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Designing distribution network tariffs under increased residential end-user electrification: Can the US learn something from Europe?

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Abstract

As decarbonization policies lead to the electrification of the transportation, buildings, and other end-use sectors, it will be necessary to expand distribution network capacities, at significant cost. Most US utilities currently recover both energy and network costs via time-invariant (flat) charges for kilowatt-hour (kWh) usage. While energy costs do vary with kWh usage, network costs vary instead with peak kilowatt (kW) demand, so recovering network costs via flat per-kWh charges can provide no incentives to shift peak demand to reduce the need for expensive network expansion. Time-of-use (TOU) tariffs that vary the cost per kWh to reflect changes in generation costs, for instance, give incentives to shift all electric vehicle (EV) charging to low-price periods, potentially raising kW demand in those periods and increasing network expansion costs. Efficiency (and, we will argue, equity) requires separating energy charges from network charges, with appropriate rate designs for each. Accordingly, this paper considers rate designs that unbundle energy and network charges and uses a realistic case study to investigate the implications of combining TOU energy charges with various network tariffs in the face of increased EV penetration. Our results provide support for the adoption in the US of ex-ante subscribed capacity tariffs (subscription charges), which have been used in Europe for many years.

Keywords: Electricity retail rates, Electric vehicles, Electricity distribution networks, Efficiency, Equity, Electrification

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1. Introduction

While the average cost of generating electricity in the US has steadily declined since 2010, the cost of delivering electricity – via the transmission and distribution networks – has risen (Aniti, 2021). Distribution and transmission network costs are expected to increase significantly in the future as wind, solar and storage replace fossil generation and as the transportation, buildings and other sectors are electrified to meet decarbonization commitments. In this paper, we focus on single-family residential distribution feeders, where there is relatively low diversity of customer loads compared to parts of the distribution network that host multiple housing types and customer classes (e.g., commercial and industrial).[1] As the diversity of individual customer loads declines further, perhaps because EV penetration increases and many customers charge their EVs at the same time, the need for network capacity tends to increase faster than the total consumption of electrical energy. In almost all US states, electric utilities recover distribution costs, along with energy costs, from residential and small commercial customers based on customers' monthly electricity consumption, regardless of the timing of that consumption. We refer to these as flat volumetric tariffs. Yet many utilities' distribution costs are fixed in the short run, reflecting past investments, and in the longer run are driven by the need to make incremental investments to handle periods of higher kW demand (Pérez-Arriaga et al., 2017). The factors that drive these costs are not reflected in flat volumetric tariffs.

The impact of residential electric vehicle (EV) charging on low-voltage distribution grids under flat volumetric tariffs has been studied extensively. For example, Muratori (2018) discovers that even if system-wide impacts are small due to low overall EV penetration, clustered EV adoption may require widespread upgrades for distribution grid equipment like small-scale transformers. More recently, Needell et al. (2023) estimate electricity demand curves at high penetrations of EV and rooftop photovoltaic (PV) systems in New York, NY and Dallas, TX, finding that workplace

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[1] Diversity is traditionally measured by the *diversity factor (DF)*: the ratio of the sum of the non-coincident peak demands of a set of users to the peak in their total demand. This DF is equal to one if demands are perfectly correlated and higher otherwise. The higher the diversity factor is, roughly, the higher the total kWh consumption of that set of users that can be provided with a given network capacity.

$DF = \frac{\sum_{j=1}^{n} \max_{i \in t}(Demand_{i,j})}{\max_{i \in t}(\sum_{j=1}^{n} Demand_{i,j})}$ where *n* is the total number of users (indexed by *j),* and *t* is the set of timesteps.

charging and delayed overnight charging are effective strategies for reducing peak demand and the need for investment in distribution capacity. Gschwendtner et al. (2023) assess the impact on local system peak of plug-in behavior – when and for how long drivers decide to charge.

While there is broad consensus that flat volumetric network tariffs are not cost-reflective (Pérez-Arriaga et al., 2017) and discourage electrification (Schittekatte et al., 2023), regulatory commissions across the US have taken a range of approaches to designing alternative tariffs (described in detail in Appendix A). Most utilities have offered optional (opt-in) time-of-use (TOU) rates since the early 2000s. Customers who enroll in these TOU rates could save money by shifting their consumption to "off-peak" periods. However, as of 2021 only 9% of US residential customers were enrolled on TOU rates (Faruqui and Tang, 2023), even though 73% of residential customers have advanced meters capable of supporting such rates (US EIA, 2023), shown in Figure 1. To combat this trend, a small number of states has enacted policies to make TOU rates the default option (Kavulla, 2023). In all these states there is no retail competition, so the distribution utility is also the energy supplier, and the TOU rate bundles energy, distribution, and transmission costs. In several states, EV-specific TOU rates have been introduced. End users opting into these rates are often not required to enroll on a time-varying tariff for their remaining household demand, and in some cases, it is impossible for EV owners to pay more than the default flat volumetric rate.

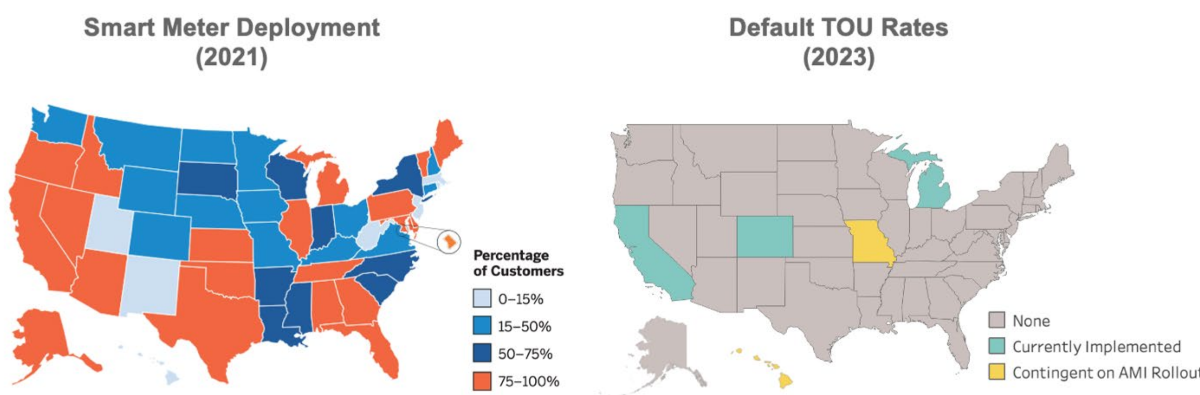

Figure 1: Smart meter deployment among US households (left) and default TOU rate adoption (right). Map at left from Kavulla (2023). Default TOU rates shown for each state's largest distribution utility.

Default TOU rates foster electrification by signaling how the marginal cost of electricity generation varies within days and across seasons (see e.g., Schittekatte et al., 2022). In addition, at current EV adoption levels EV owners can pay less for charging than under flat volumetric rates, and other consumers would receive the indirect benefit of lower peak wholesale prices without bearing substantial costs of network expansion. A study by the California Public Utility Commission (CPUC) found that "the increase in electricity sales from electrification may outweigh the costs of distribution investments, causing a downward pressure on residential electricity rates compared to present rates," a benefit to not just EV owners but all grid users (CPUC, 2023).

However, when local concentrations of EVs rise and wholesale price patterns are poorly aligned with demands on distribution networks, TOU rates may increase network congestion. A per-kWh charge alone, even a time-differentiated one, provides no disincentive for consumers to limit their maximum instantaneous kW consumption. As consumers defer EV charging to off-peak hours, TOU rates may result in local demand peaks at the onset of off-peak periods similar to the impact of the time-varying rates for water heaters introduced in the 1970s. And because residential EV charging is such a large load compared to other household appliances, it is possible that the higher and more highly correlated loads from EV charging can exceed existing network capacity even at low EV adoption levels, leading to steeply rising costs for distribution network upgrades. Such a reduction in the diversity of loads would impact various portions of the distribution network hierarchy, including individual household service connections, single feeders, and multiple feeders aggregated at a substation – what Boiteux and Stasi (1964) refer to as the individual and semi-individual networks. After years of stagnant demand, utilities are now requesting regulatory approval for grid modernization projects that enable electrification in support of state decarbonization goals; for example, in September 2023, National Grid and Eversource in Massachusetts filed draft plans for peak load-related upgrades totaling $2B between 2023 and 2030 (National Grid, 2023; Eversource, 2023). Notably, these plans do not model or consider alternative rate structures, which could mitigate the need for the high levels of grid reinforcement proposed.

In this paper, we study how to complement TOU energy charges with separate distribution network tariffs to deal with the problem of bunched EV charging in response to changes in energy charges. We consider TOU network tariffs along with a selection of alternative tariff designs that have been implemented outside the US. To perform the analysis, we conduct a realistic case study using simulated residential load and driving profiles at increasing levels of EV adoption, calibrated for Massachusetts. We study three types of network tariffs – fixed, per-kWh, and capacity (per-kW) – and analyze the results of households minimizing their electricity costs. We consider three key metrics: annual peak demand, levelized cost of EV charging, and cost shifts between EV and non-EV households.

We focus on the performance of alternative network tariffs combined with a TOU energy tariff because consumers react to the aggregate price. More complicated network tariffs beyond those tested here and load control programs have been proposed in the literature, but we restrict the scope of this study to relatively simple designs that have been implemented successfully in Europe (see Appendix A).

Our results should make clear to utilities and their regulators the importance of separating network charges from TOU energy rates. A bundled TOU rate that covers both energy and network costs could in fact perform worse than bundled flat volumetric rates from a total system cost (energy plus network) perspective by requiring unnecessary network expansion. This recommendation is not exclusive to states with vertically integrated utilities but can equally be applied to states with unbundled tariffs (e.g. the three California IOUs) or retail competition.[2] In the latter cases, while the separation between energy and network costs is inherent to the regulatory model, often flat or TOU volumetric tariffs are in place to recoup distribution costs.

The problem of correlated charging demand is urgent even though at the national level EVs currently only make up about 1% of total light duty vehicles (AFDC, 2022), since adoption can be highly spatially concentrated. In California, EVs accounted for 19% of new light duty vehicles sold in 2022 (State of California, 2023). In some neighborhoods, an EV can be found charging in almost every garage. Thus, local network effects will be felt long before EVs have achieved a significant

[2] Today, 13 states and Washington, D.C. have full retail electricity competition (RESA, 2022).

share of the total vehicle fleet. The high adoption scenarios studied here may already reflect what is happening in small pockets of the distribution network.

Steinbach and Blaschke (2023) identify a related equity issue if early EV adoption continues to be correlated with income. In the absence of tariff reform, higher-income individuals tend to have charging schedules that align with local network peaks, so their EV adoption will necessitate network upgrades paid for by all electricity consumers.

Our main finding is that distribution network tariffs for which consumers subscribe to certain maximum kW demand levels, with some time differentiation, can be a pragmatic approach to better control the impacts of rising EV penetration on network costs. With EV adoption as low as 15%, we observe new EV-driven peak demands. When paired with a TOU energy tariff, fixed and per-kWh distribution network tariffs fail to contain steep increases in network costs and benefit one customer group (EV households or non-EV households) at the expense of the other. While a network tariff levied ex-post on actual peak kW demand achieves the lowest distribution network cost, it is difficult to implement and does not provide customer protections against bill shocks. In contrast, a subscription charge performs reasonably well for all considered assessment criteria, offering a compromise between network costs, impacts on local distribution peaks, and tariff complexity. Whereas some tariff designs rely on perfectly rational consumer behavior to achieve their desired impact, a subscription charge is robust to heterogeneity in consumer reactions to the tariff; its performance on all criteria actually improves when a small portion of customers ignore price signals. Our sensitivity analyses indicate that time-differentiated subscription charges are less effective when heating electrification is considered, a topic for future work.

This paper is organized as follows: Section 2 provides background on network tariff design and introduces our research contribution. Section 3 introduces the process for creating simulated load profiles and specifies the methodology employed. Section 4 presents the results and sensitivity analyses. Section 5 discusses the implications of the results for tariff development. Section 6 concludes and offers policy recommendations.

2. Literature Review and Contribution

Distribution network tariff reform has gained attention in the academic community in recent years due to three major trends: the adoption of rooftop PV under net metering, residential electrification, and the roll-out of smart meters.

First, under net metering, consumers who install solar PV systems are compensated for their generation at the full retail rate. Because almost all states with net metering currently recover both energy and network costs through bundled flat volumetric rates, this means that solar consumers can reduce the amount they pay not just for energy, but also for the network they continue to rely on. Because embedded network costs are largely unaffected by solar adoption, the result is an increase in the costs that must be covered from customers without PV systems (Johnson et al., 2017). Equity concerns with net metering have spurred network tariff reforms all over the globe (Simshauser 2016; Schittekatte et al., 2018; Costello and Hemphill, 2014).

Second, under a flat volumetric residential tariff that recovers both energy and network costs, the per-kWh charge substantially exceeds the marginal cost of energy. This inefficiency serves to discourage the adoption of heat pumps and electric vehicles. For example, in Massachusetts today, it is cheaper to run a natural gas boiler than a heat pump at outdoor temperatures below 35F (Michaels and Nachtrieb, 2022), and a customer who replaces their natural gas space heating with a cold climate heat pump (CCHP) system will likely pay more in annual energy costs, independent of the installed cost of the system itself (Sergici et al., 2023). When these devices (which can be scheduled) are adopted, tariffs without time differentiation make it more likely that they will contribute to increasing peak demand.

Third, the roll-out of smart electricity meters has allowed utilities to collect electricity consumption data at hourly or sub-hourly intervals. Previous meter models rendered it impossible to determine the time of day when customers consumed electricity. Today, over 73% of US households are estimated to have a smart meter (Cooper et al., 2021).

A central objective of tariff design is to provide good incentives for consumption while producing adequate revenue to recover the utility's costs. Efficiency requires that a network tariff be structured so that network users are charged according to the cost they impose on the system. This will provide incentives that limit overinvestment. In addition, network tariffs should be simple and predictable, non-discriminatory towards certain customer groups, and recover regulated costs. Passey et al. (2017) show that under flat network tariffs, the costs consumers pay rarely reflects the costs they impose on the system. This leads to inefficient incentives for grid usage and to cost shifts between grid users.

In theory, the most efficient network tariff contains two parts: a forward-looking charge that reflects the long-run marginal cost of upgrading the network at each location and a complementary fixed charge to recover the residual costs of past network investments (Strbac and Mutale, 2005; Pérez-Arriaga et al., 2017).[3] While there is consensus around this framework, there is considerable disagreement in the literature on how it should be interpreted to design network tariffs in practice.

