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# The Role of Electricity Tariff Design in Distributed Energy Resource Deployment

Elisheba Spiller, Ricardo Esparza, Kristina Mohlin, Karen Tapia-Ahumada and Burcin Unel

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# The Role of Electricity Tariff Design in Distributed Energy Resource Deployment

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## Abstract

This paper simulates the effect of more advanced residential electricity tariffs on household adoption of distributed energy resources (DERs). We employ an end-user DER investment and operational engineering optimization model, and adapt it to include an economic utility function, calibrated to the observed hourly residential electricity consumption data from 2016 in the Commonwealth Edison service territory in Chicago, in order to represent household-level preferences for electricity consumption. We simulate the effect of a spectrum of electricity tariffs, from the status quo flat volumetric tariffs to more sophisticated tariffs that are reflective of electricity generation and distribution system costs. We find that tariffs that are more time variant lead to greater reductions in coincident peak demands than flat volumetric tariffs, both from load shifting as well as from adoption of DERs. Regarding the effect of electricity tariff design on DER investments, we find that at current DER purchase costs investments in rooftop photovoltaic (PV), batteries and natural gas distributed generators are not privately optimal under any of our tariff design scenarios based on current cost levels for electricity and gas in the Chicago study area. However, with continued reductions in PV technology costs, rooftop PV may see a greater adoption rate under some of the more cost-reflective tariffs. We also demonstrate a greater incentive to invest in electrification of household space heating in the form of heat pumps under cost-reflective tariffs. These findings provide insights on electricity tariff design and the role of DERs in the future decarbonized electricity system, and highlight the need to consider region-specific costs and conditions when analyzing the effects of electric tariff reform.

## Keywords

Electricity pricing, time-variant pricing, engineering simulations, distributed energy resources

## JEL classification numbers

Q4, Q5

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# Contents

# 1. Introduction

A major shift is taking place in the electricity industry, where electricity customers are beginning to adopt distributed energy resources (DERs) such as rooftop photovoltaic (PV) systems, smart appliances and other technologies that allow them to interact with the grid in a different way. With these DERs, customers can achieve cost savings on their electricity bills and increase flexibility in their consumption patterns, while also helping to drive reductions in carbon emissions and other pollutants. Among the most important but sometimes overlooked drivers of residential DER adoption are the underlying electricity prices and pricing structure (i.e., residential electricity tariff design), because these are the fundamental determinants of the electricity cost the customer avoids paying by investing in a DER. Given the decarbonization goals of many US states , achieving adoption of DERs can help them meet their climate policy goals. Thus, the effect of electricity tariffs on energy consumption and environmental outcomes is relevant to the ongoing energy transition toward a decarbonized energy system.

Electricity tariffs will define the private savings from DER investments and operation for consumers, but in turn DERs can also affect aggregate distribution system costs, leading to societal benefits. For example, when a rooftop PV system is adopted in a place with high network congestion, the local electricity generation can help alleviate the congestion and lower distribution system costs by reducing the need to upgrade distribution capacity. On the other hand, when rooftop PV systems are concentrated and present at high levels in areas with little congestion, the result may be that investments are required to ensure that the network is capable of accepting electricity exports. Ensuring that there is investment in DERs, and that they are operated in places and at times that maximize social benefits, is important for achieving decarbonization goals at lower cost.

One of the ways in which policymakers can help ensure low-cost decarbonization is to identify and implement electricity tariffs that send cost-reflective price signals and thereby align customer incentives with system benefits (for further discussions on this issue, see, e.g., Joskow and Wolfram 2012, and Revesz and Unel 2020).[1] In order to align private incentives with system benefits, the prices and tariffs customers face need to reflect the costs for all parts of the electricity system. Real-time pricing of electricity supply has long been noted as a potential

[1] In this setting, cost-reflective implies that the prices customers face reflect the costs they place on the system. Theoretically, the most cost-reflective tariffs would reflect all social and system costs, including the marginal cost of electricity generation, social damages from pollution, energy losses, congestion on the grid that may drive new capacity investment, and so on.

source of efficiency gains by providing private incentives to adjust consumption in a way that will increase net system benefits (Borenstein 2005; Borenstein and Holland 2005; Alcott 2011). Previous research also shows that it is possible to approximate some of those benefits through implementing less granular pricing policies, such as peak-time pricing (Faruqui and Sergici 2010; Blonz 2016; Mays and Klabjan 2017).[2] However, in contrast to time-variant pricing reflective of electricity generation costs, there has been less focus on how retail pricing for electricity delivery service can be structured to reflect distribution system costs (see Perez-Arriaga and Bharatkumar 2014 for a detailed description of distribution system costs and how tariffs can be structured to reflect these). Therefore, whether previous research and results still apply when distribution system costs are also reflected in time-variant pricing structures is an open question. Furthermore, much of this research is based on short-term behavioral responses to changes in electricity prices and does not reflect more medium- to long-term responses such as investment in smart energy technologies and DERs, which provide new opportunities for automating the response of electricity load to changes in price.

