cost savings through managed charging, though the impacts vary by fleet. FDFV tariffs generally result in smaller savings potential, but they can still offer benefits for some fleets, depending on their operational patterns. Overall, the data suggest that managed charging is most beneficial for fleets with flexible operational schedules and higher energy demand, and that having both time-variant demand and time-variant volumetric charges provides a greater opportunity for maximizing those savings than under tariffs that do not have any time variation.

In terms of peak demand management, shown in Figure 7, the model electric transit fleets (particularly *cngsocal*'s model electric fleet) exhibit the greatest ability to reduce their peak demand, followed closely by the model electric refuse fleet and the model electric San Diego delivery fleet. In contrast, the model electric Texas delivery and school bus fleets see the lowest peak demand reductions under managed charging, likely because of their less flexible operational schedules and a natural alignment of dwell hours with off-peak hours. Looking at the tariff structures, the effectiveness of reducing peak demand follows a clear hierarchy: FDTV is the most effective at reducing peak demand, followed by FDFV, TDFV, TDTV, and finally NDTV. This suggests that the combination of a flat demand rate with time-variant volumetric pricing may offer some fleets the best opportunity to control and reduce peak loads.

Figure 7. Peak Demand Comparison Across Different Fleets and Tariff Types for Unmanaged and Managed Charging Scenarios



For more insight into these results, we run several partial correlation regressions to understand how different characteristics of the tariffs (e.g., the inclusion or exclusion of time variation, levels of prices, price differentials) and of the fleets (e.g., overlap between dwell periods and high price periods, VMT, minimum time needed to charge) affect the outcomes under unmanaged and managed charging, including unmanaged bills and bill and peak demand savings from charging management.

The regressions are as follows:

$$Y_{jT} = \beta X_j + \delta X_T + \mu + \epsilon,$$

where *j* indicates fleet and *T* indicates tariff. *Xj* represents fleet characteristics (including VMT and minimum hours needed to charge), X_T represents tariff characteristics (e.g., highest volumetric/demand rates, price differentials, existence of time variation in demand or volumetric rates), and *u* represents fixed effects (including fleet type fixed effects and utility fixed effects). See Table 4 for descriptions and definitions of the characteristics included. Because some of the fleets have multiple clusters, we create a weighted average of the fleet characteristics (such as a weighted VMT for the entire fleet) based on the share of vehicles that are part of each cluster. These characteristics do not vary within a fleet, so we are unable to include fleet fixed effects. Furthermore, some of the tariffs do not have associated characteristics (e.g., tariffs with flat demand or volumetric tariffs would not include time variation) or have highly correlated variables; thus, each regression selects the appropriate group of tariff characteristics depending on the tariff under analysis.

Table 4. Descriptions and Definitions of Fleet and Tariff Characteristics

Characteristic	Definition
Fleet VMT	Cluster -weighted average daily vehicle miles traveled across entire fleet.
Minimum hours needed to charge	Based on our assumptions of battery size and associated charger, the minimum number of hours a fleet would need to recharge its vehicles fully at maximum charging speed.*
Overlap between dwell period and TOU peak period	Given our simulation of the dwell period (the hours in which the vehicle is not in operation), the number of hours the fleet's dwell periods overlap with the TOU peak period—for either the demand charge or the volumetric charge, depending on the setting.
Highest volumetric/demand rate	The highest price the tariff includes for either the volumetric or demand charge. For flat rates, this will be the only price.
Volumetric/demand price differential	The ratio between the peak and off-peak prices for either the volumetric charge or the demand charge (we do not include shoulder periods in this differential calculation).
Volumetric rate is TOU	Indicator = 1 if volumetric rate is TOU, 0 otherwise.
Flat demand charge	Indicator = 1 if demand charge is flat, 0 otherwise.
TOU demand charge	Indicator = 1 if demand charge is TOU, 0 otherwise.

* One simplifying assumption we make is that the charger speed runs consistently throughout the battery cycle. In reality, however, chargers slow down when they approach full charge. Incorporating this slowdown would extend the time it takes to charge fully. See Barnes (2020).

Because each tariff has unique characteristics, we run five separate regressions: tariffs with flat volumetric rates, tariffs with flat demand rates, tariffs with no demand rates, tariffs with TOU volumetric rates, and tariffs with TOU demand charges. This allows us to identify impacts such as the effect of TOU demand charges paired with a TOU volumetric charge relative to those paired with a flat volumetric rate.

5.1. Tariffs with no demand charges

In our first regression, we estimate the impact of fleet and tariff characteristics on (the log of) unmanaged bills, bill savings, and kW savings for tariffs with no demand charges. Here we include either the highest volumetric rate or the volumetric price differential (equal to zero if no time variation); given the high levels of correlation between the two variables, we include only one variable at a time (Table 5, columns 1 and 2). We also include the overlap between the fleet's dwell period and TOU peak period. On fleet characteristics, Table 5 demonstrates that fleets with greater VMT will face higher unmanaged bills because of greater kWh consumption. However, they will also have a somewhat greater opportunity to save on their bills. We find that fleets that require longer hours to recharge (due to larger batteries) face higher unmanaged bills and have less opportunities for savings. On tariff characteristics, we find that more expensive volumetric rates result in greater unmanaged bills but also provide greater opportunities for bill savings.