In one camp, acknowledging the difficulty of calculating location-specific long-run marginal costs, Borenstein et al. (2021) argue that because most network investments have already been made,[4] the most important network tariff revision consists of shifting the non-marginal costs of those prior investments from a flat volumetric charge to a fixed charge – see also Borenstein (2016) and Borenstein and Bushnell (2022). The authors model several scenarios in which the long-run marginal transmission and distribution costs are set to zero, effectively ignoring forward-looking distribution network costs. To improve equity and promote electrification, they argue for an income-graduated fixed charge (IGFC) similar to a progressive income tax. Drawing on this idea, the California state legislature passed a bill in 2022 that requires the CPUC to implement fixed charges based on customers' income with at least three distinct tiers. In response, the California investor-owned utilities recently proposed rates with fixed charges ranging from $15 to $128 per

[3] The first paper that has a coherent discussion of distribution marginal costs is Boiteux and Stasi (1964), which proposes that customer charges reflect forward-looking network costs to "spread out the peak”" and “fill out the hollows.”

[4] For distribution networks, there are three kinds of incremental capital expenditures: replacement, reinforcement (e.g., to deal with increase in wildfires) and demand-driven. Demand-driven expansion costs should be priced based on the associated long-run marginal costs.

month, which have been the subject of fierce debate (Faruqui, 2023; Engstrom and Deehan, 2023).

Using smart meter data from 100,000 customers in the Chicago area, Burger et al. (2020) arrive at a similar recommendation: a two-part tariff with a per-kWh charge set equal to the social marginal cost of energy and an income-based fixed charge so that low-income customers pay less than under current flat volumetric rates. The authors also find a strong correlation between a customer's peak demand and income. In order to overcome the administrative challenge of collecting income information, Batlle et al. (2020) propose a residual cost allocation scheme whereby users would be charged according to their historical consumption, which can be a reliable proxy for household wealth (Borenstein et al., 2021).

In the other camp, Pérez-Arriaga et al. (2017) adhere to an "efficient ideal" approach, proposing that forward-looking costs should be calculated precisely at each network node, which is only feasible since the deployment of advanced metering infrastructure. In the same spirit, Morell-Dameto et al. (2023) combine a simple fixed charge to cover residuals costs with a highly spatially and temporally granular per-kWh component that reflects forward looking network expansion costs. Abdelmotteleb et al. (2018) recommend a fixed charge plus a peak-coincident network charge based on each customer's demand during the annual peak hour at each network level. Using smart meter data from Danish consumers, Gunkel et al. (2023) advocate for a two-part tariff that includes an individual peak and a system-coincident peak charge. Winzer and Ludwig (2022) conduct an exercise in optimal tariff design and propose a grid-responsive tariff to alleviate network congestion, where devices would respond to real-time price signals. Finally, Govaerts et al. (2023) investigate the "Long-Run Incremental Cost" approach to optimally calibrate network tariffs.

The papers in this second camp present innovative approaches that may inspire future regulatory proceedings, but their methods are far more advanced than those we examine here. Moreover, even if it were possible to accurately calculate forward-looking network expansion costs at each network node, regulators are likely to deem it unacceptable to break a decades-long norm of charging network users in the same customer class on the same tariff. On the other hand, the first camp largely ignores the likelihood of future network investments driven by highly correlated newly-electrified demand. Papers like Borenstein et al. (2021) effectively assume that all network investments have already been made and consumers must simply pay for them. The authors stress that flat volumetric network charges discourage electrification, but ignoring the effects of network tariff design on future network investment requirements would only be correct in a system with stagnant demand. Ignoring the incentive effects of alternative network tariffs is inappropriate in a world in which demand is projected to grow and massive grid expansion is forecasted to be necessary to meet decarbonization targets (International Energy Agency, 2023). Our approach and the recommendations that follow fall somewhere in between these two camps, mirroring recent pragmatic European network tariff design efforts. We focus on simple solutions that do not rely on precise forward-looking cost calculations but consider the possibility of distribution network upgrades driven by peak kW demands.

There is a small body of literature that takes a similar approach. These studies predominantly address the distributional impacts of traditional network tariff approaches in light of consumer adoption of solar PV and battery storage. Schittekatte (2020) uses a bi-level optimization to simulate how consumers with the option to invest in distributed energy resources (DERs) like solar PV may respond to three different network tariff designs. Hoarau and Perez (2019) consider adoption of both DERs and EVs, ultimately concluding that the diffusion of EVs can help mitigate grid defection concerns, but that tariff structures that provide incentives for DER owners tend to be harmful for EV owners. Simshauser (2016) proposes a demand charge to mitigate cost shifts between solar and non-solar households in Queensland, Australia. Using electricity consumption data from two network operators in Great Britain, Küfeoğlu and Pollitt (2019) demonstrate that under current network tariff structures, EV adoption applies downward rate pressure on network charges (the opposite impact of PV adoption). These papers typically assume scenarios of flat load and revenue neutrality, where all network costs are sunk. They do not consider outcomes where customers increase net demand through heat pump and EV adoption, and where additional network investments are required to meet peak demand but can be avoided, reduced, or deferred through appropriate tariff design. The assumption of zero marginal demand-driven distribution cost does not align with utility planning to support end-use electrification of transportation, buildings and other sectors (National Grid, 2023; Eversource, 2023).

The one recent exception is Hennig et al. (2022). The authors lay out a framework for assessing network tariff performance, focusing on cost efficiency, cost recovery, and implementation burden. In a case study, the authors test four network tariff designs under EV adoption, where the distribution utility upgrades distribution transformers once they reach 95% of their capacity. The case study illustrates how to use the framework in practice, but it uses a sample of only 50 consumers in Germany and unfortunately considers network tariffs in isolation, with no analysis of the interaction between network and energy tariffs.

This paper fills important gaps in the existing literature by simulating a realistic case study that 1) focuses on the interaction between network and TOU energy tariffs on peak load under a growing EV load scenario, 2) analyzes impacts of rate design on incentives for electrification via a levelized cost of charging calculation, 3) evaluates the cost impacts of different tariff designs both on consumers with and without EVs, and 4) uses 400 individual household load profiles for Massachusetts. Our analysis is inspired by existing network tariff designs in Europe, which seem largely to have escaped the attention of regulators and analysts in the US.

3. Methods

In this section, we present a high-level summary of the methodology for our case study, calibrated on realistic Massachusetts residential electricity consumption and driving data. A full description of the approach can be found in Appendix B. Figure 2 illustrates the components of our approach, which we outline in the subsections below.

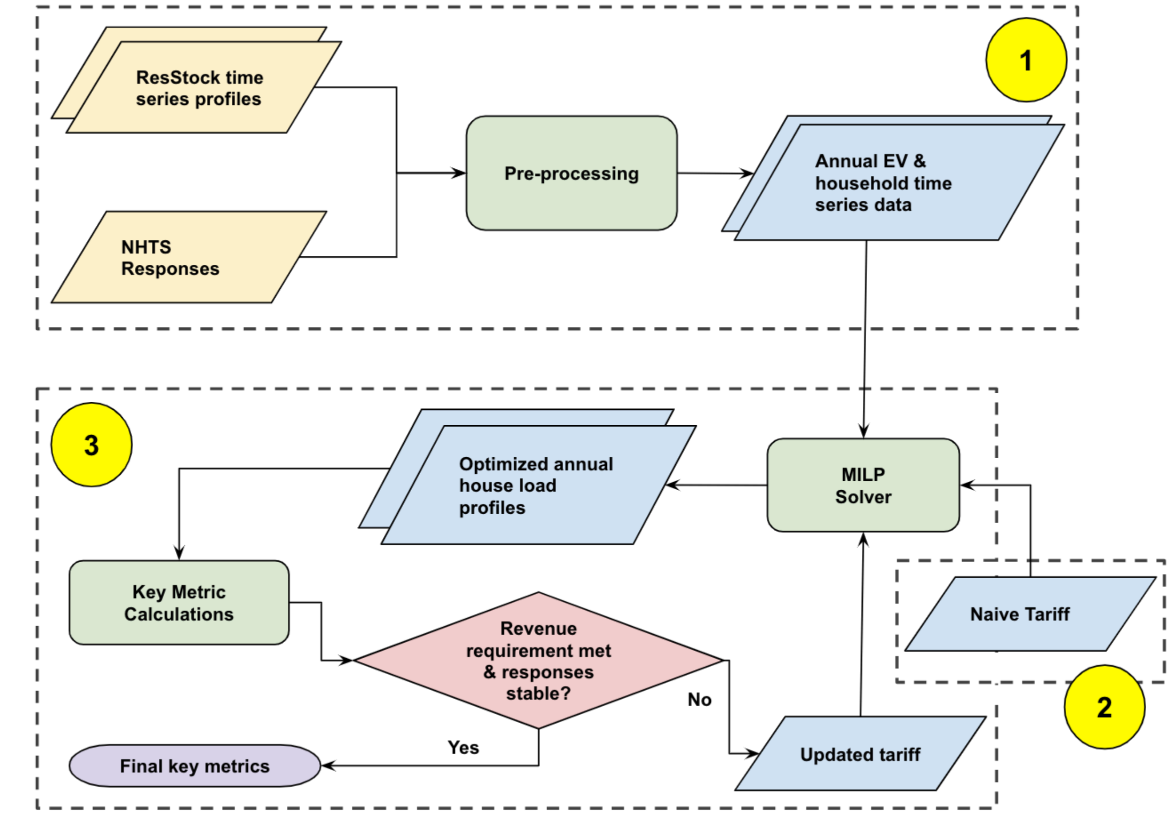

Figure 2: Methodology flowchart; ResStock is a database of synthetic hourly load profiles for representative US homes. NHTS is the National Household Travel Survey, in which respondents log their travel behavior. The processes covered in each numbered cluster are covered in their corresponding sections (3.1 – 3.3).

3.1 Users and Behavior

In order to assess the performance of different network tariff designs under increasing EV adoption, we must simulate how consumers will respond to the tariffs' price signals.

We obtain 400 synthetic load profiles from NREL's ResStock database (Wilson et al., 2022), drawn randomly from single-family home archetypes in the state of Massachusetts and representative of the local diversity found on a typical distribution feeder. We treat as exogenous hourly energy consumption given by these profiles, broken out by end-use type (heating, appliances, lighting, etc.). Using the National Household Travel Survey (NHTS), we assign to each household a simulated driving profile that indicates when its EV is at home and how many miles it is driven per day. Travel patterns, especially miles driven per day, are relatively stable across the US (Federal Highway Administration, 2017).

3.2 Network Tariffs

We test variations on three standard formats for network tariff design: fixed, per-kWh, and capacity (based on kW demand).[5] Table 1 shows the key details of each tariff, with representative costs shown for 0% EV adoption.

Table 1: Summary of network tariff designs under consideration

Tariff Type	*Variant*	*Number of Periods*	*Cost at 0% EV Adoption*	*Description*
Fixed	–	-	$1131/year	Each consumer pays the same amount regardless of consumption.
Per-kWh	Non-Time-differentiated (Flat)	1	$0.11/kWh all hours	Per-kWh charge with no time variation.
	Time-differentiated (TOU)	2 (intraday)	$0.08/kWh off-peak $0.16/kWh on-peak	Per-kWh charge with time variation identical to the TOU energy component. The on-peak charge is set at two times the off-peak charge.
Capacity	Ex-post measured (demand charge)	1	$170/kW-year	Assessed based on the consumer's maximum hourly demand during the entire year.
	Ex-post measured (demand charge)	3 (intraday)	$30/kW off-peak $70/kW mid-peak $88/kW on-peak	Assessed based on the consumer's maximum hourly demand in each period during the entire year.
	Ex-post measured (demand charge)	6 (intraday & seasonal)	$46/kW on-peak (winter) $51/kW on-peak (non-winter) $38/kW mid-peak (winter) $42/kW mid-peak (non-winter) $16/kW off-peak (winter) $17/kW off-peak (non-winter)	Assessed based on the consumer's maximum hourly demand in each period during the season.
	Ex-ante contracted (subscription charge)	6 (intraday & seasonal)	$40/kW on-peak (winter) $43/kW on-peak (non-winter) $31/kW mid-peak (winter) $34/kW mid-peak (non-winter) $13/kW off-peak (winter) $14/kW off-peak (non-winter)	Calculated by adding a 1 kW buffer to the optimized load profiles under the ex-post measured capacity tariff.

[5] We model whole-house tariffs in which all residential load is subject to the tariff terms. In this way, the tariffs are "technology-agnostic," unlike the EV-specific tariffs discussed in Appendix A.

Below, we describe how tariff prices for each incremental adoption level are calculated. For all network tariff types, we assume the energy price to be exogenous and energy costs recovered via a simple two-part TOU rate, calculated using the same methodology as the two-part TOU network charge, calibrated under 0% EV adoption on a (flat) supply charge of $0.102/kWh. On-peak energy hours are weekdays 8:00 AM – 8:59 PM.

Fixed

The fixed tariff is the total revenue requirement after equilibrium is reached to cover all capital and operating network costs (see Section 3.3) divided by the number of grid users (400).

Per-kWh

The 1-part per-kWh tariff is the total revenue requirement divided by aggregate annual consumption. The 2-part TOU per-kWh tariff mirrors National Grid's G-3 rate. Peak hours are Monday through Friday 8:00 AM to 8:59 PM, and the on-peak rate is set at two times the off-peak rate. Further details are provided in Appendix B.

Capacity

We test two types of capacity tariffs: ex-post measured (demand charge) and ex-ante contracted (subscription charge).

<u>Ex-Post Measured (Demand Charge)</u>

An ex-post measured capacity charge (also called a demand charge) involves measuring the maximum demand during the billing period. In practice, it is calculated either by 1) averaging several instantaneous demand readings during each hour and taking the maximum of those averages; or 2) taking the maximum instantaneous reading. In our case study, this implementation detail is not relevant because we work with hourly consumption data.

We test three different demand charges: 1-part, 3-part, and 6-part (i.e., 3-part seasonal). For each tariff, the charge in each period is calculated by dividing a portion of the revenue requirement by the sum of each customer's maximum demand in that period. We elaborate on the simple 1-part demand charge (which takes the maximum across all hours of the year) by adding time differentiation. The key idea is that EV customers will minimize their costs by limiting their EV charging demand below their maximum non-EV demand in each period. A single period (e.g., all hours of the year) allows for more bandwidth to charge without incurring additional cost. Introducing additional periods results in a lower aggregate peak demand, as discussed in the results. For the 3-part demand charge, we define 3 periods: off-peak from 12:00 AM - 7:59 AM (plus weekends), on-peak from 8:00 AM to 8:59 PM (same on-peak period as the TOU energy component), and mid-peak from 9:00 PM - 11:59 PM. The 3-part seasonal demand charge maintains the three intraday periods from the 3-part tariff and adds the concept of seasonality. We define a "winter" period consisting of December - March and a non-winter period that contains all other months. Full implementation details can be found in Appendix B.

Ex-Ante Contracted (Subscription Charge)

Unlike a demand charge, in a subscription charge, the consumer selects a capacity level *in advance*. In practice, consumers often can change their subscribed level as often as monthly. This works similarly to an Internet plan where customers select their bandwidth from a menu of options. In some implementations, if the customer exceeds the subscribed level, its power is cut off; in other cases, a penalty charge is imposed. Customers can determine their contracted (i.e., subscribed) level by looking back at their historical consumption. As described in Appendix A, for many years subscription network charges have been in place in France, Spain, and Italy to recoup part of the network costs.