Although the effect of electricity price structures on electricity consumption has been studied quite extensively, there are few research studies on the effect of tariff design on DER deployment and operation. Darghouth et al. (2016) and Boampong and Brown (2018) find that retail tariff design is an important factor in the adoption of distributed PV systems, and, according to Brown and Sappington (2016a, 2016b, 2017) and Simshauser (2016), can theoretically lead to efficient distributed generation deployment. One of the remaining questions is whether and to what extent tariff design can lead to more efficient adoption of a portfolio of DERs.

Furthermore, not only can cost-reflective tariffs align customer incentives with system costs, they can also help to reduce unintended cross-subsidies between customers who own DERs and those who do not (Boampong and Brown 2018). If underlying rates are inefficient and don't accurately reflect costs, the tariff design can lead to DER owners being overcompensated for their generation (Eid et al. 2014; Simshauser 2016; Schittekatte et al. 2018). And, because many DER owners have higher incomes, lower-income individuals without DERs may be disproportionately negatively affected by inefficient tariff structures, which could shift costs

[2] It is a central assumption to our analysis that consumers have the proper information to make an economically optimal decision, and that they would respond optimally to this information. Some empirical research has provided evidence to suggest that electricity consumers respond to average prices rather than marginal or non-linear prices, especially in the context of tiered rates, making alternative tariffs less efficient than intended (Ito 2014) and the consumers' behavior suboptimal. However, these non-financial-induced actions are outside the scope of our paper.

toward the non-DER-owning customer class (Hledik and Greenstein 2016; Burger et al. 2020). Thus, tariff design affects DER adoption and deployment in a way that can have significant effects on electricity system costs, as well as distributional implications across different groups of electricity users.[3]

This paper adds to the literature by analyzing the effect of electricity tariffs — both existing inefficient ones and more efficient, cost-reflective options — on DER adoption and use.

Our main findings demonstrate that, at current electricity prices and levels of costs for DERs, many of these technologies are not privately optimal investments.[4] For rooftop PV and electric heat pumps, we find that the underlying tariff does indeed matter in terms of the incentives it creates to invest in these technologies. Although we find that, given the current capital costs of PV and current electricity price levels in the Commonwealth Edison (ComEd) service territory, rooftop PV is not a profitable investment, when PV costs begin to lower the tariff will strongly affect the customer's incentive to invest, as well as their choice of PV system size. With respect to heat pumps, we find that there is an incentive to invest only under the tariff scenario with the lowest volumetric rate. We also find that batteries and natural gas distributed generators are not profitable to any household in our sample under any of our tariff design scenarios. However, we do not model all the benefits these technologies provide (including black start capabilities and reliability benefits), and thus are likely underestimating the private incentives to invest in these technologies.

We also find important results related to effects on long-run distribution costs. Our findings indicate that all time-variant rates will produce benefits to the distribution system in terms of avoided long-run costs by reducing coincident peak maximum demands across households (relative to a flat tariff), simply due to changes in consumption patterns. Investment in rooftop PV also has the potential to produce large gains in long-run distribution cost reductions, although these gains do not vary widely by tariff.

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[3] Certain cross-subsidies imposed by the utilities are applied consciously in an effort to reduce electricity cost burden on low-income customers by shifting the costs towards non-low-income groups, e.g., the CARE program provided by Californian utilities, which reduces bills for low-income customers by 20–35%, depending on the utility (see https://www.cpuc.ca.gov/care). These types of cross-subsidies are not considered in this discussion; instead, the more relevant cross-subsidies we are concerned with are the inadvertent shifting of costs from DER owners to non-DER owners, especially if the DER owners tend to be richer.

[4] Non-financial incentives likely lead customers toward adopting DERs, such as concern for the environmental impacts of consumption and desire for clean local power, among others. However, without more granular data on customer demographics, we are unable to capture these sorts of non-financial incentives in our model.

The results of this research can help inform electricity market regulators of advantages and disadvantages of different electricity tariff designs, and the effects on customers, DER adoption and system costs of requiring the utility (i.e., the distribution system operator) to offer one tariff design over another. In a separate paper, we analyze the effects of different tariff designs on emissions of carbon dioxide, sulfur dioxide and nitrogen oxides (see Unel et al. 2020).