Table 5. Results for Tariffs with No Demand Charges

	Log bill unmanaged	**Log bill unmanaged**	**Log bill savings**	**Log bill savings**	**Log kW savings**	Log kW savings
Fleet VMT	0.00855** (0.000506)	0.00900*** (0.000543)	0.0846*** (0.0050)	0.0843*** (0.00498)	−0.000506 (0.000733)	−0.000518 (0.000732)
Minimum hours needed to charge	0.0740*** (0.00873)	0.0669*** (0.00936)	0.218* (0.086)	0.224* (0.0859)	−0.0483*** (0.0126)	−0.0481*** (0.0126)
Highest volumetric rate	2.917*** (0.149)		4.445*** (1.467)		0.00435 (0.123)	
Volumetric price differential		2.161*** (0.165)		5.763*** (1.512)		−0.109 (0.222)
Overlap between dwell period and TOU peak period	0.0337*** (0.00502)	0.0295*** (0.00538)	0.271*** (0.0496)	0.270*** (0.0494)	−0.0121* (0.00727)	−0.0121* (0.00726)
Fleet type fixed effects	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Utility fixed effects	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Observations	**1,410**	**1,410**	**1,410**	**1,410**	**1,410**	**1,410**
R-squared	**0.892**	**0.875**	**0.642**	**0.644**	**0.206**	**0.206**

Note: Coefficients listed with standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As is also reflected quite clearly in Figure 7, without any demand charge, the fleet has no incentive to mitigate kW usage, leading to no statistically significant kW savings and an overall low R-squared for the regression (columns 5 and 6 of Table 5).

5.2. Tariffs with flat demand charges

For tariffs with flat demand charges, we run a similar regression, shown in Table 6, and find that greater VMT requirements lead to higher unmanaged bills but also higher opportunities for kW and bill savings.[18] Again, needing more time to charge increases unmanaged bills and reduces opportunities for bill and kW savings, which is likely a function of having more charging during peak hours and a reduced ability to shift out of them. Crucially, we find that more expensive demand charges increase unmanaged bills but also increase the opportunity for both bill savings and peak demand reductions, as fleets respond to high prices by shifting the timing of their charging patterns. Finally, having volumetric TOU rates and larger peak to off-peak volumetric price ratios in addition to flat demand charges increases unmanaged bills. However, having a TOU volumetric portion of the tariff, combined with greater differences between peak and off-peak price volumetric prices, actually increases kW reductions, as fleets subjected to such rates need to balance more expensive volumetric peak prices with responsiveness to demand charges.

[18] Flat demand tariffs are paired with both TOU and flat volumetric charges. Thus the correlation between volumetric price differential and highest volumetric charge is low, and it is feasible to use both in the same regression.

Table 6. Results for Tariffs with Flat Demand Charges

	Log bill unmanaged	Log bill unmanaged	Log bill savings	Log bill savings	Log kW savings	Log kW savings
Fleet VMT	0.00287*** (9.7e-5)	0.00287*** (9.7e-5)	0.0182*** (0.000487)	0.0182*** (0.000483)	0.0138*** (0.000199)	0.0138*** (0.000198)
Minimum hours needed to charge	0.0466*** (0.00169)	0.0466*** (0.00169)	−0.376*** (0.00843)	−0.376*** (0.00835)	−0.190*** (.00344)	−0.190*** (.00343)
Highest demand rate	0.0614*** (0.000901)	0.0613*** (0.000901)	0.0977*** (0.00449)	0.0954*** (0.00446)	0.0233*** (0.00184)	0.0239*** (0.00183)
Highest volumetric rate	9.611*** (0.122)	9.670*** (0.122)	0.748 (0.609)	0.967 (0.604)	−0.0527 (0.249)	−0.112 (0.248)
Volumetric price differential	−7.048*** (0.203)	−7.546*** (0.274)	17.68*** (1.012)	5.673*** (1.356)	−10.25*** (0.413)	−6.990*** (0.557)
Volumetric rate is TOU		0.0576*** (0.0214)		1.390*** (0.106)		−0.377*** (0.0434)
Fleet type fixed effects	Y	Y	Y	Y	Y	Y
Utility fixed effects	Y	Y	Y	Y	Y	Y
Observations	**10,242**	**10,242**	**10,242**	**10,242**	**10,242**	**10,242**
R-squared	**0.919**	**0.919**	**0.932**	**0.933**	**0.860**	**0.861**

Note: Coefficients listed with standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Tariffs with TOU demand

For tariffs with TOU demand charges, as seen in Table 7, greater VMTs lead to higher unmanaged bills but also greater opportunities for bill savings, while requiring more hours to charge significantly reduces the potential for kW reductions.[19] More expensive demand charges increase opportunities for bill savings but lower the kW reduction potential from managed charging.

[19] In these regressions, we include highest demand and volumetric rate in one specification and replace these two variables with price ratios, given the high correlation between the two.

Table 7. Results for Tariffs with TOU Demand Charges

	Log bill unmanaged	Log bill unmanaged	Log bill savings	Log bill savings	Log kW savings	Log kW savings
Fleet VMT	0.0118*** (0.00069)	0.0119*** (0.00075)	0.0763*** (0.0044)	0.0764*** (0.0044)	0.0648*** (0.00409)	0.0648*** (0.00408)
Minimum hours needed to charge	0.0785*** (0.0119)	0.0774*** (0.0129)	0.384*** (0.0759)	0.383*** (0.0758)	−0.934*** (0.0705)	−0.934*** (0.0703)
Highest demand rate	0.00489 (0.00801)		0.113** (0.0512)		−0.0931* (0.0475)	
Highest volumetric rate	11.04*** (0.769)		−0.625 (4.915)		−6.884 (4.561)	
Volumetric price differential		13.84*** (2.026)		30.64** (11.93)		−1.323 (11.07)
Demand price differential		−0.0314*** (0.0858)		0.0437 (0.0505)		−0.133*** (0.0469)
Overlap between dwell period and TOU peak period	−0.000352 (0.00671)	−0.00937 (0.00728)	−0.0708* (0.0429)	−0.0770* (0.0429)	0.0199 (0.0398)	0.0197 (0.0398)
Fleet type fixed effects	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Utility fixed effects	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Observations	**966**	**966**	**966**	**966**	**966**	**966**
R-squared	**0.804**	**0.77**	**0.606**	**0.607**	**0.494**	**0.496**

Note: Coefficients listed with standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Greater peak-to-off-peak demand price ratios reduce unmanaged bills and opportunities for bill savings, likely because most fleets are generally charging in off-peak hours, thereby limiting their exposure to high bills but also reducing their ability to reduce costs by shifting load.[20] More expensive volumetric charges and greater peak-to-off-peak volumetric price ratios increase unmanaged bills, while only large peak-to-off-peak volumetric price ratios provide statistically significant opportunities for bill savings. Finally, the greater the overlap between a fleet's dwell period and the

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[20] As greater numbers of MHDVs come online, their night-peaking characteristics may have the capacity to shift the utility's peak period overnight. Thus in a future night-peaking system, these results would no longer hold.