To calculate the subscription tariff charges, we run the optimization under the 3-part seasonal demand charge, which provides customers' maximum usage in each of the 6 periods.[6] We calculate the subscription level as the maximum usage in each period plus a 1 kW buffer, rounded to the nearest whole kW value. This is meant to mirror the exercise a household would do to determine its subscription level (albeit with historical consumption data rather than perfect foresight), with the buffer representing a small amount of aversion to exceeding the historical peak values and incurring a penalty or lost load.[7] When the subscription level for the different

[6] We also modeled 1- and 3-part subscription charges, which perform worse than the 3-part seasonal variant. To avoid obscuring our key recommendations, these are not discussed or presented in the Results section.
[7] Note that third parties such as retail suppliers could assist consumers with selecting the ideal subscription level.

periods is determined, we re-run the optimization but with a hard physical cap equal to the assigned subscription value per time period. Because it is not possible for a household to exceed its pre-subscribed value in our model, we do not define a penalty cost function.

Note that in this run the optimized EV charging profile will be different than in the initial run to obtain the ideal subscription level because no extra distribution network costs are incurred to charge beyond the optimal demand level (under demand charges) up to the subscribed physical cap. For example, a customer whose maximum demand during the winter on-peak period under a demand charge is 3 kW would subscribe at 4 kW. If that customer purchases an EV, she will incur no additional distribution-related costs if the home's total demand (inclusive of EV charging) does not exceed 4 kW. The buffer therefore allows EVs to charge optimally at a higher level than under a demand charge. The subscription cost (in $/kW) for each period is the share of the revenue requirement divided by the sum of subscription levels across all customers.

Alternative approaches that were not pursued

While many papers (Backe et al., 2020; Nouicer et al., 2023; Muratori and Rizzoni, 2015) consider top-down load control or load management programs to achieve peak demand savings, the complexity of actively managing load becomes significant at high EV adoption levels. Furthermore, distribution utilities have not historically adopted "non-wires" approaches that reduce peak demand; growing peak demand is often used as a justification for making capital investments (Werner and Jarvis, 2022). To make our recommendations relevant regardless of the willingness of utilities to engage in load management programs, we do not incorporate centralized control of charging activity. Rather, each household acts independently to minimize its costs, acting on the aggregate network and energy price signal. We recognize that the addition of targeted load control on top of well-designed tariffs could provide even more savings for customers and will address this question in ongoing and future work. Another alternative approach could be to slightly vary the timing of the TOU periods for different users to create heterogeneity in charging behavior. We do not pursue this idea here as it violates the non-discriminatory principle.

3.3 Optimization and Key Metrics

We vary the exogenous EV adoption level, using 5% adoption increments, and assume that each EV responds rationally to price signals when plugged in. We solve a mixed integer linear program for each household to minimize annual electricity costs (detailed in Appendix B). Consumers react to the aggregate price, including both energy and distribution network charges.

We assume that the 400 households are electrically connected in the same neighborhood and distribution grid. Increases in their annual aggregated coincident peak demand lead to linearly-increasing network costs (the revenue requirement), which are recuperated via the distribution network tariff. While we consider distribution at only one layer, in reality it is a cascade of layers (Morell-Dameto et al., 2023), with impacts aggregating up, correcting for increasing diversity through the entire distribution hierarchy (Boiteux and Stasi, 1964). The problem of correlated EV charging is especially apparent at the lowest distribution layers, especially residential feeders with low load diversity. If we considered more layers, the impact of correlated charging would be less pronounced; the higher you aggregate up the more you can leverage load diversity. In this way, our approach considers the "weakest link" of the cascade.

For each incremental level of electrification, we first compute a naive solution where the tariff price levels are set to collect the revenue requirement at 0% EV adoption. Using the resulting annual peak demand from the naive run, we recalculate the tariff prices to recover the *new* revenue requirement. Equilibrium is reached when the household responses do not deviate from the previous iteration, and the full revenue requirement is collected. The revenue requirement is proportional to the annual system peak, described in (1).

$$RevReq = BNC + LRMC \cdot (SP_t - SP_0) \tag{1}$$

LRMC is the long-run marginal cost of expanding the network, set at $50/kW for the low-cost network expansion scenario and $150/kW for the high-cost network expansion scenario.[8] These values are taken from studies commissioned by the CPUC on the avoided cost of distributed energy resources (Energy+Environmental Economics, 2022) and the distribution cost impacts of

[8] Both values are annualized over the lifetime of the equipment entered into service.

transportation electrification (Cutter et al., 2021). We treat these values as representative endpoints of a cost spectrum, rather than exact predictions. The baseline network cost (*BNC*) is defined as the product of the annual aggregate consumption at 0% adoption times Eversource's flat volumetric network charge in Eastern Massachusetts as of August 2023 ($0.11845/kWh) (Eversource, 2023). We assume that all distribution network costs are allocated to the flat volumetric network charge. SP_t is the aggregate system peak for the electrification level *t* and SP_0 is the aggregate system peak at 0% electrification.

We assess each tariff design based on three metrics: peak demand (which is linearly associated with total network costs), cost impacts for EV households, and cost impacts for non-EV households. EV charging costs determine whether and how much customers will save compared to fuel costs with an internal combustion engine vehicle. Non-EV household costs capture the distributional impacts of each tariff option and indicate whether each will be acceptable from an equity perspective, especially when considering that EV adoption until now has correlated strongly with income (Lee et al., 2019). Ideally, only EV households should pay the incremental network costs due to increased EV adoption. Yet in practice and in our simulations distribution network tariffs reflect not only forward-looking costs but also sunk costs of prior investments (*BNC* here). The implications are discussed further in Section 5.2.

We compute the following statistics for each tariff and at 5% incremental levels of EV adoption. We specify a brief description and equation for each (2-4).

Annual peak: the maximum hourly demand for the aggregated load over all consumers, measured in kW:

$$max_{i \in \{1,..,8760\}} \, (AggDemand_i) \tag{2}$$

where $AggDemand_i$ is the sum of all individual demands in hour i

Levelized charging cost: the average cost paid by EV households for EV charging, calculated as the total incremental EV-driven costs divided by total incremental EV-driven consumption, measured in $/kWh:

$$\sum_j^{n=400} EV_j(Cost_{EV,j} - Cost_{NoEV,j}) \; / \; \sum_j^{n=400} EV_j(Cons_{EV,j} - Cons_{NoEV,j}) \tag{3}$$

where EV_j is 1 if the household has an EV and 0 otherwise

Distributional impact: the average percentage change in network cost (*NWCost*) paid by non-EV households compared to a scenario of flat volumetric network and energy tariffs at 0% EV adoption, i.e. the "status quo" (SQ), measured in $/year/household:

$$\left(\sum_j^{n=400}(1-\ EV_j)(NWCost_j\ -\ NWCost_{SQ,j})/NWCost_{SQ,j}\right)\ /\ \sum_j^{n=400}(1-EV_j) \qquad (4)$$

Under the assumptions outlined in this section, we isolate the impact of network tariff design on each of these key metrics, while capturing how charging incentives are determined by the interaction of the TOU energy tariff and network tariff design.

It is worth discussing briefly how these metrics relate to consumer welfare. We assume that there is no welfare loss from deferring EV charging to a later hour as long as the vehicle has sufficient charge by departure time to fulfill that day's driving needs. Using this assumption, consumer welfare is negatively related to total electricity cost. Since we assume EV adoption to be exogeneous, the absolute value of the network tariff charge has a limited impact on our computed metrics. Rather, the design of the network charge drives the results. We discuss this further in Section 5.2.

4. Results

This section is divided into two subsections. First, we present results for each key metric above. We include two cases for each metric to represent a range of possible incremental investment costs (LRMC); low ($50/kW) and high ($150/kW). Second, we perform sensitivity analyses to consider how the tariffs perform under different energy pricing plans, consumer behavior, and concurrent adoption of heat pump systems.

4.1 Evaluation of Tariffs Against Key Metrics

We first discuss the results for the growth in annual peak under the different network tariff designs. We then analyze the levelized charging cost for EV households. Finally, we discuss distributional impacts.

4.1.1 Annual Peak

Figure 3 shows the annual coincident peak demand for each tariff at 5% adoption increments. The annual peak is identical for both LRMC cases because only relative price differences impact a household's response, not the absolute value of the LRMC. The fixed, 1-part per-kWh and 2-part TOU per-kWh tariffs produce the same result because the network tariff either has no impact on or magnifies the price differential in the energy tariff.

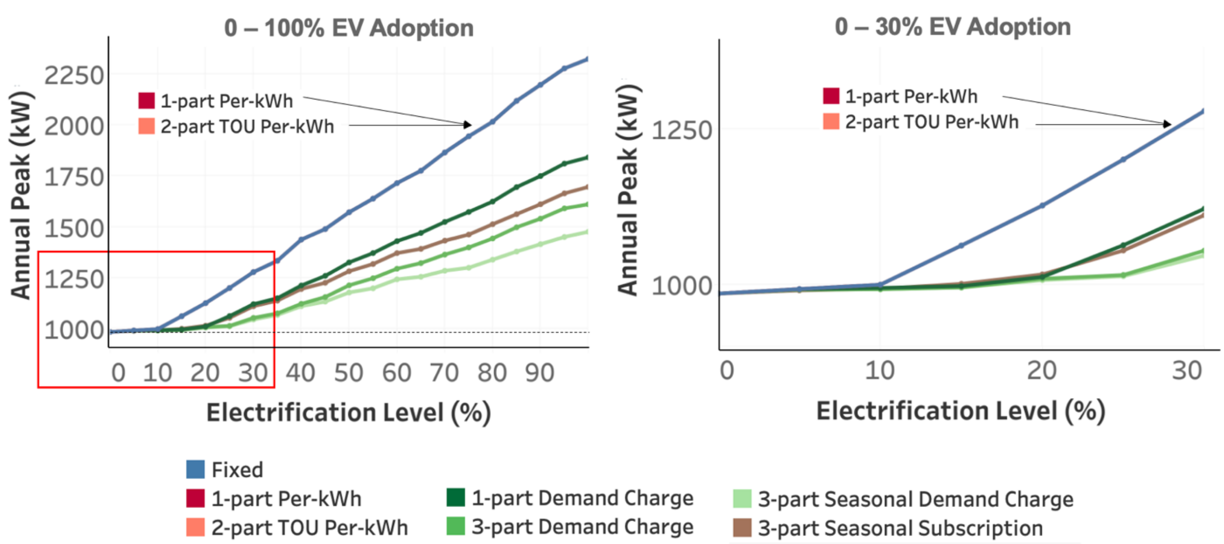

Figure 3: Annual peak demand at 5% EV adoption increments for seven network tariffs tested (left), with 0 – 30% adoption highlighted (right). The fixed, 1-part per-kWh, and 2-part TOU per-kWh tariffs all produce the same aggregate peak demand because the network tariff either reinforces or has no distortionary effect on the energy tariff. As early as 15% adoption, network tariff designs that fail to mitigate the correlated response to the off-peak energy window diverge from capacity tariffs.

This energy price differential results in all EVs charging at the charger's full capacity at the start of the off-peak period. For the fixed, 1-part per-kWh, and 2-part TOU per-kWh tariffs, as early as 15% EV adoption this new EV-driven peak exceeds the historically most important early-evening peak driven by (exogenous) non-EV demand, as shown in Figure 4.[9] In contrast, under the capacity tariffs charging is limited to a level such that the aggregate of EV and non-EV demand stays beneath the maximum non-EV demand in that period to avoid incurring additional network

[9] It is worth noting that because customers react to the aggregate price, the fact that the energy and network charges have the same on- and off-peak hours is not relevant. Even if the off-peak blocks did not overlap, rational EV owners would wait until the hour with the lowest combined price, producing the same "snapback" effect.

cost. In this way, even though we still observe an EV-driven peak under the capacity tariffs, the peak is reduced. For example, at 50% EV adoption, the annual peak under the 3-part seasonal demand charge (1,179 kW) is 20% higher than the baseline (displayed as a dotted black line in Figure 3), compared to 60% higher (1,572 kW) for the fixed, 1-part per-kWh, and 2-part TOU per-kWh tariffs. We also observe that adding more time periods to the demand charge improves its ability to mitigate peak impacts and thus to defer network upgrades. Under the subscription charge, we lose a portion of peak demand mitigation in exchange for easier implementation due to the 1 kW subscription buffer. However, overall, the subscription charge performs significantly better than fixed or per-kWh network tariffs.

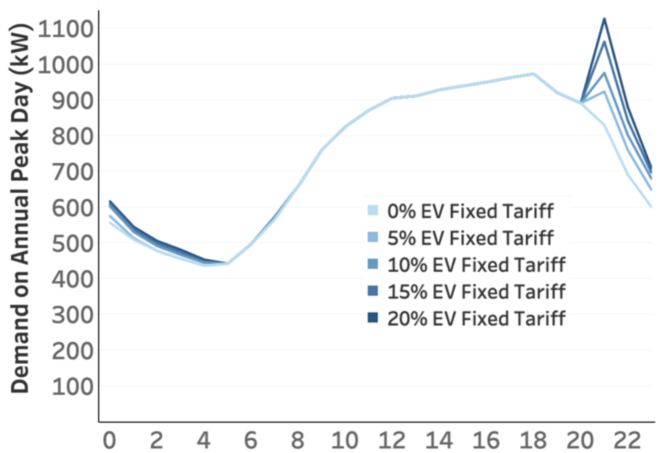

Figure 4: Hourly aggregated demand during the annual peak day at 0, 5, 10, 15 and 20% EV adoption under the fixed network tariff. In each case, EVs respond to the start of the off-peak period in the energy tariff; at early levels of adoption the EV-driven peak does not exceed the early-evening peak from non-EV household electricity consumption.

4.1.2 Levelized charging cost for EV Households

Figure 5 shows the average levelized charging costs for EV owners. Almost all EV households can achieve the minimum charging cost. This means that they adhere perfectly to price signals and fulfill their driving needs without either exceeding their pre-EV peak demand in each demand period (for capacity tariffs) and charge nearly entirely during the off-peak period. This result is likely an overestimation due to our assumption of perfect ability of end users to forecast their individual peak usage. The result for the subscription charge provides a more realistic estimate because customers would know their subscription level in advance and then program EV charging to stay beneath that limit.