# 2. Methods and data

Our methodology allows us to test the effect of electricity prices on DER adoption, environmental outcomes, distributional impacts, and network costs, and integrates a simulation model of household electricity demand and investment in energy technologies/DERs, a reference network model, and an economic dispatch model.

## 2.1 Demand Response and Distributed Resources Economics Model (DR-DRE) 2.0

The Demand Response and Distributed Resources Economics Model (DR-DRE) 2.0, developed at the Massachusetts Institute of Technology Energy Initiative, simulates the effect of different electricity tariffs on investment in and operation of DERs, and the resulting hourly loads of each end user for the full year. The DER investment options allowed for in DR-DRE 2.0 are rooftop solar PV, electric battery storage (non-electric vehicle), electric heat pumps and natural gas-fired distributed generation (DG). Tariff values and structures are inputted into DR-DRE 2.0, and outputs include DER investment decisions, synthetic hourly load shapes, fuel consumption, emissions, and thermal demands from heating, ventilation and air conditioning (HVAC). The customer's new, synthetic load shapes are determined through a cost-minimization algorithm, whereby the customer decides on investments and electricity consumption, such as reducing their total energy costs in response to the electricity tariff while maintaining a comfortable temperature in their home.

For the purposes of this research project, we updated DR-DRE to include an explicit representation of household preferences in the form of a utility function and calibrated the parameters in the model to observed ComEd load data.[5] Given computational limitations, we

[5] The original DR-DRE required the implementation of a dead-band control and a penalization function to control for space heating and cooling requirements around a specified set point, resulting in synthetic user profiles that were not

created clusters of households with similar usage profiles and generated representative load profiles for each cluster. As further described in Bharatkumar et al. (2019), we then used weather data to estimate, via regression techniques, the portion of the cluster's representative hourly load that is used for space heating and cooling (which we refer to as thermal load). We calculate the resulting non-thermal loads as the difference between observed total loads and regression-estimated thermal loads. We then use the resulting non-thermal loads to calibrate the model such that the cluster's representative customer preference parameters create synthetic non-thermal loads that closely mimic regression-estimated patterns of non-thermal electricity consumption. Furthermore, we calibrate the HVAC system and building materials parameters to create synthetic thermal loads that are of similar magnitudes to our regression-estimated thermal loads. Thus, the model's synthetic loads will reflect the preference parameters specific to the cluster's representative customer under a baseline tariff scenario with a flat (non-time varying) volumetric rate.

We impose net energy metering (NEM),[6] which means that the customer receives the retail rate for every kWh of injections into the grid in each time period (this is true in both the avoided cost sense and for excess generation unused by the household within the hour). Under time-varying tariffs, the customer will receive the hourly volumetric portion[7] of the rate for any kWhs exported during that hour. However, natural gas distributed generators do not receive compensation for exports to the grid, as these generators are generally not connected to the grid in the same way as solar PV or batteries, nor is there an existing compensation scheme for that technology, other than its ability to reduce a customer's bill.

In DR-DRE 2.0, the decision to invest in DERs (including rooftop PV, batteries, heat pumps and natural gas DG) is made endogenously through a total cost-minimization algorithm subject to a utility constraint.

Importantly, DR-DRE 2.0 deals with heat pumps in a different way than other DERs, because all households have some sort of heating option already. Thus, for the heat pump option we assume that customers make the decision to invest in a heat pump if their existing boiler is at the end of its useful life. Essentially, the model forces the customer to choose between whether to invest in

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based on observed load data. The modified version uses preference parameters calibrated to observed loads to create a set of hourly synthetic user loads. For an in-depth discussion of the calibration technique and the utility function, see Bharatkumar et al. (2019).

6 We remove the NEM assumption for a sensitivity analysis related to battery adoption; see Table 11.

7 This will include any volumetric costs, including the cost for supply and distribution, but won't include fixed costs.

electric heating or gas heating in order to minimize total costs (inclusive of the upfront costs and lifetime costs for both the gas and electric options). For all other DERs, the decision is whether to invest or not; there is no alternative and the investment is not forced.

For all DERs (besides heat pumps), DR-DRE 2.0 has the customer make the investment if they receive a positive net present value (NPV) relative to no investment; NPVs will thus be determined by how much DERs can offset costs, how much lifetime revenue they can receive through NEM (under a 3% discount rate) and the upfront cost.

## 2.2 Creating representative household loads from smart meter data

Solving DR-DRE 2.0 for hourly time steps over a one-year period takes approximately 30 seconds. Hence, it would have taken a prohibitively long time to run the model for our full sample of more than 40,000 customers. We therefore created clusters of customers based on important characteristics of their load profiles, arriving at 45 representative customers.