TOU peak period applicable to demand charges, the more difficult it is for the fleet to shift its charging away from peak periods; this thus reduces the potential for bill savings and kW reductions from charging management.

5.4. Tariffs with flat volumetric rates

Tariffs with flat volumetric rates are paired with either TOU or flat demand charges, as seen in Table 8. For tariffs with flat volumetric rates, greater VMTs increase bills but also provide greater opportunities for both bill savings and kW reductions.[21] Requiring more hours to charge increases unmanaged bills and reduces opportunities for bill savings and kW reductions. Pairing flat volumetric tariffs with a TOU demand charge instead of a flat demand charge, particularly when the demand price differential is large, reduces unmanaged bills but also reduces the opportunity to save on the bill by managing charging.[22] This may be due to a natural overlap between the demand peak periods and dwell periods for these fleets, resulting in comparatively low unmanaged bills and a reduced opportunity to incur savings.

[21] Any reductions in peak demand is due to the existence of a demand charge; any flat volumetric tariff without a demand charge—a tariff type that does not appear in our dataset—would create no incentive to reduce peak demand.
[22] Note that only 492 tariffs have a TOU demand charge; hence including the overlap between dwell and peak periods would significantly reduce the observations in the regression.

Table 8. Results for Tariffs with Flat Volumetric Charges

	Log bill unmanaged	Log bill unmanaged	Log bill savings	Log bill savings	Log kW savings	Log kW savings
Fleet VMT	0.00345*** (0.000112)	0.00345*** (0.000112)	0.0439*** (0.001)	0.0439*** (0.00101)	0.0157*** (0.000269)	0.0157*** (0.000269)
Minimum hours needed to charge	0.0517*** (0.00199)	0.0517*** (0.002)	−0.757*** (0.0174)	−0.757*** (0.0175)	−0.208*** (0.00466)	−0.208*** (0.00459)
Highest demand rate	0.0405*** (0.000838)	0.0369*** (0.00079)	0.301*** (0.0073)	0.266*** (0.00687)	0.0145*** (0.00196)	−0.00183 (0.00181)
Highest volumetric rate	0.967*** (0.0174)	0.965*** (0.0175)	−0.0151 (0.152)	−0.0283 (0.153)	0.0145 (0.0408)	0.00295 (0.0402)
Demand price differential	−0.0274*** (0.00144)		−0.165*** (0.0126)		−0.188***	−0.0274*** (0.00144)
Demand charges are TOU		−0.287*** (0.0194)		−0.691*** (0.169)		−2.652*** (0.0445)
Fleet type fixed effects	Y	Y	Y	Y	Y	Y
Utility fixed effects	Y	Y	Y	Y	Y	Y
Observations	**13,406**	**13,406**	**13,406**	**13,406**	**13,406**	**13,406**
R-squared	**0.868**	**0.867**	**0.757**	**0.754**	**0.76**	**0.767**

Note: Coefficients listed with standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Our analysis finds that when a TOU demand charge has more expensive demand rates, savings opportunities increase. However, when tariffs with flat volumetric rates have more expensive volumetric prices, unmanaged bills increase, while the high volumetric price alone provides no opportunity for the fleets to achieve bill savings or kW reductions.

5.5. Tariffs with TOU volumetric rates

Tariffs with TOU volumetric rates are paired with no demand charges, as well as TOU and flat demand charges, as seen in Table 9. We run a third set of regressions where we include indicators if the tariff has no demand and flat demand charges (because these are correlated with variables such as highest demand rates and peak to off-peak price differentials, they cannot be included in the same regression).[23]

Table 9. Tariffs with TOU Volumetric Charges

	Log bill unmanaged	Log bill unmanaged	Log bill unmanaged	Log bill savings	Log bill savings	Log bill savings	Log kW savings	Log kW savings	Log kW savings
Fleet VMT	0.00820*** (0.00043)	0.00796*** (0.000407)	0.00833*** (0.000430)	0.0669*** (0.00325)	0.0670*** (0.00321)	0.0677*** 0.00320)	0.0178*** (0.00237)	0.0178*** (0.00207)	0.0193*** (0.00188)
Minimum hours needed to charge	0.0770*** (0.00746)	0.0813*** (0.00696)	0.0754*** (0.00737)	0.242*** (0.0557)	0.242*** (0.055)	0.231*** (0.0549)	−0.332*** (0.0407)	−0.325*** (0.0355)	−0.349*** (0.0322)
Volumetric price differential	1.886*** (0.176)		2.139*** (0.183)	3.909*** (1.312)		5.913*** (1.363)	−6.539*** (0.958)		−0.418 (0.800)
Demand price differential	−0.0147*** (0.00394)			0.0254 (0.0295)			0.00353 (0.0215)		
Overlap between peak and off-peak vol. rate	0.00993** (0.00452)	0.00937** (0.0042)	0.00623 (0.00446)	0.0782** (0.0337)	0.0603* (0.0311)	0.0622* (0.0332)	−0.048* (0.0246)	−0.0916*** (0.0214)	−0.107*** (0.0195)
Highest demand rate		0.0379*** (0.0029)			0.188*** (0.0229)			0.372*** (0.0148)	
Highest volumetric rate		3.259*** (0.159)			4.599*** (1.256)			−1.779*** (0.81)	
Flat demand charge			0.270*** (0.0519)			1.336*** (0.386)			2.269*** (0.227)
No demand charge			−0.0223 (0.0486)			−0.873** (0.362)			−2.969*** (0.212)
Fleet type fixed effects	Y		Y	Y		Y	Y		Y
Utility fixed effects	Y		Y	Y		Y	Y		Y
Observations	13,406		13,406	13,406		13,406	13,406		13,406
R-squared	0.868		0.867	0.757		0.754	0.76		0.767

Note: Coefficients listed with standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

[23] These indicators equal one if the demand charge is flat or there is no demand charge and zero otherwise.