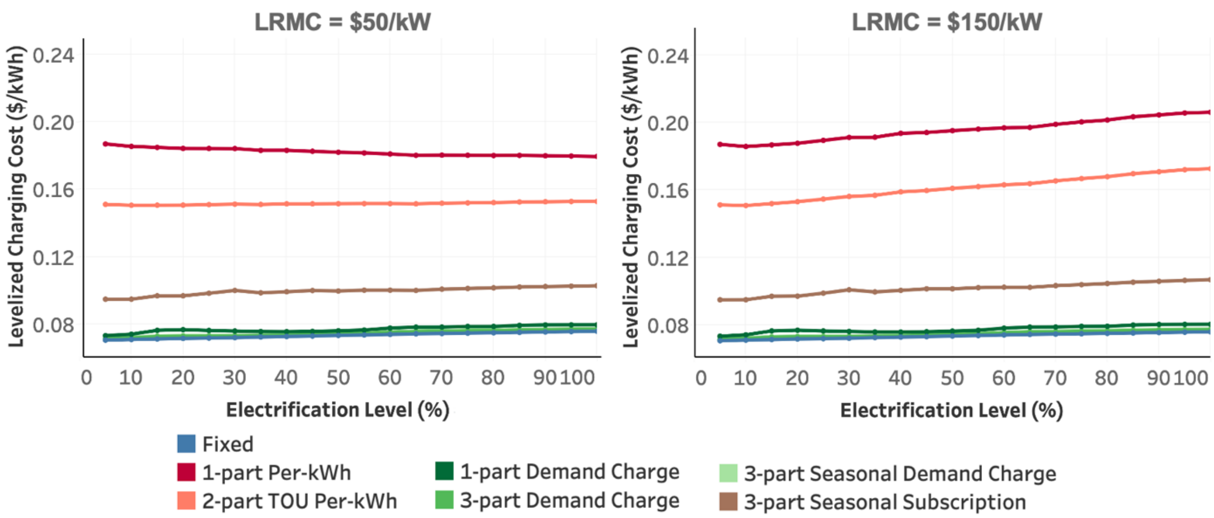

Figure 5: Levelized charging costs for EV owners for low (left) and high (right) LRMC cases. Under the fixed and demand charges, EV customer' costs are nearly equivalent to the off-peak energy price because they can fulfill their charging needs without increasing peak demand or charging during the on-peak energy window.

What is clear from these results is that per-kWh network tariffs perform poorly from a levelized charging cost perspective. The average EV in our sample consumes 3,075 kWh annually. When the network revenue requirement is collected using per-kWh tariffs, EV households contribute more to cost recovery than under other tariff designs. Introducing TOU per-kWh network tariffs helps to some extent to lower the levelized costs of charging, but they remain significantly higher than under the other alternative network tariff designs. The slight upward curve of the per-kWh tariffs under the high LRMC case reflects the fact that the revenue requirement (driven by peak demand) is growing faster than aggregate electricity consumption. The opposite occurs in the low LRMC case.

4.1.3 Difference in Network Costs for Non-EV Households

Figure 6 shows the change in annual network costs paid by non-EV households under the different network tariff designs. Positive values reflect cost increases and negative values represent savings compared to network costs under 0% EV adoption with flat volumetric energy and network tariffs. We focus on network costs because those are non-optional. A consumer whose energy tariff costs increase under a TOU plan might be able to switch to a flat volumetric rate, something we expect to occur in practice, though we do not model this possibility.

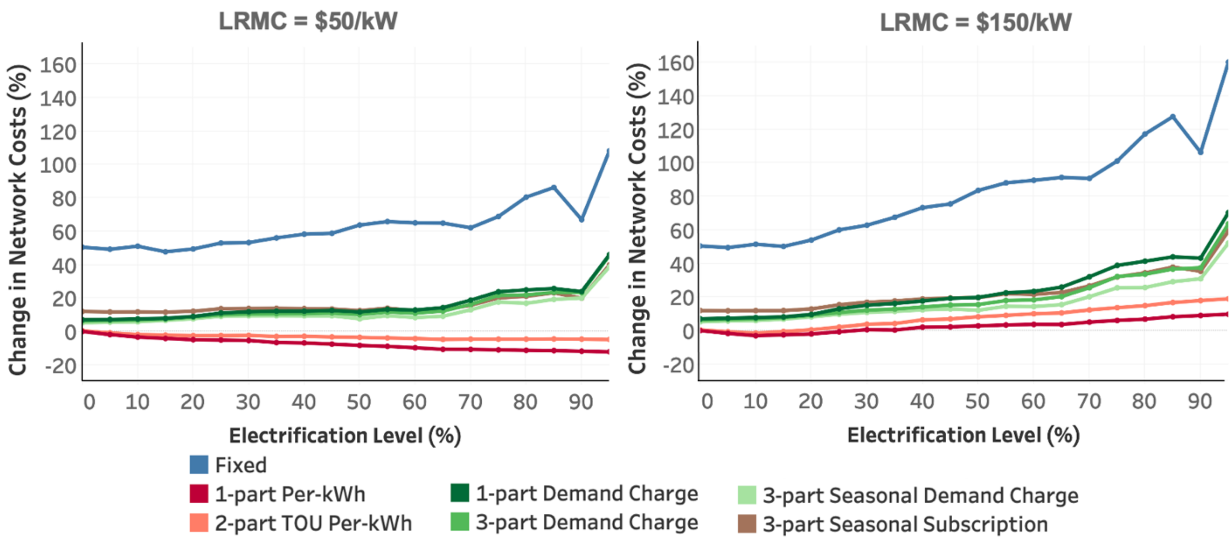

Figure 6: Change in annual network costs for non-EV households for the low (left) and high (right) LRMC cases.

An (undifferentiated) fixed tariff performs the worst at all EV adoption levels, as all new peak-related costs that are entirely driven by EV charging are shared equally among all households. Importantly these peak-related costs are high under fixed charges (see Figure 3), as no incentive is provided to schedule EV charging to limit the overall local peak. The 1-part per-kWh tariff performs best, as EV owners have no mechanism to reduce their network costs by shifting demand to off-peak hours. While the subscription tariff results in higher revenue collection from electrified households compared to the 3-part and 3-part seasonal demand charges, this benefit to non-electrified households is offset partially by the higher annual peak under the subscription.

This metric is highly sensitive to the assumed cost of network expansion. At $50/kW, the average non-electrified household saves money under both per-kWh tariffs at all levels of EV adoption. In other words, EV owners are cross-subsidizing non-EV owners. At $150/kW, this is only true at low EV adoption levels before a new EV-driven peak triggers network upgrades.

4.2 Sensitivity Analyses

We conduct three types of sensitivity analysis. First, we suppose some EV owners charge upon returning home, ignoring the price signals. Next, we test the impacts of using another energy tariff instead of a TOU rate. Finally, we explore the concurrent electrification of heating and transportation.

4.2.1 Price-Insensitive Charging Behavior

We first consider that a small portion (30%) of EV drivers ignore the tariff price signals and charge immediately upon returning home. We examine the impact on annual peak demand in Figure 7. As above, the annual peak values are the same in both LRMC cases.

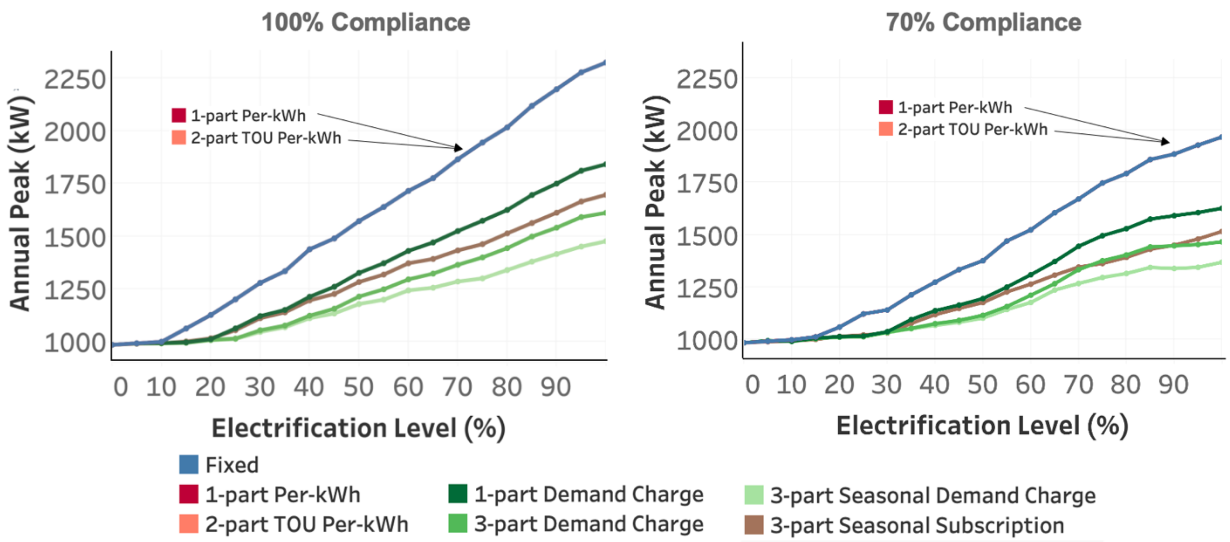

Figure 7: Annual peak demand for base case (100% compliance, left) and with 70% compliance (right) among EV owners to tariff price signals. When a small number of EV owners deviate from rational behavior, the aggregate peak demand is lower than when all EV owners respond rationally in a correlated manner.

We obtain the surprising result that when 30% of EV owners ignore the price signal and charge immediately upon arrival home, the annual network peak is *lower* than when all EV owners comply. This reflects the fact that with 100% price sensitivity, all owners charge at the same time. If a portion of EV owners charge immediately on returning home rather than delaying until lower-priced hours, this introduces diversity that reduces aggregate peak demand. The benefits of capacity charges are not dependent on all consumers responding to them.

4.2.2 Varying the Energy Tariff

So far, all network tariffs have been combined with a simple two-part TOU energy tariff. While recent US tariff reforms indicate a trend towards TOU pricing, there are still many states where flat volumetric tariffs are the norm. In contrast, in states with retail competition, some retailers have begun to offer dynamic energy tariffs that pass through wholesale electricity prices. In this sensitivity analysis, we explore these two extremes of the energy tariff spectrum.

On one end of the spectrum, we test a variant with a flat volumetric network tariff and flat volumetric energy charge, as is common in most of the US today, which we label the "Status Quo."[10] On the other end of the spectrum, we consider a scenario where customers are exposed to the wholesale energy price. We use hourly day-ahead prices at the ISO New England hub for the year 2018 combined with the 3-part seasonal subscription network tariff, labeled "Subscription LMP." Figure 8 shows the annual peak for the original tariffs plus the two additional scenarios.

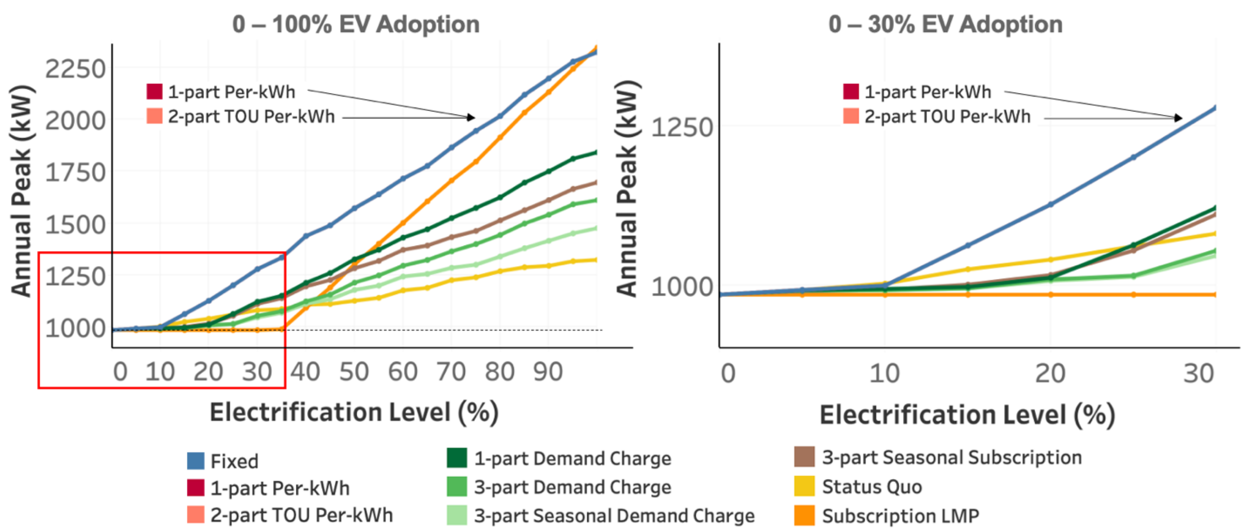

Figure 8: Annual peak demand with additional two scenarios representing the ends of the energy tariff design spectrum: dynamic (Subscription LMP) and flat volumetric (Status Quo).

First, we comment on the Status Quo scenario. Paradoxically, beyond 40% EV adoption, the Status Quo scenario performs the best among all network tariffs for annual peak. With flat volumetric energy and network tariffs, there is no incentive to delay charging. Every vehicle therefore charges upon arriving at home. Differences in arrival times add diversity, and peak aggregate demand is lower than the correlated "snapback" we observe with a TOU energy rate.

Second, at low adoption rates, the Subscription LMP scenario with a dynamic energy tariff produces a lower annual peak than any network tariff with TOU energy pricing. This reflects the fact that the lowest prices in the day-ahead wholesale market typically occur during overnight

[10] Note that there is also a variant where a consumer could opt into a flat volumetric energy tariff with a competitive retailer but still be subject to a time-varying and/or capacity-based network tariff. We did not model that scenario here.

hours, when household non-EV demand is low. However, beyond 40% EV adoption, the Subscription LMP performs worse than any capacity charge, and by 100% EV adoption even performs worse than the fixed tariff. When the day-ahead wholesale price is passed through directly, all EV owners, with perfect foresight, defer charging until the lowest price hour. With a TOU energy tariff, some EVs have not yet arrived home at the start of the off-peak window, so charging is more spread out in time. It is important to note, however, that we do not model the feedback between EV load shifting and wholesale prices. At high EV penetration, if all charging occurred in a single hour, the wholesale price in that hour would increase. We discuss this limitation of our study in Section 5.2.

Interestingly, the Status Quo tariff also performs the best in terms of change in network costs for non-EV households, as illustrated in Figure 9. While EV owners contribute the same amount to network costs under the Status Quo as under the 1-part per-kWh network tariff scenario (paired with a TOU energy tariff), the Status Quo has a lower annual peak (and therefore lower revenue requirement), so non-EV households pay less.