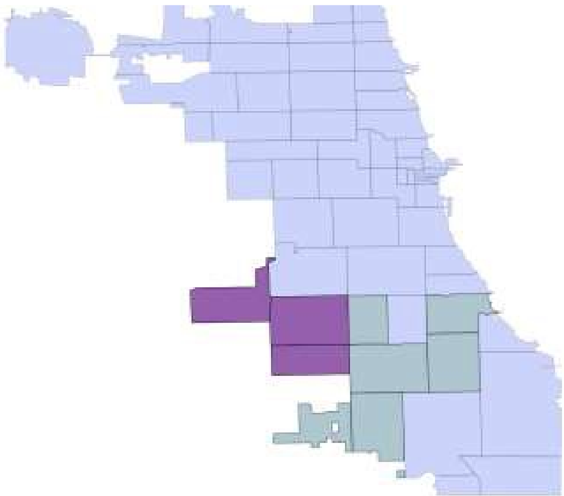
### *2.2.1 ComEd smart meter data*

Our main dataset on customer loads is the 2016 five-digit zip code anonymous advanced metering infrastructure (AMI) interval data from ComEd (2020). This dataset provides us with half-hour consumption data for most residential and small commercial customers in the ComEd service territory, and identifies customer location based on their five-digit zip code and an anonymous identifier. The dataset is restricted, however, to remove large, identifiable customers using the 15/15 rule: each zip code-level group must contain at least 15 customers, and none of those customers may have more than 15% of the total load at that zip code. Customers who exceed the 15% rule are dropped from the dataset. In our data subset, this excludes any large industrial and commercial customers.

Because ComEd's AMI deployment began in November 2009 and was scheduled to take 10 years, not all residential customers had AMI data during 2016. Therefore, with guidance from ComEd engineers we identified three zip codes within the service territory (see Figure 1) that resulted in 55,635 residential customers and a very high percentage of full-year coverage. For the purposes of our modeling, we keep only customers with a full year's coverage of data, which reduced our sample to 54,412 users.

FIGURE 1

### ComEd service territory, with the three selected zip codes in purple, Chicago, IL



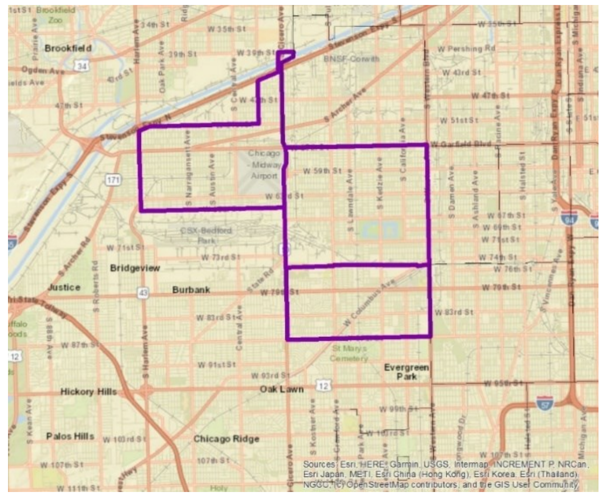



Table 1 shows some summary statistics of the customers within each of the identified zip codes, and Figure 2 shows the average load shape during summer and winter (solid red and blue lines, respectively), with error bars showing standard deviations.