Again, with these tariffs, we see that greater VMT increases unmanaged bills but also provides greater opportunities for bill savings and kW reductions. Requiring more hours to charge increases unmanaged bills and potential for bill savings but reduces kW reduction opportunities. For these tariffs, having more expensive volumetric rates or larger peak-to-off-peak volumetric price ratios increases both unmanaged bills and bill savings opportunities. However, high volumetric prices also limit a fleet's opportunity to reduce its peak demand, as it faces conflicting incentives: Reducing its consumption during volumetric peak hours requires an increase in its maximum demand at other times of day, which will then trigger a higher demand charge. Of course, if this increase in a fleet's maximum demand occurs during off-peak hours for the demand charge, it can still save by making this shift.

Once TOU volumetric rates are paired with demand charges, we see that larger peak-to-off-peak price ratios in the demand charges reduce unmanaged bills, likely due to a natural overlap between charging hours and off-peak hours. Pairing TOU volumetric rates with flat demand charges or more expensive demand rates leads to greater unmanaged bills for our modeled fleets but provides greater opportunities for bill and kW savings. By contrast, the absence of a demand charge reduces the bill savings and kW reduction opportunities.

6. Discussion and Conclusions

This study provides valuable insights into how different tariff structures and fleet characteristics can influence the cost of charging and maximum demand outcomes of medium- and heavy-duty EV fleets. Our findings show that managed charging can substantially reduce both electric bills and peak demand, with the extent of these benefits heavily dependent on the underlying tariff structure and fleet operational characteristics.

One key finding is that TOU tariffs, particularly those that include a demand component, can be highly effective at promoting cost-saving charging behaviors. Fleets with longer dwell periods may benefit significantly from TOU tariffs. These fleets can shift charging to off-peak periods, minimizing electric bills without disrupting service. In contrast, fleets with shorter dwell periods may face limited opportunities for cost savings, as their opportunities to charge may coincide with peak tariff hours.

Our regression analysis reveals several critical factors that influence customer cost-saving and peak demand reduction opportunities, showing how tariff structures and fleet characteristics jointly affect customer cost management and peak reduction potential. VMT is a significant determinant, as higher VMT is associated with higher unmanaged electric bills as a result of greater energy consumption. However, fleets with higher VMT also have greater opportunities for cost savings under managed charging, mainly due to their larger battery size and faster chargers; this allows them to optimize charging schedules more effectively. Minimum charging duration also plays an important role in cost-saving potential: Fleets with longer charging needs generally incur higher unmanaged bills but may have limited opportunity to lower their bills through managed charging because of their fewer or shorter flexible charging periods.

TOU rates offer substantial opportunities for reducing both electric bills and peak demand, especially for fleets with flexible schedules and high VMT, since these fleets can shift charging to off-peak times to maximize savings. In contrast, tariffs that include both flat demand and volumetric rates, while relatively straightforward, offer limited savings potential and may be more suitable for fleets with lower sensitivity to time-based charges. Finally, peak-to-off-peak rate differentials significantly affect cost savings; larger differentials provide a stronger incentive for fleets to optimize charging during off-peak hours, further reducing costs and alleviating grid stress.

These findings underscore the importance of tariff designs that make it possible to reward sound load management by a variety of fleets, given their diverse characteristics and operational constraints. By providing a menu of tariffs with a variety of structures and peak-to-off-peak differentials, utility providers can encourage fleets to adopt managed charging practices that reduce grid congestion and lower their operational costs.

The results of this study demonstrate the potential for managed charging to provide substantial cost savings for electric vehicle fleets in comparison with unmanaged charging while alleviating peak demand pressures on the grid. Among the tariff structures analyzed, those with either TOU demand or volumetric components (especially those with both) consistently deliver the highest cost-saving opportunities to our fleets in comparison with other tariffs, especially for fleets with adaptable charging schedules and significant daily mileage requirements.

Future research could enhance these findings by exploring tariffs that expose customers more directly to commodity prices that are determined in an organized wholesale market, which would enable further exploration into the benefits of more variable pricing. Additionally, expanding the analysis to consider regional variations in utility rates and grid infrastructure could lead to more targeted tariff recommendations that account for geographic and operational diversity.

This research provides actionable insights for both utility providers and fleet operators. Well-designed tariffs that incentivize managed charging can support the economic viability of electric fleets, allow for broader adoption of sustainable transportation solutions, and contribute to a more balanced and resilient electricity grid.

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Appendix A: Electric Tariffs Basics

As a general matter, electric utilities charge rates for service based on what is required to recover their costs. In the case of investor-owned utilities, which are usually subject to comprehensive economic regulation by a state entity, rates are typically designed to recover capital investments over long time horizons, including a specified rate of return to shareholders, as well as anticipated operating costs. The outstanding sum of unrecovered investments is called the “ratebase.” For a given year, the “revenue requirement” is the rate of return multiplied by the ratebase, plus operations and maintenance costs (Hempling 2017). By starting with the revenue requirement and an estimate of how customers will use the utility system over the course of a given year, utilities, with regulatory oversight, design tariffs such that the aggregate amount paid by all customers for their anticipated energy usage over the course of the year will add up to the revenue requirement.

Although utility tariffs are designed first and foremost to *recover* from customers costs incurred by or expected to be incurred by the utility, they also send *price signals* that provide an incentive for customers to shape their behavior.[24] When considering the need to design tariffs to create optimal incentives, it is important to recognize that in addition to some operating costs varying based on the timing of customers' consumption, future utility investment needs will be shaped by the customers' consumption behavior, including the timing of their energy consumption (Turk et al. 2024). For example, if all customers use the system heavily at the same time, and together they tax the limits of what the system can do, the utility company will need to invest in capacity improvements; however, the same intensity of energy usage by individual customers might burden the system less if their most intense usage does not occur at the same time as that of other customers.