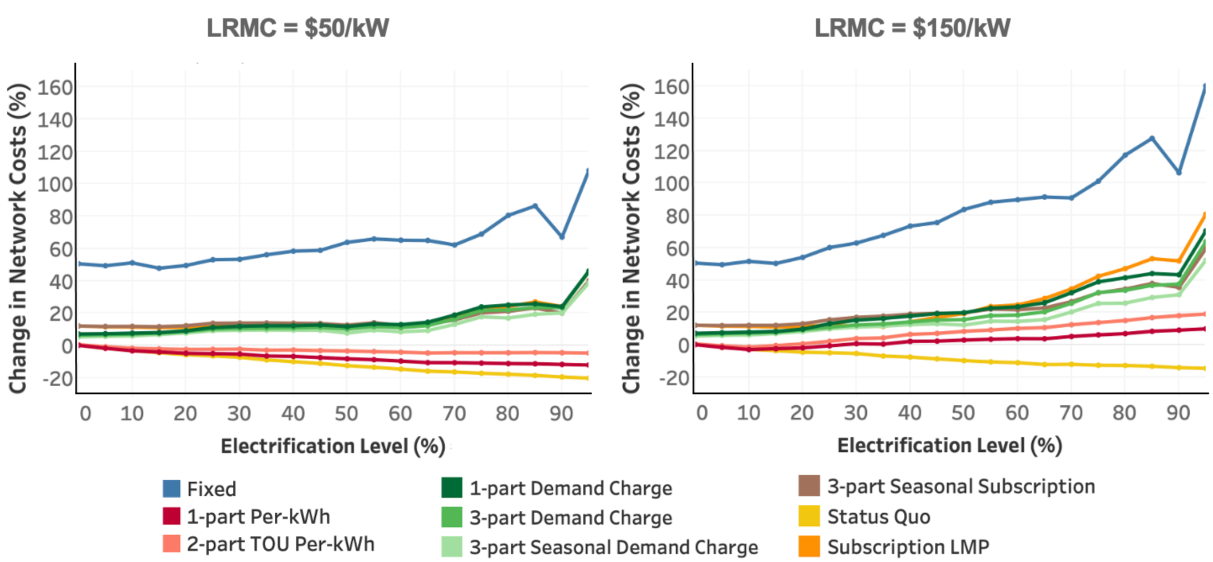

Figure 9: Change in network cost under all tariff scenarios. The Status Quo tariff performs best because EV households have no opportunity to reduce costs by shifting demand, resulting in more revenue collected.

This begs the question: if the Status Quo tariff performs so well, then why move away from it? As Figure 10 shows, the Status Quo tariff has one major drawback: the effect on the levelized cost of charging. When EV households have no opportunity to save money by shifting charging demand, they pay the highest price among all scenarios at almost all EV adoption levels. The Status Quo represents an unstable equilibrium. While it produces a favorable global outcome (lowest network costs), EV drivers will opt for TOU rates when available because the potential for savings is considerable, as shown by Borlaug et al. (2020). The availability of that option will likely increase EV adoption. And while some utilities may believe that they can achieve demand shifting using only behavioral nudges, Bailey et al. (2023) show that when financial incentives are removed, the timing of charging reverts to the original schedule (i.e., charging immediately upon returning home).

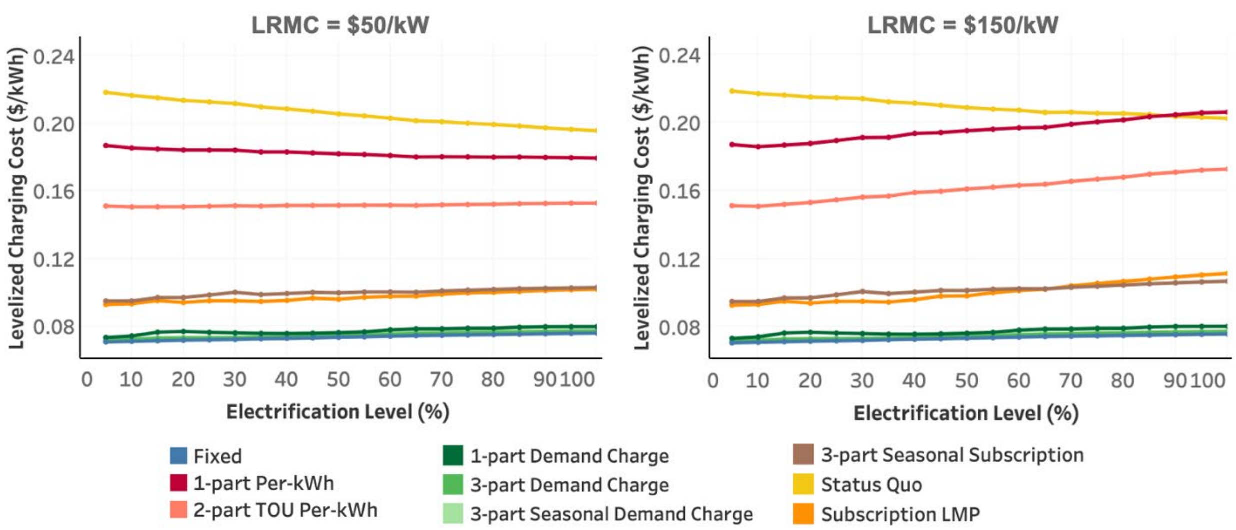

Figure 10: Levelized charging cost under all tariff scenarios. The Status Quo performs worst at almost all levels of EV adoption for both LRMC cases.

4.2.3 Concurrent Heating and Transportation Electrification

Finally, we consider how each network tariff performs when households adopt not only EVs but also air-source heat pumps (CCHP). While the economics of heating electrification in Massachusetts are not as favorable as for transportation, significant state and federal incentives are expected to produce strong uptake (ISO New England, 2023a). Heat pumps represent a significant load that is highly correlated with temperature, especially during winter in cold regions.

To simulate this scenario, for each household that is assigned an EV, we replace their original hourly load profile with one that includes a CCHP system where the existing heating system serves a backup. Like the rest of the non-EV household load, the heat pump demand is treated as exogenous, even though some time-shifting is possible in practice. While it is unlikely that heat pump adoption would overlap perfectly with EV adoption (Davis, 2023), it is reasonable to assume a substantial overlap. Figure 11 compares the annual peak under each tariff for the "EV Only" case (left) and "EV + HP" case (right).

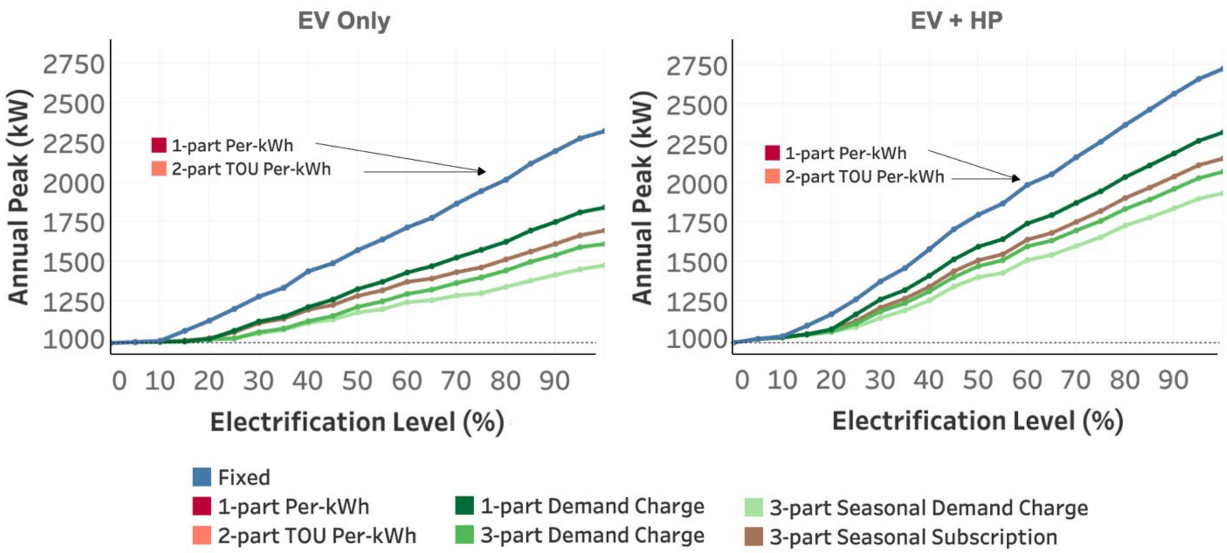

Figure 11: Annual peak demand under all tariffs with EV adoption only (left) compared to concurrent adoption of EVs and heat pumps (right).

We observe that when concurrent heat pump adoption is considered, capacity network tariffs still produce a significant improvement over fixed and per-kWh tariffs. However, even the most effective network tariff yields a significant increase in peak demand: 42% at 50% adoption and 96% at 100% adoption of EVs and CCHPs.

5. Discussion

In this section, we first provide a brief assessment of the results. Next, we make recommendations for network tariff implementation based on our case study. Finally, we discuss limitations to our approach.

5.1 Overall Assessment and Recommendation

Table 2 provides a summary of the key metrics for each network tariff for the low and high LRMC cases at 50% EV adoption (with no heat pump adoption) assuming a TOU energy tariff. According to ISO New England's 2023 Transportation Electrification Forecast, this milestone is expected to be reached by 2035 (ISO New England, 2023b). Note that 50% adoption in concentrated areas of the grid, which is relevant for these results, can happen a lot earlier than overall 50% adoption.

Table 2: Key metrics for each network tariff at 50% EV adoption under low and high LRMC

Network Tariff	*Annual Peak (kW)*		*Levelized Charging Cost ($/kWh)*		*Change in Network Cost for non-EV owners (%)*	
LRMC	*$50/kW*	*$150/kW*	*$50/kW*	*$150/kW*	*$50/kW*	*$150/kW*
Fixed	1572		$0.07	$0.07	63%	84%
1-part Per-kWh	1572		$0.18	$0.19	-8%	3%
2-part TOU Per-kWh	1572		$0.15	$0.16	-4%	8%
1-part Demand Charge	1326		$0.08	$0.08	12%	20%
3-part Demand Charge	1213		$0.07	$0.07	10%	16%
3-part Seasonal Demand Charge	1178		$0.07	$0.07	8%	12%
3-part Seasonal Subscription	1283		$0.10	$0.10	13%	20%

The results in Table 2 indicate a tradeoff among assessment criteria. Whereas the fixed tariff performs best in levelized charging cost, it shifts costs to non-EV owners and performs worst in network costs for them. The reverse is true for per-kWh network tariffs. Capacity-based tariffs (demand and subscription charges) offer a compromise, providing a significant reduction in levelized charging cost compared to the per-kWh tariffs while increasing network costs for non-EV owners by only a modest amount compared to the fixed network tariff. While we do not observe an outcome in which costs decrease for both EV and non-EV households compared to the status quo, capacity-based tariffs most closely approach this outcome, demonstrating that incentivizing electrification (a priority for many US states) need not be pursued at the expense of broader affordability goals.

The 3-part seasonal demand charge achieves the lowest annual peak and levelized cost. However, the subscription charge (which does not perform badly on any of the key criteria) offers implementation advantages over demand charges, as discussed below. As Public Utility Commissions attempt to balance stakeholder interests in promoting electrification, a tariff design that does not create big winners or losers may be the most palatable.

US utilities that have pushed back against time-varying rates often cite customer confusion and expected bill impacts as the reason for their opposition. Because utilities are penalized for customer confusion and bill shocks, utilities are likely to oppose complicated tariff designs. Hennig et al. (2022) acknowledge this fact, including “simplicity” and “implementation burden” as core criteria for network tariff assessment. There are also experimental studies that show that at some point increasing tariff complexity blunts impacts on consumer behavior (Jacobsen and Stewart, 2022).

Nothing in everyday consumer spending resembles an ex-post measured capacity charge. For customers accustomed to paying flat volumetric charges and unaware of their consumption at any given moment, the concept of being charged based on their maximum demand may be an unacceptably large change. Under demand charges, customers are often not shielded from risk; accidentally running multiple appliances concurrently for a few minutes could result in hundreds of dollars in incurred costs. A demand charge also suffers from the opposite problem; for knowledgeable customers who set a high demand early in a billing period, there may be no incentive to manage demand for the remainder of the period.

Thus, while the 3-part seasonal demand charge does well in our simulations, consumers may resist it, and regulators may be averse to implementing it. A subscription charge overcomes these problems in several ways. First, a subscription charge has a cognitive advantage; it gets consumers’ attention and makes optimization easier. If a customer must subscribe in advance and is prompted to resubscribe from time to time – e.g., with estimated savings and a default option to continue at the same level – it forces them to think about how they can minimize costs. When the demand charge just gets buried in the tariff, they may not focus their attention on the optimization. Second, the structure is similar to popular phone and internet plans, whereby customers pay for a maximum level of service that cannot be exceeded without incurring penalties. A familiarity with these types of plans will help explain the logic of subscription charges and ease the transition to new network tariffs. Third, a subscription can be implemented in a way that protects consumers from high bills. For example, smart meters can be programmed such that if instantaneous demand exceeds the subscribed level, the meter is temporarily disconnected. This immediate feedback will help coach customers to not turn on high-power devices simultaneously or to purchase devices that make it possible to program which appliances get turned off first (Mou et al., 2017).[11] If meters are tripped frequently due to exceeding the subscription level and customers want to increase their subscription, they may do so for the following billing period. Fourth, a subscription offers more bill certainty, which is important for customers on tight monthly budgets. Even without perfect foresight, customers can better predict their costs using their ex-ante contracted value compared with an ex-post charge. There are several variants of subscription charges (i.e., "smart subscriptions") that could be used in a transitional period, for example starting out using a soft cap with a small penalty fee calculated as a function of when the subscription value is exceeded, eventually shifting to a hard cap (DNV-GL 2019). Fifth and last, customers signing up for certain levels of maximum demand they want to have access to better aligns the horizon of consumer decisions with the horizon of network planning, i.e., subscription plans can help utilities to plan future networks.

These benefits help explain why several EU member states have already adopted subscription charges. A 2023 report by the EU Agency for the Cooperation of Energy Regulators (ACER) on network tariffs highlights examples from Italy, Portugal, Spain, and Slovenia, among others, and recommends a "gradual move to increasingly power-based distribution tariffs to recover those costs which show correlation with contracted or peak capacity" (ACER, 2023, p. 72). Because of extensive retail competition, European countries tend to have unbundled electricity bills, whereby different cost categories are broken out line-by-line. This makes it easier to implement a subscription charge for just the distribution network portion of the bill; however, there is no reason why US states without retail competition could not unbundle their electricity bills as well. In states and countries with retail competition, the distribution (wires) provider could help educate customers on selecting the proper subscription level.

Reforming network tariffs is not motivated solely by reducing costs. In a 2022 letter to Congress, US electric utilities warned of a critical shortage in both labor and equipment (the latter due to supply chain disruptions) to meet basic quality of service standards. This problem will only grow as utilities face an estimated $1 trillion of upgrades to support aggressive electrification targets

[11] One such device – called a "smart splitter" – allows customers to connect a washing machine and EV charging cable to the same 240V breaker slot (NeoCharge, 2023) and prevents them from being on simultaneously.

(along with routine replacement of aging infrastructure) (NEMA, 2023). If demand due to electrification grows rapidly, workforce shortages will not only be a barrier to basic reliability but also to achieving climate goals. Utilities will be forced to either undertake involuntary curtailments or block customers from installing technologies like heat pumps and residential EV chargers. While a subscription network tariff does not obviate the need for network upgrades, our case study showed that it can significantly delay increases in annual peak loads, so that network investments can be spread out over time.