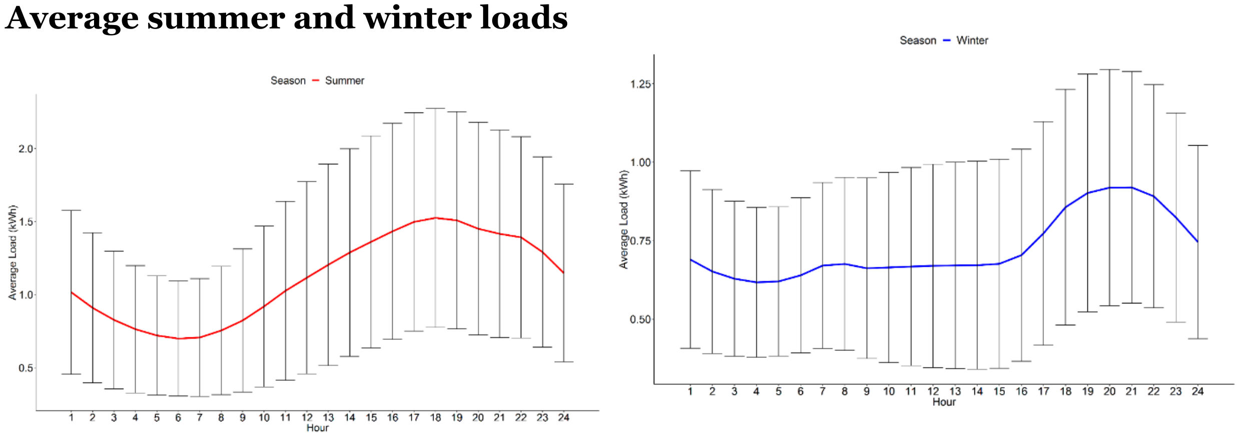
TABLE 1

## Summary statistics of sub-sample ComEd residential customers

| Zip code | No. of customers | Total demand (MWh/yr) | Peak demand (kW) | Single family no electric heat (%) | Advanced metering infrastructure coverage (%) |
|---|---|---|---|---|---|
| 60629 | 33,593 | 162,081 | 50,183 | 76 | 82 |
| 60638 | 22,010 | 116,286 | 41,922 | 83 | 85 |
| 60652 | 13,769 | 82,843 | 28,529 | 90 | 88 |

FIGURE 2

## Average summer and winter loads




Importantly, we did not have information on existing customer-level appliance use or DER adoption. However, ComEd engineering staff stated that the adoption levels of solar power were negligible in the Chicago region. Thus, we ran a simple test on our sample to look at zero net AMI loads (which could correspond to times of solar generation). We found no customers with zero net loads during sun hours, and instead found that zero loads were randomly distributed throughout the day. These results indicate that it is highly unlikely that anyone owns solar panels (although a larger customer with a small panel could potentially not have any zero net loads). Thus, we assume that there is no prior adoption of rooftop PV in our sample of customers.

We further restricted the sample to single-family homes without electric heat, for two reasons. First, as demonstrated in Table 1, only a very small percentage of customers have electric heat, and given that these customers will have very different consumption patterns, we dropped homes with electric heat. Second, because multi-family customers are more likely to be renters and less likely to be able to adopt DERs, we dropped customers within the multi-family class. However, this reduction allowed us to keep 81% of the total sample of residential customers, resulting in 44,185 customers in single-family homes.

### *2.2.2 Clustering approach*

To develop clusters of representative customer categories, we first employed VISDOM, a python tool used for organizing and creating visualizations of data,[8] to create a data dictionary of load shapes, based on the observed 44,185 loads. Then, we ran a k-means algorithm[9] to cluster the customers by the variability in load shapes (i.e., describing the variability of the users' loads across all of VISDOM's dictionary of load shapes, defined as "entropy"[10]) and the size of the load shapes (at a daily level, during summer peaks and during winter peaks). This resulted in five clusters, a description of which is shown in Table 2.

TABLE 2

**Description of the five initial clusters from k-means algorithm**

| Cluster | Entropy | Daily load percentile | Summer mean peak load percentile | Winter mean peak load percentile | No. of customers in each cluster |
|---|---|---|---|---|---|
| 1 | 7.97 | 0.61 | 0.87 | 0.68 | 16,770 |
| 2 | 8.01 | 0.28 | 0.58 | 0.31 | 10,595 |
| 3 | 7.45 | 0.69 | 0.87 | 0.68 | 8,630 |
| 4 | 6.63 | 0.50 | 0.63 | 0.43 | 2,516 |
| 5 | 7.48 | 0.29 | 0.54 | 0.27 | 5,674 |

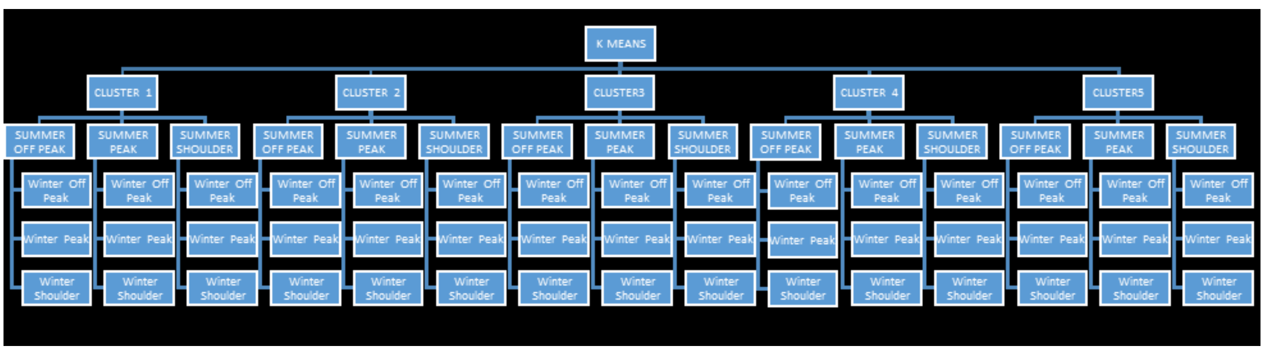
We then split each cluster into three different groups based on the temporal location of customers' summer peaks: specifically, if a customer's summer maximum demands occurred