Tariffs that do not reflect the complexity that drives costs—costs already incurred or costs that will be incurred in the future based on current behavior—may be easy for customers to understand and plan for, but they can result in unfairness or inefficiency over various time horizons. Consider, for example, a world in which days are divided into two equal parts, period 1 and period 2, and power is always cheaper to supply per kWh during period 1 than during period 2. If all customers use the same amount of power in approximately the same way, but half of them consume power only during period 1 and the other half consume power only during period 2, then a pricing system whereby all customers are charged the same per-kWh price for energy (one that is an average of the prices during the two periods) would be both inefficient and not cost-reflective. The period 1 customers would be overpaying in relation to the costs they caused, and the period 2 customers would be underpaying. Moreover, if the customers had any control over their consumption, they would consume inefficient quantities

[24] Such price signals can be effective only if customers are aware of the tariffs, understand the incentives provided by the tariffs, and are able to adjust their consumption accordingly. Some customers may have a better understanding of the tariff structures than others or a better ability to adapt in order to respond. See Turk et al. (2024).

based on these inaccurate price signals: The period 1 customers would tend to consume more than the efficient quantity, and the period 2 customers would tend to consume less than the efficient quantity. Ultimately, because the period 1 customers overconsume, it might become necessary to build more capacity to meet their demand, and the capital expenditure on that new plant would increase the ratebase, potentially driving up the prices for everyone.

Some of these problems can be mitigated by building complex, cost-reflective tariff structures (see for e.g., Spiller et al 2023a and Pérez-Arriaga and Bharatkumar 2014). Bills can be determined by a set of several "billing determinants," so that various aspects of a customer's consumption behavior influence the total bill.

Demand-based billing determinants provide for a portion of the bill to be calculated based on the maximum demand a customer imposes on the overall system. This can be appropriate for elements of the electric system that were designed to meet a certain level of demand or that might need to be increased in size in the future if demand rises above some threshold.

Volumetric billing determinants provide for a portion of the bill to be calculated based on the total amount of energy a customer consumes during a certain period of time, which may be an entire billing period (e.g., a month) or some shorter period (e.g., a given price for all kilowatt-hours consumed during weekday mornings or a different price each hour). This is most appropriate for aspects of service that vary based on the total amount of energy consumed—for example, the utility's fuel cost associated with generating a certain amount of power or the utility's per-kWh cost of procuring the power its customers need from some other party. However, in many cases, system costs that do not meaningfully vary based on the total amount of energy consumed are also collected on a volumetric basis; this is especially common for mass market customers, who are often subject to tariffs where the only variable charges are volumetric.

Either type of billing determinant can be more finely tuned based on other parameters, such as time. For example, the impact of a particular customer's peak demand varies depending on whether that peak demand is coincident with most other customers' peak demand, or whether it occurs at a time when the system as a whole is less utilized or even underutilized. Where customers are contributing to raising overall system peak, they are likely to be driving future system needs; by contrast, if a customer's demand during overall system peak is low and they have an individual peak at a time when overall system usage is low, they may not be contributing significantly to future system needs. In fact, a customer with those characteristics may be using the system in a manner that is beneficial to other customers, by allowing equipment that would otherwise be underutilized to be more fully utilized. Demand-based billing determinants can differentiate between these kinds of users by separately assessing demand during system peak and off-peak periods.

Volumetric charges can also be time-based—and because the cost to generate power varies in real time throughout the year, the basis for such pricing may be more straightforward than the time consideration in demand-based billing determinants.

Time-variant volumetric charges can be based on various levels of granularity, ranging from simple peak/off-peak distinctions to unique prices that vary hourly.

Appendix B: Fleet Data

Table B1. Fleet Characteristics, Dwelling Times, Daily Mileage, and Vehicle Types Across Different Fleets and Clusters

Fleet name	Fleet type	Cluster #	Cluster share	Dwelling time	Dwelling time (hours)	Average daily mileage	Vehicle type*
CNG, SoCal	Transit	1	60%	9 p.m. ~ 5 a.m. 10 a.m. ~ 1 p.m.	13	247	BEV-005
CNG, SoCal	Transit	2	40%	11 a.m. ~ 4 a.m.	18	140	BEV-004
ORNL, Transit	Transit	1	40%	9 p.m. ~ 5 a.m. 8 a.m. ~ 3 p.m.	17	96	BEV-001
ORNL, Transit	Transit	2	60%	9 p.m. ~ 4 a.m. 4 p.m. ~ 6 p.m.	11	159	BEV-004
Delivery Box Truck, San Diego	Delivery	1	17%	10 p.m. ~ 7 a.m.	10	156	BEV-014
Delivery Box Truck, San Diego	Delivery	2	27%	6 p.m. ~ 9 a.m.	16	163	BEV-014
Delivery Box Truck, San Diego	Delivery	3	56%	6 p.m. ~ 8 a.m.	15	151	BEV-014
Parcel Delivery, Texas	Delivery	1	34%	7 p.m. ~ 9 a.m.	15	130	BEV-011
Parcel Delivery, Texas	Delivery	2	38%	8 p.m. ~ 7 a.m.	12	131	BEV-011
Parcel Delivery, Texas	Delivery	3	28%	7 p.m. ~ 7 a.m.	13	104	BEV-011
School Bus, SoCal	School bus	1	100%	6 p.m. ~ 6 a.m.	13	116	BEV-018
Refuse Truck, Miami	Refuse	1	56%	1 p.m. ~ 4 a.m.	16	96	BEV-007
Refuse Truck, Miami	Refuse	2	44%	12 p.m. ~ 4 a.m.	17	84	BEV-014

* The vehicles' ID and their characteristics are provided in detail in Table B.2.