Finally, our results also indicate the limitations of even relatively granular network charges coupled with TOU energy charges (and later real-time pricing). When considering the concurrent electrification of home heating and transportation, we observe a significant increase in aggregate peak demand. If we relax some of our network tariff design principles (i.e., simplicity, non-discrimination, and existing widespread implementation), there are several alternatives to the network tariffs tested in our case study. These include daily capacity charges, auctions for network capacity (Morell-Dameto et al., 2023), supplementary load control, and price setting based on equilibria estimations. Yet moving from the flat volumetric tariffs ubiquitous today in the US to these advanced and untested approaches would likely face significant resistance from utilities and regulators. In the near term, simple network tariff designs like those implemented in Europe are effective at limiting peak demand growth. They also offer a bridge to the complementary measures that will become necessary as we reach higher levels of EV adoption and more volatile wholesale prices.

5.2 Limitations of Our Approach

Here we outline five key limitations in our case study.

First, we do not calibrate the levels of the network charges to actual forward-looking network costs. Our case study focuses on the incentives driven by tariff structures and/or time-variation; under our assumption of rational price responsiveness, the absolute magnitude of each tariff does not impact customers' load shapes, only relative prices. Yet these will matter for distributional impacts and incentives to electrify. In future work, a two-part network tariff can be considered consisting of a capacity charge based on forward looking costs and (differentiated) fixed charges to collect the residual part of network costs and mitigate distribution impacts.

Second, we treat EV adoption and energy prices as exogeneous. For the former, we might expect adoption to be a function of the levelized cost of charging, at least to some extent. However, we know that other factors, including purchase incentives, availability of public charging, and gasoline prices have a larger impact on adoption than electricity cost (Bushnell et al., 2022). For the latter, it is possible that the correlated response of flexible loads like EVs and heat pumps would impact wholesale electricity prices and thus affect TOU and dynamic retail energy rates. In any case, flexible loads like EV charging would continue to react to relative price differences, so the risk of a highly correlated response would persist even if wholesale and retail energy prices are endogenous in practice.

Fourth, we assume all EV charging occurs at home with Level 2 chargers, even though one might see a mix of charger types in the future. According to a survey by Dunckley (2018), 80% of charging occurs at home, with the remaining 20% at workplace and public stations. Our case study therefore represents a sort of worst-case scenario; non-residential charging would likely help reduce coincident peak demand in the evening by shifting charging activity to daytime hours, as shown by Needell et al. (2023). Furthermore, in urban areas or places with a high proportion of rental properties, it is unlikely that all residents would be able to install dedicated charging stations at home. Our case study considers a suburban or rural residential feeder where homes have off-street parking[12] and sufficient electric panel capacity to install a Level 2 EV charger. An important extension of our research is examining residential charging in urban settings where alternative charging methods exist. In addition, the implications of charging of delivery trucks and other fleets deserves study.

Fifth, we assume that non-EV load is unaffected by changes in network tariffs, but we would expect actual consumers to shift demand to reduce costs, especially with regard to heat pump operation. However, it is useful to consider the purely inelastic case, as it captures the most

[12] According to the American Housing Survey, 63% of all housing units have a garage or carport (US Cencus Bureau, 2015).

extreme distributional impacts for customers who have not yet purchased EVs. This is the same reason we chose to apply the alternative tariffs to the entire population rather than only EV customers.

Sixth, we associate only a single EV with each house. It is likely that some multi-vehicle households will purchase a second EV before all households have their first. We will address this possibility in future work, although we expect that capacity-based tariffs will perform similarly given that each home's demand or subscription charge is based on its aggregate demand.

6. Conclusions, Policy Recommendations, and Future Work

We see a range of approaches undertaken by regulatory commissions in their design of network tariffs motivated by increasing electrification and adoption of distributed generation. Whereas Europe has experience with several advanced network tariffs with capacity-based charges, the US's first step away from flat volumetric tariffs has been towards simple TOU pricing to recover both energy and network costs. While TOU pricing encourages the adoption of EVs and other technologies that can schedule demand to take advantage of low-price periods, as adoption of these technologies increases, their highly correlated responses to price signals tends to increase peak loads and network costs. It will be essential to separate network and energy tariffs and to implement a demand charge or subscription to provide incentives to control network costs.

Based on our modeling results, we find that without such tariffs, correlated EV charging becomes a serious issue even at low adoption levels, with newly created demand peaks at 15% adoption. This is even more concerning when considering that EV adoption is highly clustered spatially and will not proceed uniformly across a distribution utility's service territory.

Our results indicate a tradeoff between reducing costs for EV owners (through fixed and capacity-based network tariffs) and non-EV owners (through per-kWh network tariffs). Per-kWh network charges lead to high charging costs and lack a price signal to limit aggregated demand peaks. While fixed network charges foster electrification by lowering the cost of charging, they shift costs from EV owners to others and again lack a mechanism to mitigate peak demand. Demand charges perform well but are difficult to implement, especially when transitioning from flat volumetric tariffs. Taking all this into account, we propose a 3-part seasonal subscription network tariff as a pragmatic compromise that performs relatively well on all dimensions.

A well-designed subscription tariff has the potential to 1) mitigate the need for local capacity upgrades, especially at early adoption levels, 2) reduce the cost burden on non-EV households, and 3) provide low levelized charging costs for EV owners, a key motivator for EV adoption. The use of special TOU rates to promote EV adoption by US utilities today will yield worse results once low adoption levels are surpassed, which is likely to occur soon in some neighborhoods.

Our sensitivity analyses indicate that simple network tariffs are less effective when dynamic, real-time energy prices, which economists generally favor, and heating electrification are considered. With real-time energy pricing, at high EV adoption levels, a subscription charge yields a similar annual peak as under a fixed network tariff. And when EV and heat pump adoption proceed in lock step, we observe rapid increases in peak demand. In future work, we will investigate how simple network tariff design can be supplemented with innovative solutions to further mitigate these problems.

Bibliography

Abdelmotteleb, Ibtihal, Tomás Gómez, José Pablo Chaves Ávila, and Javier Reneses. 2018. "Designing Efficient Distribution Network Charges in the Context of Active Customers." *Applied Energy* 210: 815–26.

ACER. 2023. "Report on Electricity Transmission and Distribution Tariff Methodologies in Europe." European Union Agency for the Cooperation of Energy Regulators. https://www.acer.europa.eu/Publications/ACER_electricity_network_tariff_report.pdf.

AFDC. 2022. "Alternative Fuels Data Center: Vehicle Registration Counts by State." Alternative Fuels Data Center. 2022. https://afdc.energy.gov/vehicle-registration.

Aniti, Lori. 2021. "EIA. Major Utilities' Spending on the Electric Distribution System Continues to Increase." U.S. Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=48136#:~:text=Annual%20spending%20on%20electricity%20distribution,2000%20after%20adjusting%20for%20inflation.

Backe, Stian, Güray Kara, and Asgeir Tomasgard. 2020. "Comparing Individual and Coordinated Demand Response with Dynamic and Static Power Grid Tariffs." *Energy* 201 (June): 117619. https://doi.org/10.1016/j.energy.2020.117619.

Bailey, Megan R., David P. Brown, Blake C. Shaffer, and Frank A. Wolak. 2023. "Show Me the Money! Incentives and Nudges to Shift Electric Vehicle Charge Timing." National Bureau of Economic Research.

Batlle, Carlos, Paolo Mastropietro, and Pablo Rodilla. 2020. "Redesigning Residual Cost Allocation in Electricity Tariffs: A Proposal to Balance Efficiency, Equity and Cost Recovery." *Renewable Energy* 155: 257–66.

Boiteux, Marcel, and Paul Stasi. 1964. "The Determination of Costs of Expansion of an Interconnected System of Production and Distribution of Electricity." *Marginal Cost Pricing in Theory and Practice, Prentice-Hall Inc., Englewood Cliffs, NJ*.

Borenstein, Severin. 2016. "The Economics of Fixed Cost Recovery by Utilities." *The Electricity Journal* 29 (7): 5–12. https://doi.org/10.1016/j.tej.2016.07.013.

Borenstein, Severin, and James B. Bushnell. 2022. "Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency." *American Economic Journal: Economic Policy* 14 (4): 80–110. https://doi.org/10.1257/pol.20190758.

Borenstein, Severin, Meredith Fowlie, and James Sallee. 2021. "Designing Electricity Rates for an Equitable Energy Transition." *Energy Institute Working Paper* 314.

Borlaug, Brennan, Shawn Salisbury, Mindy Gerdes, and Matteo Muratori. 2020. "Levelized Cost of Charging Electric Vehicles in the United States." *Joule* 4 (7): 1470–85.

Burger, Scott P., Christopher R. Knittel, Ignacio J. Pérez-Arriaga, Ian Schneider, and Frederik Vom Scheidt. 2020. "The Efficiency and Distributional Effects of Alternative Residential Electricity Rate Designs." *The Energy Journal* 41 (1).

Bushnell, James B., Erich Muehlegger, and David S. Rapson. 2022. "Energy Prices and Electric Vehicle Adoption." Energy Institute WP 326. Energy Institute at Haas. https://haas.berkeley.edu/wp-content/uploads/WP326.pdf.

Cooper, Adam, Mike Shusterr, and Joseph Lash. 2021. "Electric Company Smart Meter Deployments: Foundation for a Smart Grid (2021 Update)." Washington, DC: Institute for Electric Innovation. . https://www. edisonfoundation.net/-/media/Files/IEI/publications/IEI_Smart_Meter_Report_April_2021.pdf.

Costello, Kenneth W., and Ross C. Hemphill. 2014. “Electric Utilities’‘Death Spiral’: Hyperbole or Reality?” *The Electricity Journal* 27 (10): 7–26.

CPUC. 2023. “Distribution Grid Electrification Model.”

Cutter, E., E. Rogers, A. Nieto, J. Leana, J. Kersey, N. Abhyankar, and T. McNair. 2021. “Distribution Grid Cost Impacts Driven By Transportation Electrification.” San Francisco, CA: Energy+Environmental Economics. https://www.ethree.com/wp-content/uploads/2021/06/GridLab_2035-Transportation-Dist-Cost.pdf.

Davis, Lucas W. 2023. “The Economic Determinants of Heat Pump Adoption.” National Bureau of Economic Research. https://www.nber.org/papers/w31344.

DNV-GL. 2019. “Effective and Cost Reflective Distribution Tariffs.” https://www.dnv.com/Publications/effective-and-cost-reflective-distribution-tariffs-162913.

Dunckley, J. 2018. “Electric Vehicle Driving, Charging, and Load Shape Analysis: A Deep Dive Into Where, When, and How Much Salt River Project (SRP) Electric Vehicle Customers Charge.” *Electric Power Research Institute*.

Energy+Environmental Economics. 2022. “2022 Distributed Energy Resources Avoided Cost Calculator Documentation.” https://willdan.app.box.com/v/2022CPUCAvoidedCosts.

Engstrom, Jenn, and Laura Deehan. 2023. “New Proposed Income-Based Fixed Charges in California Would Devalue Energy Conservation.” CALPIRG. August 14, 2023. https://pirg.org/california/resources/new-proposed-income-based-fixed-charges-in-california-would-devalue-energy-conservation/.

Eversource. 2023a. “2023 Summary of Eastern Massachusetts Electric Rates for Greater Boston Service Area.” https://www.eversource.com/content/docs/default-source/rates-tariffs/ema-greater-boston-rates.pdf?sfvrsn=875c1c95_6.

———. 2023b. “Electric Sector Modernization Plan: Accelerating a Just Transition to a Reliable and Resilient Clean Energy Future.” https://www.mass.gov/doc/gmacesmp-drafteversource/download?_gl=1%2Ako8zfs%2A_ga%2ANzUwNDI5MDE3LjE2NTA5ODEyMjQ.%2A_ga_SW2TVH2WBY%2AMTY5MzkyMDE2OS4zNi4xLjE2OTM5MjM1NzQuMC4wLjA.

Faruqui, Ahmad. 2023. “The Income Graduated Fixed Charges in California Will Harm Customers with Low Electric Bills.” PV Magazine USA. May 8, 2023. https://pv-magazine-usa.com/2023/05/08/the-income-graduated-fixed-charges-in-california-will-harm-customers-with-low-electric-bills/.

Faruqui, Ahmad, and Sylvia Tang. 2023. “Equitable Rate Design; A Survey of Best Practices.” Clean Energy Leadership Institute, September 20.

Federal Highway Administration. 2017. “2017 National Household Travel Survey.” Washington, DC: U.S. Department of Transportation. https://nhts.ornl.gov.

Govaerts, Niels, Kenneth Bruninx, Hélène Le Cadre, Leonardo Meeus, and Erik Delarue. 2023. “Signaling Future or Historical Distribution Grid Costs via Tariffs? A Welfare Analysis of Long-Run Incremental Cost Pricing.” *Utilities Policy* 82: 101537.

Green Mountain Power. 2021. “Integrated Resource Plan.” https://greenmountainpower.com/wp-content/uploads/2021/12/2021-Integrated-Resource-Plan.pdf.

Gschwendtner, Christine, Christof Knoeri, and Annegret Stephan. 2023. “The Impact of Plug-in Behavior on the Spatial–Temporal Flexibility of Electric Vehicle Charging Load.” *Sustainable Cities and Society* 88: 104263.

Gunkel, Philipp Andreas, Claire-Marie Bergaentzlé, Dogan Keles, Fabian Scheller, and Henrik Klinge Jacobsen. 2023. “Grid Tariff Designs Coping with the Challenges of Electrification and Their Socio-Economic Impacts.” arXiv. https://doi.org/10.48550/arXiv.2210.03514.

Hennig, Roman J., David Ribó-Pérez, Laurens J. de Vries, and Simon H. Tindemans. 2022. “What Is a Good Distribution Network Tariff?—Developing Indicators for Performance Assessment.” *Applied Energy* 318: 119186.

Hoarau, Quentin, and Yannick Perez. 2019. “Network Tariff Design with Prosumers and Electromobility: Who Wins, Who Loses?” *Energy Economics* 83 (September): 26–39. https://doi.org/10.1016/j.eneco.2019.05.009.

International Energy Agency. 2023. “Electricity Grids and Secure Energy Transitions.” https://iea.blob.core.windows.net/assets/70f2de45-6d84-4e07-bfd0-93833e205c81/ElectricityGridsandSecureEnergyTransitions.pdf.

ISO New England. 2023a. “Final 2023 Heating Electrification Forecast.” April 28. https://www.iso-ne.com/static-assets/documents/2023/04/heatfx2023_final.pdf.

———. 2023b. “Final 2023 Transportation Electrification Forecast.” April 28. https://www.iso-ne.com/static-assets/documents/2023/04/transfx2023_final.pdf.

Jacobsen, Grant D., and James I. Stewart. 2022. “How Do Consumers Respond to Price Complexity? Experimental Evidence from the Power Sector.” *Journal of Environmental Economics and Management* 116 (October): 102716. https://doi.org/10.1016/j.jeem.2022.102716.

Johnson, Erik, Ross Beppler, Chris Blackburn, Benjamin Staver, Marilyn Brown, and Daniel Matisoff. 2017. “Peak Shifting and Cross-Class Subsidization: The Impacts of Solar PV on Changes in Electricity Costs.” *Energy Policy* 106 (July): 436–44. https://doi.org/10.1016/j.enpol.2017.03.034.