[8] See Kwac et al. (2014) for a description of the VISDOM tool.
[9] For a description of the k-means methodology, see Kwac et al. (2014) and Steinley (2006).
[10] Entropy is defined as the log of the expected probability of load C occurring, thus it is unitless. See Kwac et al. (2014) for more details.

during peak hours, off-peak hours or shoulder hours.[11] To do this, we followed the peak definitions as defined by ComEd in their time-of-use tariffs. We then further split those clusters into three more groups based on the timing of the winter peaks (peak, off-peak and shoulder). This resulted in nine different combinations of each five clusters, or 45 different final clusters — as illustrated in Figure 3.[12] Appendix B lists the 45 cluster types and number of households within each cluster, as well as showing the resulting yearly average load shapes for each cluster. In the rest of this paper, we use these 45 clusters to represent 45 customer types with different load-shape characteristics. For a more detailed description of the clustering process, see Esparza et al. (2019).

FIGURE 3

## Decision tree for clustering

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[11] When we conducted the clustering analysis, we did so with the raw data from the ComEd service territory, selecting only homes that have no electric heating. Thus, their maximum demands almost always happen during the summer. During optimization, certain households adopt heat pumps (see Results section), but we did not redo the clustering approach, even though these households may see a shift to winter maximum demands. In including households that later shift to winter peaking in clusters that have summer peaks, we still capture the households' underlying preference for use of air conditioning in the preference parameter calibration.

[12] One extra benefit of this approach is that each household is represented within the cluster that most accurately matches its load shapes.

## 2.3 Electricity system and DER technology cost assumptions

In our tariff design scenarios, we consider not only electricity distribution costs but also the upstream costs of electricity transmission and generation.[13] The ComEd service territory belongs to the wholesale electricity market organized by the regional transmission organization PJM. Thus, ComEd (or the retail supplier of the customer's choice) will pass on costs (potentially with administrative markups) from long-term contracts and/or spot market purchases from PJM, as well as any transmission, generation capacity and other potential charges. Our data and related assumptions on electricity system and technology costs are outlined below. Depending on how all the different electricity system cost elements are recovered from residential customers (e.g., as flat or time-variant or fixed charges), they may affect incentives to invest in DERs. Our tariff design scenarios in the following section are therefore designed to represent both the most common ways to recover these costs, as well as the most cost-reflective approach for doing so.

### *2.3.1 Distribution network costs*

**Embedded costs**

For data on embedded distribution system costs to construct our cost-reflective tariffs, we use ComEd's embedded cost of service study (ECOSS) from December 2015, which identifies the amount of revenue collected for each customer class and breaks it down by cost type (customer related, meter related, distribution related and distribution taxes).[14] As can be seen in Table 3, the total cost of service is highest for single-family homes without electric heat, as this class makes up the largest percentage of ComEd residential customers.

[13] Transmission costs are included as an adder to the volumetric portion of the rate.
[14] All ECOSS are created administratively, and thus the underlying method of applying costs to classes may reflect errors or biases in cost allocation. We assume away these biases or errors and allocate the costs to the classes in the same manner as applied by the utility.

TABLE 3

### 2015 ComEd embedded cost of service study by customer class

| Cost category | Single family no electric heat | Multi-family no electric heat | Single family with electric heat | Multi-family with electric heat |
|---|---|---|---|---|
| Customer-related costs | $289,282,811 | $98,541,853 | $5,205,590 | $15,950,146 |
| Metering services costs | $127,931,383 | $61,431,608 | $1,994,011 | $9,220,059 |
| Distribution-related costs | $702,724,819 | $123,414,259 | $12,466,799 | $27,231,279 |
| IL electricity distribution tax | $23,358,481 | $5,138,087 | $824,628 | $1,794,492 |
| No. of customers in this class | 27,383,584 | 13,149,378 | 426,817 | 1,973,540 |
| Sales (million MWh) | 20.2 | 4.4 | 0.7 | 1.6 |

We utilize the information in this table to create the cost-reflective tariffs described in the following section. For example, we divide the customer- and metering-related costs by the number of customers in that class in order to identify the customer-specific fixed charges, and we use distribution-related costs to calculate the residual costs after imposing a distribution capacity charge.