Table B2. Vehicle Types and Characteristics Including Battery Capacity, Efficiency, and Range

ID	Occupation	Manufacturer	Model	Battery capacity (kWh)	Efficiency (kWh/mile)	Range (miles)	Description
BEV-001	Transit	Proterra	ZX5 (35-foot)	225	1.5	120 (80%)	Charge to 100% and operate until 20%
BEV-004	Transit	Proterra	ZX5+ (40-foot)	450	1.7	211 (80%)	Charge to 100% and operate until 20%
BEV-005	Transit	Proterra	ZX5 MAX (40-foot)	675	1.8	300 (80%)	Charge to 100% and operate until 20%
BEV-007	Delivery (heavy)	Nikola	TRE BEV	753	2.15	280 (80%)	Charge to 100% and operate until 20%
BEV-011	Delivery (medium)	Freightliner	MT50	226	1.33–1.51	135 (80%)	Charge to 100% and operate until 20%
BEV-014	Delivery (medium/heavy)	Freightliner	eM2	194 | 291	0.84 | 1.27	184 (80%)	Charge to 100% and operate until 20%
BEV-018	School	Thomas Built Buses	Saf-T-Liner C2 Jouley	Up to 226	1.64	124 (90%)	Charge to 100% and operate until 10%

Appendix C: Fleet Charging Characteristics

Table C1. Vehicle Types and Characteristics Including Battery Capacity, Efficiency, and Range

Fleet name	Fleet type	Cluster #	Vehicle type	Average daily mileage	Efficiency (kWh/mile)	Charging need per vehicle (kWh)	Time available to charge (hours)	Estimated power need (kW)	Charger type (kW)
CNG, SoCal	Transit	1	BEV-005	247	1.8	445	13	34.2	50
CNG, SoCal	Transit	2	BEV-004	140	1.7	237	18	13.2	19.2
ORNL, Transit	Transit	1	BEV-001	96	1.5	144	17	8.5	19.2
ORNL, Transit	Transit	2	BEV-004	159	1.7	271	11	24.6	50
Delivery box truck, San Diego	Delivery	1	BEV-014	156	0.84	131	10	13.1	19.2
Delivery Box Truck, San Diego	Delivery	2	BEV-014	163	0.84	137	16	8.6	19.2
Delivery Box Truck, San Diego	Delivery	3	BEV-014	151	0.84	127	15	8.5	19.2
Parcel Delivery, Texas	Delivery	1	BEV-011	130	1.33	173	15	11.5	19.2
Parcel Delivery, Texas	Delivery	2	BEV-011	131	1.33	175	12	14.5	19.2
Parcel Delivery, Texas	Delivery	3	BEV-011	104	1.33	138	13	10.6	19.2
School Bus, SoCal	School Bus	1	BEV-018	116	1.64	190	13	14.6	19.2
Refuse Truck, Miami	Refuse	1	BEV-007	96	1.94	186	16	11.7	19.2
Refuse Truck, Miami	Refuse	2	BEV-014	84	1.94	163	17	9.6	19.2

Appendix D: Tariff Selection Details

In the process of analyzing utility rates for commercial fleets, we excluded certain irrelevant or unrelated rates from the analysis. These exclusions are based on their specificity to nonfleet operations, agricultural applications, or other services unrelated to electric vehicle charging. The following categories and rate types were filtered out from the dataset:

- **Unbundled or delivery-only rates***:* Rates that were clearly labeled as "delivery only" or lacked bundled energy components, based on the URDB metadata and "bundled" field, were excluded. This ensures that the retained rates reflect the full cost of electricity supply, which is essential for comparability across regulated and deregulated states.

- **Occupational categories***:* Rates associated with specific occupations, organizations, or activities that are not relevant to fleet operations, such as academic, air-conditioning, Coast Guard, farmer, church, hospital, community facilities.

- **Energy use and equipment***:* Rates focused on specific types of energy use or equipment not applicable to electric vehicle fleet charging, including Air Force, all-electric, battery storage, Cargill rates, coal bed methane, comfort service, electric thermal storage, green energy, hydraulic power.

- **Specialized agricultural or industrial rates:** Rates meant for agricultural or industrial sectors, including agricultural, fixed load, fish farming, flood lights, grain drying, irrigation, peanut, rice mills.

- **Residential and private use***:* Rates that were restricted to residential or private applications, such as fraternity, club house, senior housing, sprinklers, life-line usage, municipal.

- **Government or institutional use***:* Rates tailored specifically for governmental, institutional, or educational entities, which do not apply to fleet operations, including government, military, internal city service, library, institutional.

- Miscellaneous non-fleet-specific services*:* Other non-fleet-specific services and charges that were excluded, such as maintenance, marina, recreational services, residential solar buy-back programs, security lighting, school rates, volunteer fire department.

This exclusion process ensures that the analysis focuses solely on rates applicable to fleet operations and does not include those that pertain to unrelated sectors or specialized applications. However, for certain fleets, the exclusion criteria were slightly adjusted. For instance, in the case of school bus fleets, rates related to schools and educational institutions were not excluded, as they are directly relevant to the operation and charging schedules of these fleets. This nuanced approach allows the analysis to maintain relevance and accuracy for each specific fleet type, ensuring the exclusion criteria reflect its unique operational needs.

Figure D1. Example Tariff with Negative Off-Peak Volumetric Pricing

Schedule 6A - General Service, Energy Time-of-Day Option									
Customer Charge	$53.00	/month						$5.60	/month
Energy Charge									
All kWh under 50 kWh/kW (Jun-Sept)	28.1562	¢/kWh	9.94%	-0.06%	3.70%	-0.66%	0.28%		
All additional kWh (Jun-Sept)	10.3099	¢/kWh	9.94%	-0.06%	3.70%	-0.66%	0.28%		
All kWh under 50 kWh/kW (Oct-May)	24.9170	¢/kWh	9.94%	-0.06%	3.70%	-0.66%	0.28%		
All additional (Oct-May)	9.1238	¢/kWh	9.94%	-0.06%	3.70%	-0.66%	0.28%		
Off-Peak kWh (Jun-Sept)	-8.3358	¢/kWh	9.94%	-0.06%	3.70%	-0.66%	0.28%		
Off-Peak kWh (Oct-May)	-7.3768	¢/kWh	9.94%	-0.06%	3.70%	-0.66%	0.28%		
Voltage Discount (≥ 2,300 V)	$0.61	/kW			3.70%	-0.66%	0.28%		
Subscriber Solar Energy Charge (Schedule 73)									
(no interval meter)	7.125	¢/kWh		-0.06%	3.70%	-0.66%	0.28%		
(with interval meter-solar generation)	5.925	¢/kWh		-0.06%	3.70%	-0.66%	0.28%		
(with interval meter-solar delivery)	Under Schedule 32	/kW			3.70%	-0.66%	0.28%		