Kavulla, Travis. 2023. “Why Is the Smart Grid So Dumb? Missing Incentives in Regulatory Policy for an Active Demand Side in the Electricity Sector.” Energy Systems Integration Group. https://www.esig.energy/wp-content/uploads/2023/01/Why-Is-the-Smart-Grid-So-Dumb-Missing-Incentives-in-Regulatory-Policy-for-an-Active-Demand-Side-in-the-Electricity-Sector.pdf.

Küfeoğlu, Sinan, and Michael G. Pollitt. 2019. “The Impact of PVs and EVs on Domestic Electricity Network Charges: A Case Study from Great Britain.” *Energy Policy* 127 (April): 412–24. https://doi.org/10.1016/j.enpol.2018.12.012.

Lee, Jae Hyun, Scott J. Hardman, and Gil Tal. 2019. “Who Is Buying Electric Vehicles in California? Characterising Early Adopter Heterogeneity and Forecasting Market Diffusion.” *Energy Research & Social Science* 55: 218–26.

Michaels, Harvey, and Robert Nachtrieb. 2022. “Transitioning to Heat Pumps in Cold Climates: A Systems Dynamics Analysis.” In *Proceedings of the 2022 ACEEE Summer Study on Energy Efficiency in Buildings*.

Morell-Dameto, Nicolás, José Pablo Chaves-Ávila, Tomás Gómez San Román, and Tim Schittekatte. 2023. “Forward-Looking Dynamic Network Charges for Real-World Electricity Systems: A Slovenian Case Study.” *Energy Economics* 125 (September): 106866. https://doi.org/10.1016/j.eneco.2023.106866.

Mou, Yuting, Anthony Papavasiliou, and Philippe Chevalier. 2017. “Application of Priority Service Pricing for Mobilizing Residential Demand Response in Belgium.” In *2017 14th International Conference on the European Energy Market (EEM)*, 1–5. IEEE. https://ieeexplore.ieee.org/abstract/document/7981860/?casa_token=7rjp8qP5vBcAAAAA:8WL5sYVaTv-OA5O0o4plLLJrHd7GNhAuskZQYmbjN0QmCrIXkVhzUzMj1riz5fqhL9j5oaro0es.

Muratori, Matteo. 2018. “Impact of Uncoordinated Plug-in Electric Vehicle Charging on Residential Power Demand.” *Nature Energy* 3 (3): 193–201. https://doi.org/10.1038/s41560-017-0074-z.

Muratori, Matteo, and Giorgio Rizzoni. 2015. “Residential Demand Response: Dynamic Energy Management and Time-Varying Electricity Pricing.” *IEEE Transactions on Power Systems* 31 (2): 1108–17.

National Grid. 2023. “Future Grid Plan: Empowering Massachusetts by Building a Smarter, Stronger, Cleaner and More Equitable Energy Future.” https://www.mass.gov/doc/gmacesmp-draftnational-grid/download?_gl=1%2Adfgptb%2A_ga%2ANzUwNDI5MDE3LjE2NTA5ODEyMjQ.%2A_ga_SW2TVH2WBY%2AMTY5MzkyMDE2OS4zNi4xLjE2OTM5MjM1OTcuMC4wLjA.

Needell, Zachary, Wei Wei, and Jessika E. Trancik. 2023. “Strategies for Beneficial Electric Vehicle Charging to Reduce Peak Electricity Demand and Store Solar Energy.” *Cell Reports Physical Science* 4 (3).

NEMA. 2023. “Distribution.” National Electrical Manufacturers Association. https://energytransition.nema.org/wp-content/uploads/2023/01/NEMA-QuickFacts-Distribution.pdf.

NeoCharge. 2023. “NeoCharge Smart Splitter | NeoCharge.” 2023. https://getneocharge.com/products/neocharge-smart-splitter.

Nouicer, Athir, Leonardo Meeus, and Erik Delarue. 2023. “The Economics of Demand-Side Flexibility in Distribution Grids.” *The Energy Journal* 44 (1).

Passey, Robert, Navid Haghdadi, Anna Bruce, and Iain MacGill. 2017. “Designing More Cost Reflective Electricity Network Tariffs with Demand Charges.” *Energy Policy* 109: 642–49.

Pérez-Arriaga, Ignacio J., Jesse D. Jenkins, and Carlos Batlle. 2017. “A Regulatory Framework for an Evolving Electricity Sector: Highlights of the MIT Utility of the Future Study.” *Economics of Energy & Environmental Policy* 6 (1): 71–92.

RESA. 2022. “US Energy Choice Overview: State-by-State Analysis.” April 18, 2022. https://www.resausa.org/energy-by-state/.

Schittekatte, Tim. 2020. “Distribution Network Tariff Design for Behind-the-Meter: Balancing Efficiency and Fairness.” In *Behind and Beyond the Meter*, 341–59. Elsevier.

Schittekatte, Tim, Dharik Mallapragada, Paul L. Joskow, and Richard Schmalensee. 2023. “Reforming Retail Electricity Rates to Facilitate Economy-Wide Decarbonization: Joule.” 2023. https://www.cell.com/joule/pdf/S2542-4351(23)00124-1.pdf.

Schittekatte, Tim, Dharik S. Mallapragada, Paul L. Joskow, and Richard Schmalensee. 2022. “Electricity Retail Rate Design in a Decarbonized Economy: An Analysis of Time-Of-Use and Critical Peak Pricing.” National Bureau of Economic Research.

Schittekatte, Tim, Ilan Momber, and Leonardo Meeus. 2018. “Future-Proof Tariff Design: Recovering Sunk Grid Costs in a World Where Consumers Are Pushing Back.” *Energy Economics* 70: 484–98.

Sergici, Sanem, Akhilesh Ramakrishnan, Goksin Kavlak, Adam Bigelow, and Megan Diehl. 2023. “Heat Pump–Friendly Cost-Based Rate Designs.” Aligning Retail Pricing with Grid Needs. Energy Systems Integration Group. https://www.esig.energy/wp-content/uploads/2023/01/Heat-Pump%E2%80%93Friendly-Cost-Based-Rate-Designs.pdf.

Simshauser, Paul. 2016. “Distribution Network Prices and Solar PV: Resolving Rate Instability and Wealth Transfers through Demand Tariffs.” *Energy Economics* 54: 108–22.

Smart Electric Power Alliance. 2019. “Residential Electric Vehicle Rates That Work.” Smart Electric Power Alliance. https://sepapower.org/resource/residential-electric-vehicle-time-varying-rates-that-work-attributes-that-increase-enrollment/thank-you/.

State of California. 2023. “California ZEV Sales Near 19% of All New Car Sales in 2022.” Office of Governor Gavin Newson. January 20, 2023. https://www.gov.ca.gov/2023/01/20/california-zev-sales-near-19-of-all-new-car-sales-in-2022/.

Steinbach, Sarah A., and Maximilian J. Blaschke. 2023. “Another Source of Inequity? How Grid Reinforcement Costs Differ by the Income of EV User Groups.”

Strbac, Goran, and Joseph Mutale. 2005. “Framework and Methodology for Pricing of Distribution Networks with Distributed Generation.” *Cent. Distrib. Gener. Sustain. Electr. Energy*.

Trabish, Herman. 2023. “Hawai’i Leads the Way on Advanced Rate Design with Default Time-of-Use Rates, Fixed Charge Innovations.” Utility Dive. May 9, 2023. https://www.utilitydive.com/news/hawaii-advanced-rate-design-default-time-of-use-fixed-charge-innovations/648994/.

US Cencus Bureau. 2015. “American Housing Survey.” https://www.census.gov/programs-surveys/ahs/data/interactive/ahstablecreator.html.

US EIA. 2023. “How Many Smart Meters Are Installed in the United States, and Who Has Them?” October 2023. https://www.eia.gov/tools/faqs/faq.php.

Wei, Wei, Sankaran Ramakrishnan, Zachary A. Needell, and Jessika E. Trancik. 2021. “Personal Vehicle Electrification and Charging Solutions for High-Energy Days.” *Nature Energy* 6 (1): 105–14. https://doi.org/10.1038/s41560-020-00752-y.

Werner, Karl Dunkle, and Stephen Jarvis. 2022. “Rate of Return Regulation Revisited.”

Wilson, Eric, Andrew Parker, Anthony Fontanini, Elaina Present, Janet Reyna, Rajendra Adhikari, Carlo Bianchi, et al. 2022. “End-Use Load Profiles for the U.S. Building Stock: Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification.” NREL/TP-5500-80889, 1854582, MainId:78667. https://doi.org/10.2172/1854582.

Winzer, Christian, and Patrick Ludwig. 2022. “Optimal Design of Dynamic Grid Tariffs.” SSRN Scholarly Paper.

Yuksel, Tugce, and Jeremy J. Michalek. 2015. “Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States.” *Environmental Science & Technology* 49 (6): 3974–80. https://doi.org/10.1021/es505621s.

Appendix A: Network Tariff Design in Practice

We first describe the current European practices, then we focus on the US context.

A.1 Europe's Approach to Network Tariff Design

Since the advent of smart meters, Europe has been a pioneer in network tariff design, implementing several innovative approaches to allocating distribution network costs and sending efficient price signals. Until recently, these efforts had not been coordinated at an EU level but were instead spearheaded by individual member states.

Regulation (EU) 2019/943 mandates that EU member states implement cost-reflective distribution network tariffs, which implies that future network costs need to be reflected to the grid users through the tariff. ACER (2023) reports that already 25 of the 27 assessed EU member States had some form of capacity distribution network charge in place (based on the maximum capacity in kW measured or kW contracted, with or without time-differentiation). As there are many nuances, it is hard to verify where households, connected to the lowest voltage level, are still facing more simplified distribution network charges. These simplified rates typically consist of flat volumetric charge and a fixed charge. At the time of writing, based on the analysis of ACER (2023), we estimate that at least in one third of the Member State' households are facing some sort of capacity-based and/or TOU per-kWh network charges. We highlight four examples below.

In Spain, the distribution network tariff for residential consumers consists of both TOU per-kWh and TOU capacity components. The per-kWh component has 3 periods per day, with tariff levels ranging from 0.1 euro/kWh (off-peak) to 2.9 euro/kWh (on-peak). For the capacity component, consumers subscribe ex-ante to a desired level during two periods: on-peak and off-peak.

In France, residential consumers have access to a regulated rate with a per-kWh and capacity component. For the capacity component, consumers subscribe ex-ante up to a capacity level, and the price per kW goes down with more kWs contracted (i.e., declining block). For the per-kWh component, consumers can choose between a flat volumetric tariff, a simple two-part TOU tariff, and a dynamic tariff that resembles a critical peak rate where the DSO announces one day prior whether it is a critical, peak, or off-peak day.

Italy's regulated network tariff for residential consumer's is similar to France's except it does not have a per-kWh component and the price per contracted kW does not change as the contracted amount grows.

Finally, the Flanders region in Belgium recently reformed its previously flat volumetric network tariff. The new tariff consists of a small flat volumetric charge plus a capacity charge based on each consumer's 15-minute maximum demand in each month.

These four regulated network tariffs in Europe provide inspiration for possible alternatives to the flat volumetric tariffs prevalent today in the US. While it is difficult to assess which one performs the best, and each country faces a unique set of challenges related to its clean energy transition, it is telling that all tariffs include a deterrent to maximum power consumption in the form of a capacity charge (either ex-ante or ex-post).

A.2 US Approaches

While over 73% of residential consumers have meters capable of time-varying rates (Cooper et al., 2021), the vast majority of US residential consumers pay a flat volumetric rate for their network costs (Faruqui and Tang, 2023). Many US utilities offer voluntary or mandatory capacity-based tariffs for commercial and industrial customers. However, these rates are not available to residential customers, and in contrast to Europe, capacity charges are almost wholly absent from residential network tariffs. Yet, there has been progress away from flat volumetric tariffs in recent years in a handful of states. Here, we highlight two types of tariffs that have recently gained momentum in the US: default TOU tariffs and EV-specific tariffs.

Default Time of Use

In 2020, California became the first US state to institute default TOU rates for all residential customers, with network and supply costs combined into a single, time-differentiated per-kWh charge. Customers were shifted to either a 2-part or 3-part TOU rate; the timing of each period and the ratio of on-peak to off-peak price varied according to location and distribution utility. Those who wanted to remain on a flat volumetric rate needed to explicitly request to opt out. All new residential accounts starting in October 2020 have been placed on the TOU rate.

Other states have followed California's lead. After a multi-year Advanced Rate Design proceeding, in May 2023 Hawaii's PUC ordered the utility (Hawaiian Electric) to implement a default TOU rate by July 1, 2024. The TOU roll-out will be paired with a fixed charge reform intended to shift some of the utility's fixed costs to a non-variable charge and the introduction of a "grid access" fee proportional to each customer's monthly maximum demand. This grid access fee is, as far as the authors are aware, the first instance of a demand charge being used for a default residential tariff in the US.

In Missouri, regulators recently approved a default TOU rate with an unprecedented 5:1 peak to off-peak ratio for customers of the distribution utility Evergy. In Michigan, DTE Energy rolled out a more modest default TOU rate in March 2023 (1.5:1 ratio), and Xcel Energy in Colorado has plans to do the same once advanced metering infrastructure is fully deployed. Table A.1 shows all default TOU rates currently approved in the US. It is noteworthy that no state with retail choice has yet implemented default TOU rates for network cost recovery. All examples except for Hawaii include network and energy costs bundled as a single per-kWh charge.

Table A.1: Default TOU rates approved in the US. For California, rates displayed are for PG&E's default TOU plan

State	*Utility*	*TOU Periods*	*Per-kWh charges*	*Status*
Hawaii	Hawaiian Electric	Super off-peak: 9am – 5pm Off-peak: 9pm – 9am On-peak: 5pm – 9pm	Specific prices will be determined in future rate cases but must adhere to a 3:2:1 ratio for on-peak: off-peak: super off-peak. There will also be a grid access chart similar to capacity charges in Europe, but the amount is as yet unspecified.	Approved by PUC; set to take effect by July 1, 2024
California	PG&E SDG&E SCE	Off-peak: 8pm – 5pm On-peak: 5pm – 8pm	\$0.38/kWh off-peak \$0.42/kWh on-peak (Oct - May) \$0.51/kWh on-peak (June - Sept)	Currently active
Colorado	Xcel Energy	Off-peak: 7pm – 1pm Mid-peak: 1pm – 3pm On-peak: 3pm – 7pm	\$0.11/kWh off-peak \$0.19/kWh mid-peak \$0.27/kWh on-peak	Currently active
Missouri	Evergy	Off-peak: 8pm – 4pm On-peak: 4pm – 8pm (Jun – Sep)	\$0.09/kWh off-peak \$0.38/kWh on-peak	Set to take effect November 2023
Michigan	DTE Energy	Off-peak: 7pm – 3pm On-peak: 3pm – 7pm	\$0.15/kWh off-peak \$0.16/kWh on-peak (Oct – May) \$0.21/kWh on-peak (June – Sept)	Active

These new rates are undoubtedly an improvement over flat volumetric tariffs. Consumers will finally receive price signals that dispel “the basic lie to retail consumers that every kilowatt-hour costs the same regardless of the time of day or the season of the year” (Trabish, 2023). But the issue with the default TOU rates implemented to date is that they bundle the distribution, transmission, and generation costs into a single charge.