### Long-run distribution costs

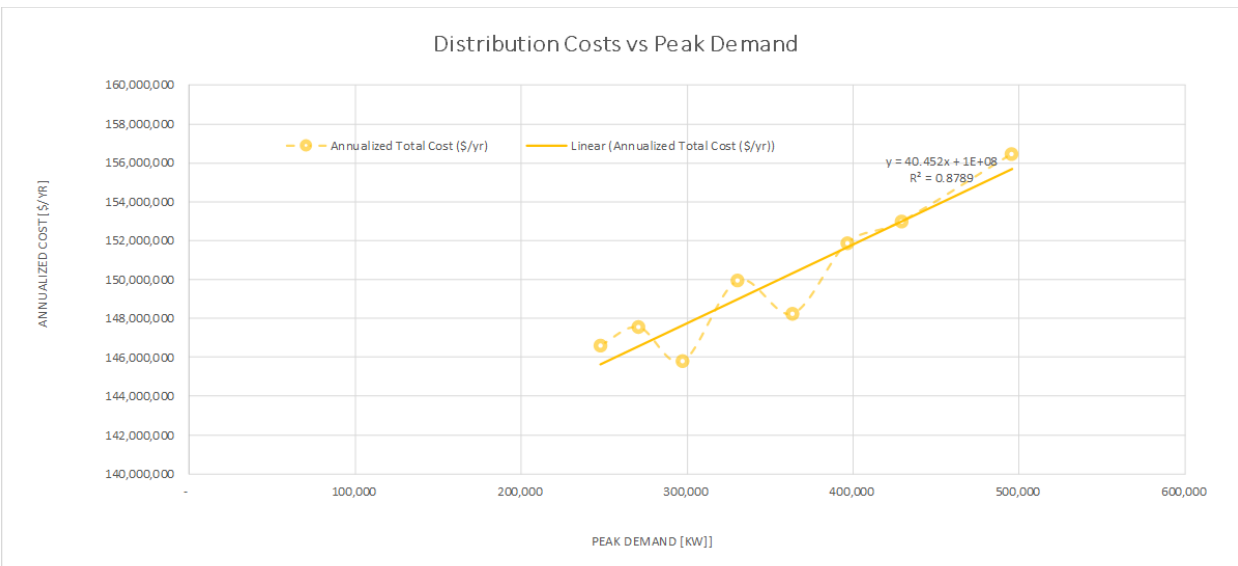
As the network is built up to accommodate coincident peak demand,[15] the long-run marginal costs of the distribution system will depend on the magnitude of the coincident peak demand. These long-run marginal costs are not identified in the cost of service studies as they are not embedded costs (i.e., costs associated with infrastructure in which the utility has already invested); instead, we identify them using a model known as the US-Reference Network Model (US-RNM) (Mateo et al. 2019).

[15] In many service territories recently there has been an increased need for ramping and flexibility of the system, especially with greater adoption of DERs. This has led to what is known as the "duck curve": a dip in midday demand during sunny hours, with a rapid increase in the late afternoon/evening as the sun goes down and demand peaks. We do not consider the potential costs of accommodating these ramping or flexibility needs in this paper.

US-RNM develops an efficient electricity network based on building footprints of the geographical area of interest (in this case, the three zip codes identified in Figure 1),and calculates the cost of the network based on a catalog of relevant equipment of the utility under study. The network is sized to accommodate active and reactive aggregate peak demand. To calculate long-run marginal costs, we run US-RNM multiple times with different levels of demand within a 25% range of the observed 2016 peak demand. With each different level of demand, US-RNM produces a cost; thus, we use these data points to trace out a curve around the observed demand. The slope of the curve ($40/kW-year), as represented in Figure 4, is therefore the long-run marginal cost (assuming existing diurnal patterns of consumption[16]); this feeds into the coincident peak demand charge (as described in more detail in the following section) in our cost-reflective tariffs.

FIGURE 4

## Long-run marginal cost of the network




[16] As new DERs and increased electrification of transport and heating come online, these patterns may very well change. Thus, our results are valid for existing patterns but shouldn't be extrapolated into future scenarios, such as when all vehicles and heating have been electrified.

### *2.3.2 Installed generation capacity system costs*

To identify the marginal cost of generation capacity, we use results from PJM's capacity market. Specifically, we use the Final Zonal Unforced Capacity (UCAP) Prices for the 2015/2016 delivery year for January–May 2016, and the 2016/2017 delivery year for June–December 2016. The prices are listed in Table 4.

TABLE 4

**Final Zonal Unforced Capacity (UCAP) Prices in the ComEd service territory**

| Year | Final zonal net load price ($/MW-day) | Corresponding $/kW-month |
|---|---|---|
| 2015/2016 | 135.81 | 4.18* |
| 2016/2017 | 101.62 | 3.12† |

* Following ComEd's methodology, we multiply the resulting price by the residential supply base uncollectible cost factor (SBUF) and the incremental supply uncollectible cost factor (ISUF). These charges in 2016 were: ISUF, 0.9936; SBUF, 1.0278 (4.14 was the $/kW-month price from the capacity market outcome). The values in the table represent the adjusted values.