June through September: On-Peak hours are from 7:00 a.m. to 11:00 p.m., Monday thru Friday, except holidays. All remaining hours are Off-Peak hours.
October through May: On-Peak hours are from 7:00 a.m. to 11:00 p.m., Monday thru Friday, except holidays. All remaining hours are Off- Peak hours.

Source: Rocky Mountain Power, a utility serving the state of Utah.
Note: This schedule typically applies to small to medium-size commercial customers.

Appendix E: Tariff Types

Table E1. Number of Rate Types by Fleet, Season, and Tariff Structure

	Transit (ornl)		Transit (cngsocal)		School bus	
Rate Types	**Summer**	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
NDFV	3,496	3,531	3,498	3,514	3,517	3,528
NDTV	221	218	221	218	222	219
FDFV	2,158	2,175	2,156	2,173	2,167	2,176
FDTV	100	102	100	102	102	103
TDFV	82	80	83	79	83	80
TDTV	79	70	79	72	79	70
	Delivery (SD)		**Delivery (Texas)**		**Refuse**	
Rate Types	**Summer**	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
NDFV	3,473	3,484	3,475	3,484	3,500	3,511
NDTV	222	214	223	217	221	213
FDFV	2,139	2,156	2,135	2,155	2,158	2,168
FDTV	100	102	104	103	100	101
TDFV	80	78	81	80	82	80

Appendix F: Clustering Methodology

In this study, we employ a clustering methodology to identify distinct patterns of vehicle use within various fleet types. The analysis begins with the vehicle state data, which contains status information for each vehicle recorded every 15 minutes. These states include Depot , Operating, Starting, and Ending. To streamline the analysis, the 15-minute intervals are aggregated into 24 one-hour time slots. Each hour is assigned a state based on the following rule: If any of the four continuous 15-minute intervals contains Operating, Starting, or Ending, the entire hour is marked as Operating. Otherwise, it is labeled as Depot. The vehicle states are subsequently transformed into a binary format, where 1 represents Operating and 0 denotes Depot.

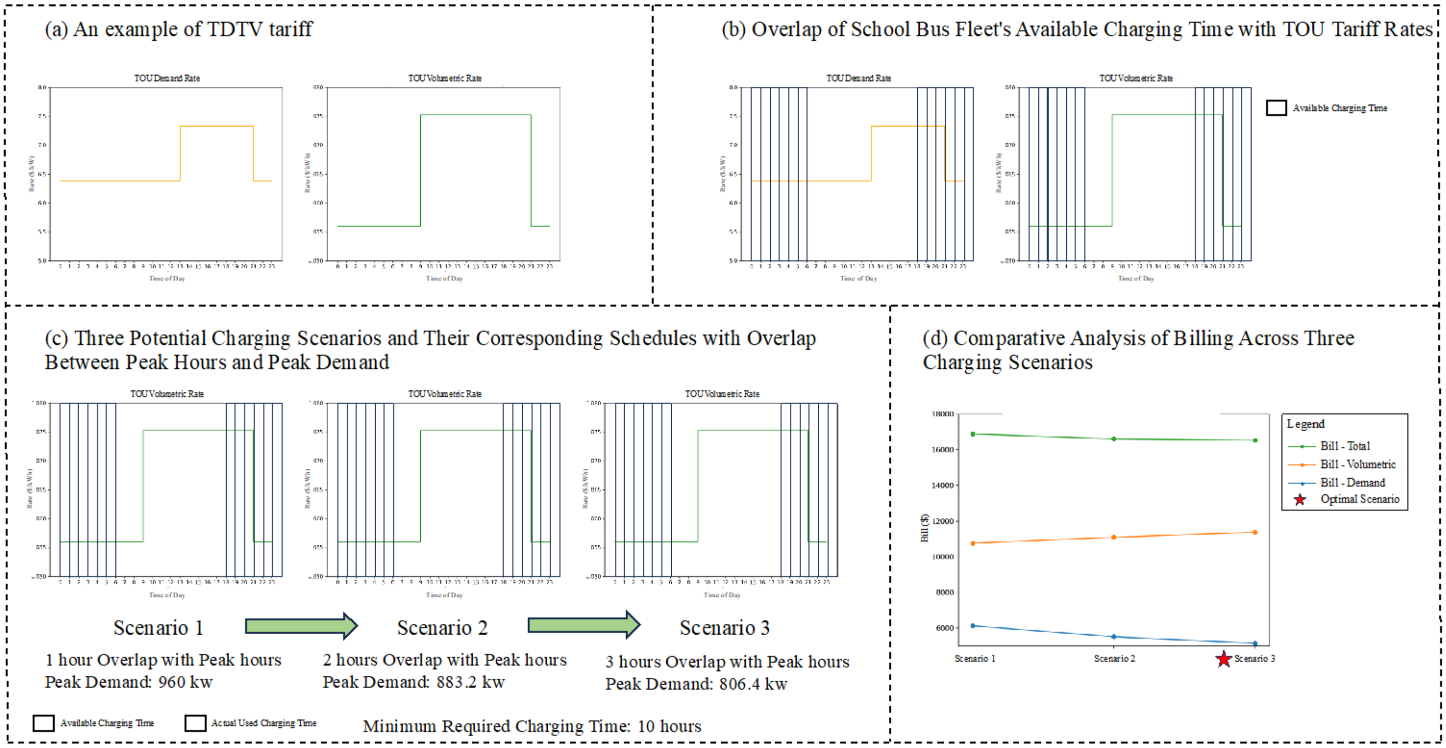
To perform clustering, we used the OPTICS (ordering points to identify the clustering structure) algorithm (Ankerst et al. 1999). A critical parameter in this algorithm is min_samples, which determines the minimum number of samples in a neighborhood for a point to be considered a core point. Various values of min_samples are tested to achieve clustering with two or three distinct clusters, and the optimal parameter that provided the most meaningful differentiation among vehicle usage patterns is selected.