EV-Specific Residential Tariffs

As an alternative or complement to whole-home TOU rates, some US utilities have also begun to offer tariffs specifically targeted at EV owners. These tariffs allow EV owners to save money by shifting their charging demand to off-peak hours or allowing the utility to curtail charging during critical periods. The EV owners are often *not* required to enroll on a time-varying tariff for their remaining household demand, and in some cases, it is impossible for EV owners to pay more compared to the default flat volumetric rate. We review a selection of these dedicated EV rates here, shown in Table A.2.

Table A.2: Examples of EV-specific residential tariffs in the US

State	*Utility*	*Details*
Minnesota	Xcel Energy	Unlimited charging between 9pm and 9am for a flat fee of $42.50/month
Massachusetts	MMWEC	$6/month credit for EV drivers that agree to limit charging to 1.25 kW between 5-9pm on weekdays
New Jersey	PSEG	Ex-post credit of $0.105/kWh credit for off-peak charging (between 9pm – 7am M-F), as measured by a compatible smart Level 2 charger
California	Sonoma Clean Power	One-time $250 enrollment bonus plus $5/month in exchange for EV owners’ authorization to curtail charging for up to 120 hours per year

A 2019 report by the Smart Electric Power Alliance (2019) estimated that across 20 utilities, 21% of eligible EV customers were enrolled on a specialized EV Rate. The report demonstrated that participation increases significantly when the rate is marketed by utilities and connected to EV purchase incentives. The Vermont utility Green Mountain Power offers a free Level 2 charger with the purchase of any electric vehicle. Customers claiming this incentive are required to enroll on one of two EV rates: a TOU rate with an off-peak period between 9pm – 9am on weekdays and a managed charging rate where the utility is allowed to curtail charging up to 5 times per month. Green Mountain Power reported that 80% of customers purchasing EVs claimed the free charger incentive and enrolled on one of the EV rates (Green Mountain Power, 2021).

Appendix B: Addendum to Methodology

B.1 Home Load Profiles

We obtain synthetic hourly residential load profiles from NREL's ResStock database (Wilson et al., 2022). ResStock simulates end use residential energy demand for representative building types, calibrated against actual building performance. In this paper, we choose a diverse sample of 400 single-family detached houses in Massachusetts; each home has a unique hourly load profile for the actual meteorological weather year 2018. We use measure package 0 ("baseline") for all households. In the sensitivity analysis described in Section 4.3.2, we use measure package 5 ("Heat pumps, min-efficiency, existing heating as backup") for households that are assigned a heat pump system. The homes do not have either battery storage or solar photovoltaic panels. Figure B.1 shows the distribution of annual consumption and annual peak demand values for the houses in our sample (under measure package 0).

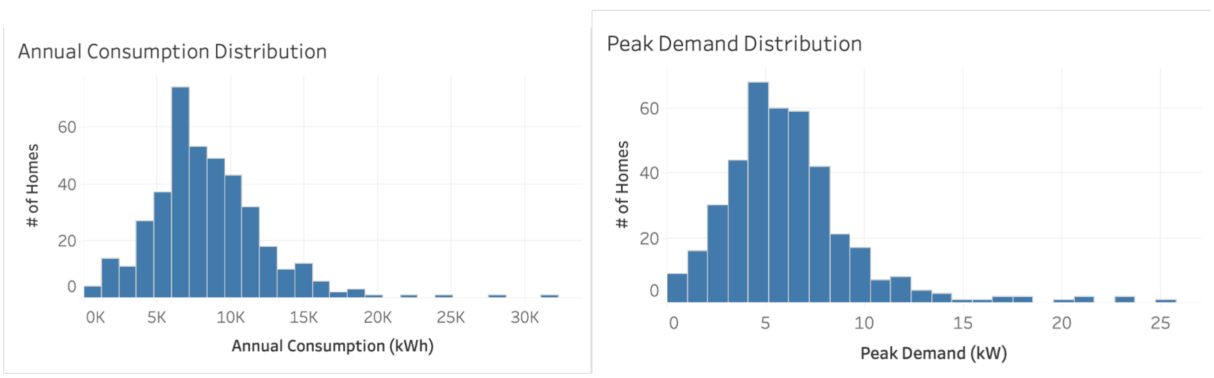

Figure B.1: Distribution of annual consumption (kWh) and peak demand (kW) for 400 single-family ResStock homes used in our study.

B.2 Constructing Annual EV Consumption Profiles

We use the National Household Travel Survey (NHTS) to generate annual vehicle usage profiles for each house. The NHTS is conducted by the US Department of Transportation every 5 years; respondents are asked to log every trip in a 24-hour period, starting at 4:00 AM local time and ending at 3:59 AM local time the next day. For each trip, the respondent includes the trip purpose, arrival and departure time, number of miles traveled, and start and end location (Federal Highway Administration, 2017). Starting with the raw NHTS trip data, we obtain, for each unique vehicle, a parameter profile that contains the earliest home departure hour, the latest home arrival hour, and the total number of miles driven in the 24-hour period. These parameters signify when the vehicle is expected to be plugged in at home and the amount of electricity required to restore the battery's state of charge.

Because the NHTS survey is not longitudinal (i.e., each survey response covers only a single day of travel behavior), we use the following procedure to translate the survey responses to annual usage profiles. We require an annual profile because we are interested in not only peak demand during certain representative days but also annual cost impacts:

1. For each ResStock household, we filter the summarized NHTS data for vehicles associated with households of the same income level and number of occupants.
2. Using the NHTS trip weights, we randomly select one weekend and one weekday parameter profile to associate with the household. These profiles provide the inputs (departure hour, arrival hour, and miles traveled) to convert from deterministic survey responses to pseudo-random travel profiles.
3. For each house, we create weekend and weekday normal distributions centered at the actual number of miles driven with a standard deviation equal to 10% of the number of miles driven. We also create discrete distributions for weekend and weekday arrival and departure hours shown in Figure B.2.
4. For each day of the year, we sample a departure hour and arrival hour from the appropriate discrete distribution and sample the daily mileage from the appropriate normal distribution (weekend or weekday).
5. We convert daily miles driven to electricity consumption using the regression computed by Yuksel and Michalek (2015). We use the average temperature during hours that the vehicle is *not* at home on the given travel day. The difference in energy efficiency throughout the year is due to both the temperature impacts on battery chemistry and cabin heating and air conditioning.

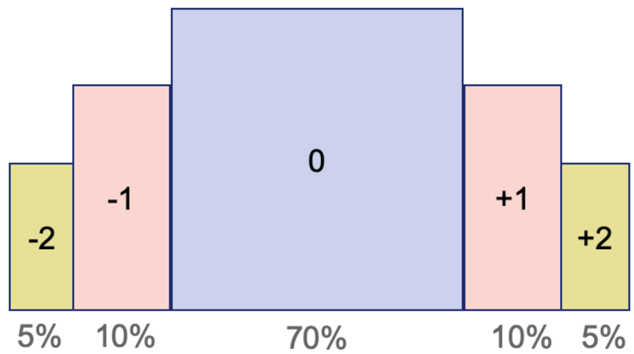

Figure B.2: Discrete distribution used to select departure and arrival hour each day. The numbers in the boxes represent the offset (in hours) from the selected NHTS profile parameter. The percentages below the boxes reflect the probability of drawing from each box.

After this procedure, each household has a unique and uncorrelated vehicle usage profile that indicates when the vehicle is home versus away, and the daily electricity consumption due to driving.

For any house where meeting the annual charging need is infeasible (i.e., the car is not plugged in long enough at home to avoid depleting the battery), we assume that house does not purchase an EV, a design choice that aligns with the approach by Wei et al. (2021)

B.3 Tariff Price Calculations

In this subsection, we provide additional detail on the calculation of tariff prices for 2-part TOU per-kWh and capacity tariffs.

2-part TOU Per-kWh Tariff

Eqs. B1–B2 indicate how the 2-part per-kWh prices are calculated, using the revenue requirement as specified in Section 3.3. The on-peak price is set at two times the off-peak price to mirror National Grid's G-3 rate.

$$RevReq = Cons_{off-peak} * Rate_{off-peak} + Cons_{on-peak} * 2 * Rate_{off-peak} \quad \text{(B1)}$$

$$Rate_{on-peak} = 2 * Rate_{off-peak} \quad \text{(B2)}$$

where $Cons_p$ is the aggregate off-peak consumption during period *p* and $Rate_p$ is the per-kWh charge ($/kWh) during period *p*.

Demand Charges

The 1-part ex-post measured capacity tariff (i.e., 1-part demand-charge) is computed by dividing the total revenue requirement by the sum of each household's maximum annual demand.

$$DemandCharge = RevReq \ / \ \sum_{j}^{n=400} max_{i\in\{1,..,8760\}}\left(demand_{j,i}\right) \qquad \text{(B3)}$$

where $demand_{j,i}$ is household *j*'s total demand in hour *i*. The resulting 1-part $DemandCharge$ has the units of $/kW; each customer's total network cost is that value multiplied by their annual maximum demand.

In multi-part demand charges, we introduce time differentiation, both intra-day and seasonal. Under the 3-part non-seasonal capacity tariff, households pay a separate charge for their maximum annual demand in each of three periods:

- On-peak: weekdays 8:00 AM – 8:59 PM
- Mid-peak: weekdays 9:00 PM – 11:59 PM
- Off-peak: weekdays 12:00 AM – 7:59 AM and weekends

To calculate the price for each period, we use the same methodology as the 1-part demand charge but divide the revenue requirement in a 3:2:1 ratio to each of the periods: in other words, we collect one half of the revenue requirement from the on-peak period, one third from the mid-peak, and one sixth from the off-peak. Within each window, the same equation is used; the portion of the revenue requirement is divided by the sum of each customer's maximum demand value within the relevant window, shown in Eqs. B4 – B6.

$$DemandCharge_{on-peak} = \frac{1}{2} RevReq \ / \ \sum_{j}^{n=400} max_{i\in\{1,..,8760\}, i\in\{on-peak\}}\left(demand_{j,i}\right) \qquad \text{(B4)}$$

$$DemandCharge_{mid-peak} = \frac{1}{3} RevReq \ / \ \sum_{j}^{n=400} max_{i\in\{1,..,8760\}, i\in\{mid-peak\}}\left(demand_{j,i}\right) \qquad \text{(B5)}$$

$$DemandCharge_{off-peak} = \frac{1}{6} RevReq \ / \ \sum_j^{n=400} max_{i \in \{1,..,8760\}, i \in \{off-peak\}} \left(demand_{j,i}\right) \quad \text{(B6)}$$

Under the 3-part seasonal capacity tariff, we maintain the three intra-day periods and add a seasonal component. Demand charges for the "winter" period (December through March) recuperate one half of the revenue requirement, and demand charges for the "non-winter" period (April through November) recuperate the other half. Customers are assessed two on-peak, mid-peak, and off-peak charges, one applying to the winter period and another for the non-winter period. To calculate the tariff levels, we use the same methodology as for the 3-part demand charge. Within each seasonal window, the same 3:2:1 ratio is applied to allocate costs to the on-peak, mid-peak, and off-peak windows. The equations are not shown but mirror those in (B4 – B6).

Subscription Charge

To calculate the subscription charges, we first compute each household's subscription level in each period as outlined in Section 3.2. We then use the same 3:2:1 allocation ratio for on-peak, mid-peak, and off-peak and assign one half of the revenue requirement to the winter season and one half to the non-winter season. The charge in each period *p* is calculated using (B7).

$$SubscriptionCharge_p = K * RevReq \ / \ \sum_j^{n=400} subscription_{j,p} \quad \text{(B7)}$$

Where *K* is the cost allocation factor (e.g., one half) and $subscription_{j,p}$ is the pre-subscribed capacity level for household *j* in period *p.*

B.4 Electrification Order

The order in which houses are selected for electrification is random and proceeds cumulatively. In other words, all EV households in the 5% electrification scenario remain EV households in the 10% scenario.

B.5 Calculating Optimal Charging Behavior

For each house in the aggregation, we solve a mixed integer linear program, where the objective is to minimize total electricity cost over one year, inclusive of both energy and network charges.

We consider non-EV load (including heat pump load) to be completely inelastic and assume that each EV responds rationally to price signals when plugged in, with perfect foresight. We assign an EV battery capacity to each household (either 40, 60, 90, or 120 kWh) according to the minimum capacity that fulfills its maximum daily electricity consumption plus a 20% buffer. This assignment captures the expectation that households that drive short distances are more likely to buy EVs with smaller batteries, which have lower associated capital costs.

The objective function for each household is defined as:

$$min \ \sum_i^{8760}\{(c_i + A_i) \cdot (N_i + E_i)\} + \sum_p \left\{max_i \left((c_i + A_i) \cdot B_{i,p}\right) \cdot DC_p\right\} + \sum_i^{8760}(maxsoc - soc_i) \cdot 1e - 4 \quad \text{(B8)}$$

where

- c_i is the charging value for each hour i (the decision variable)
- A_i is the non-EV load for each hour i
- N_i is the per-kWh network tariff (in $/kWh) for each hour i
- E_i is the per-kWh energy tariff (in $/kWh) for each hour i
- DC_p is the demand charge for each demand period p
- $B_{i,p}$ is a binary variable that indicates whether an hour i is part of a demand period p
- *maxsoc* is the battery's capacity
- soc_i is the energy in the EV battery for each hour i

The last part of the objective function ensures that EVs charge as early as possible such that the cost of charging does not increase. This is achieved by assessing a small penalty function (several orders of magnitude smaller than the per-kWh or capacity charges) for any hour when the battery is not fully charged. The model is subject to the following constraints:

$$minsoc \ \leq soc_i \ \leq \ maxsoc \quad \text{(B9)}$$

$$0 \ \leq c_i \ \leq 7.2 \quad \text{(B10)}$$

$$c_i \ \leq \ VS_i \ \cdot 1e6 \quad \text{(B11)}$$

$$soc_i = soc_{i-1} + (c_i - dch_i) \tag{B12}$$

The first constraint (B9) ensures that the battery's state of charge never goes above the battery's capacity or below a minimum state of charge, set at 20% of the capacity. The second constraint (B10) limits EV charging to the power of a standard Level 2 residential charger (30A, 240V); charging cannot be negative. The third constraint (B11) guarantees that the car can only charge when the vehicle is at home; VS_i is a binary status variable equal to 1 when the vehicle is at home and equal to 0 when the vehicle is away from home. Finally, the fourth constraint (B12) specifies that at each hour, the state of charge of the battery is equal to its state of charge in the previous time step plus the net charging value; dch_i is the amount of energy discharged by the battery, set equal to the full day's electricity consumption in the hour the vehicle departs home (in order to ensure that the vehicle is sufficiently charged before departure).

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