Once the optimal parameters are identified, the clustering algorithm is applied to the prepared dataset. Noise points—vehicles that did not fit into any of the significant clusters—are discarded from further analysis. This filtering is essential to focus on identifying representative clusters that could inform charging management strategies. The final clustering results consist of two or three clusters for each fleet type, with each cluster characterized by unique vehicle dwell times and average daily mileage.

Appendix G: Charging Schedule Optimization Example

Figure G.1 presents an example of optimizing the charging schedule for a school bus fleet under a TDTV tariff. Panel (a) showcases an example of a TDTV tariff, detailing the rates over time. In panel (b), we observe the available charging window for school buses, which runs from 6 p.m. to 6 a.m.. This window overlaps with the peak hours for both the TOU demand and volumetric rates. For most rates and fleet combinations, there is an overlap with the off-peak hours for TOU demand rates. Thus by focusing solely on ensuring that peak demand occurs during off-peak hours, as detailed in the TDFV approach, TOU demand rates may not have a significant impact on cost considerations. Panel (c) illustrates three potential charging scenarios, each with different overlaps between peak hours and peak demand. The first scenario equates the charging time to the minimum required (10 hours), resulting in a one-hour overlap with the volumetric rate's peak hours—the least overlap achievable. In this scenario, the peak demand is 960 kW. Following algorithm 1, adding another time slot extends the charging time to 11 hours, with a 2-hour overlap during peak hours, reducing the peak demand to 883.2 kW. The associated costs are expected to fluctuate, with the demand rate's contribution to the bill decreasing while the volumetric rate's portion increases. In the third and final scenario, an additional time slot is included, matching the available charging time with a 3-hour overlap during peak hours. Here the peak demand further decreases to 806.4 kW. Panel (d) reveals the billing changes across the scenarios. As the charging duration increases, the bill from the demand rate decreases and, conversely, the bill from the volumetric rate increases, demonstrating the trade-off between these two components. Overall, the total bill decreases, indicating a greater reduction in costs from demand rates. Scenario 3 emerges as the optimal scenario.

Figure G1. Example Tariff with Negative Off-Peak Volumetric Pricing



This example serves as a straightforward illustration of the algorithm, facilitated by the simplicity of the school bus fleet's single cluster. However, the general steps remain consistent for other fleet types.

Appendix H: Algorithm for Optimizing the Charging Schedule under TDTV and TDFV

Inputs

a. C : Set of all clusters in the fleet.

b. $S[c]$: Array representing the share of the fleet corresponding to each cluster $c \in C$.

c. $T_{avail}[c]$: Array of charging available time windows for each cluster $c \in C$.

d. $T_{least}[c]$: Array of minimum required charging durations for each cluster $c \in C$

e. $P_{tou,vol}$: Time-of-Use volumetric pricing parameters indicating the cost of electricity during different times of the day (applicable only for TDTV).
f. $P_{flat,vol}$: Flat volumetric pricing parameters indicating the cost of electricity (applicable only for TDFV).
g. $P_{tou,demand}$: Time-of-Use demand pricing parameters indicating the cost of peak demand during different times of the day.
h. N: Number of electric vehicles contained in the fleet
i. $P_{level}[c]$: Array of power levels for the chargers for each cluster.
j. M: Optimization model that computes the power load profile to minimize the cost based on the charging schedule.

Outputs

k. Optimal power load profile L_{opt}
l. Minimum total cost $Cost_{min}$ for the optimal scheduleBegin
m. Sort clusters in C by $S[c]$ in descending order
n. Initialize $Cost_{min}$ to infinity
o. Initialize $Schedule[c]$ to an empty schedule. $Schedule[c]$ denotes array of charging time used for each cluster $c \in C$
p. For each cluster c in sorted C **do**
q. $T_{used}[c] = T_{least}[c]$, where $T_{used}[c]$ denotes the number of charging time used for cluster c .
r. **While** $T_{used}[c] \leq T_{avail}[c]$ **do**
s. $Schedule[c] = FindSchedule\left(c, T_{used}[c], T_{avail}[c], P_{tou,vol}\right)$(for TDTV) or $FindSchedule\left(c, T_{used}[c], T_{avail}[c], P_{flat,vol}\right)$(for TDFV).
t. Aggregate $Schedule[c]$ into $Schedule_{fleet}$ to form a complete schedule for the fleet.
u. $Load = M\left(Schedule_{fleet}, P_{tou,vol}\right)$ (for TDTV) or $M\left(Schedule_{fleet}, P_{flat,vol}\right)$ (for TDFV), consider $Load_{opt}$ denotes the optimal power load profile.
v. $Cost = CalculateCost\left(Load, P_{tou,vol}, P_{tou,demand}\right)$ (for TDTV) or $CalculateCost\left(Load, P_{tou,vol}, P_{flat,demand}\right)$ (for TDFV).
w. If $Cost < Cost_{min}$ then
    i. $Cost_{min} = Cost$
    ii. $Load_{opt} = Load$
x. $T_{used}[c] = T_{used}[c] + 1$.

y. If c is the last cluster, move back to the previous cluster and increment T_{used} by 1.
z. Continue the process until all clusters have been optimized.
aa. Adjust $Load_{opt}$ to shift peak demand into off-peak hours as much as possible, considering T_{avail} and $P_{tou,demand}$.
bb. Output $Load_{opt}$ and $Cost_{min}$.

End