† The $/kW-month price from the capacity market outcome was $3.09, which is very similar to the 2016 UCAP value.

### *2.3.3 Variable electricity generation costs*

To model electricity supply in our three zip codes of interest, we developed a single-node hourly economic dispatch (ED) model parametrized to the ComEd region. The ED model is formulated as an optimization problem that minimizes the cost of scheduling generating power units over a one-year time horizon, constrained to meeting zonal demand for electricity and taking into account the presence of renewable resources, while satisfying a limited number of technical and environmental constraints. The technological and economic parameters are based on the generation units belonging to the ComEd region as provided by SNLEnergy for 2016. In addition, we incorporate metered hourly demand profiles based on the ComEd load zone and also renewable generation profiles for the year 2017, both of which can be found in PJM's data management tool.[17] This simple model gives us the hourly scheduling of all the generating units, as well as operational costs and hourly marginal prices for the system.[18] Our ED model can

[17] PJM's Data Miner 2, accessible at http://dataminer2.pjm.com/list.
[18] For more in-depth discussion of the ED model and its results, see Unel et al. (2020).

approximate observed prices quite well, producing a correlation between the two price datasets of 0.88 (see Table 8).

### *2.3.4 Cost of DER technologies*

For the purchase price of the DERs modeled (rooftop PV, batteries and natural gas DG), we gathered data from a variety of sources; see Table 5.

TABLE 5

**Cost assumption sources for DERs**

| DER type | Source | Cost/kW ($) |
|---|---|---|
| Rooftop PV | Fu et al. 2018 | 2,700 |
| Residential storage | SolarQuotes (2020) | 1,055 |
| Natural gas distributed generators | HomeAdvisor (2020) | 258 |

## 3. Tariff design scenarios

For our simulations, we designed six different tariff design scenarios. The main tariff elements are presented below and further detailed later in this section. Appendix A presents the corresponding charges/prices for each tariff design.

**Flat tariff**

- Fixed monthly customer charge
- Flat volumetric distribution charge
- Flat volumetric supply charge
- Demand charge on customer's total monthly kWs to recover PJM generation capacity costs.

**Time-of-use (TOU) tariff**

- Fixed monthly customer charge
- Flat volumetric distribution charge
- Volumetric time-of-use electric supply charge (peak hours 3–7 p.m.; shoulder hours 6 a.m.–3 p.m., 7 p.m.–12 a.m.; off-peak hours 12 a.m.–6 a.m.)
- Demand charge on customer's total monthly kWs to recover PJM generation capacity costs.

**Critical peak price (CPP) tariff**

- Fixed monthly customer charge
- Flat volumetric distribution charge
- CPP for electricity supply
    - 10 hottest days of the year: CPP during peak hours of the day as identified in the TOU rate (3–7 p.m.)
    - 10:1 peak to off-peak price ratio
- Demand charge on customer's total monthly kWs to recover PJM generation capacity costs.

**Real-time price (RTP) tariff**

- Fixed monthly customer charge
- Flat volumetric distribution charge
- Hourly real-time prices on electricity supply
- Demand charge on customer's total monthly kWs to recover PJM generation capacity costs.

**Cost-reflective rate — fixed monthly charge (CRRf) tariff**

- Fixed monthly customer charge (metering and billing)
- Distribution critical peak demand charge (based on long-run marginal cost estimate) on top 10 ComEd peak hours of the year
- Hourly real-time prices on electricity supply
- Demand charge on customer's total monthly kWs to recover PJM generation capacity costs
- Fixed per customer charge to recover residual costs.

**Cost-reflective rate — volumetric charge (CRRv) tariff**

- Fixed monthly customer charge (metering and billing)
- Distribution critical peak demand charge (based on long-run marginal cost estimate) on top 10 ComEd peak hours of the year
- Hourly real-time prices on electricity supply
- Demand charge on customer's total monthly kWs to recover PJM generation capacity costs
- Volumetric charge to recover residual costs.

As can be seen in the breakdown above, each tariff has a slightly different implementation of either supply or distribution cost recovery. We have designed these scenarios to make it possible to attribute differences in results across the tariffs to individual elements of the tariffs. For example, any differences in the flat vs the TOU, CPP and RTP tariffs will be attributed to the time granularity of the volumetric supply charges, as all other charges are the same across these four scenarios. Although there are more changes to the cost-reflective tariffs relative to the others (in terms of the distribution peak demand charge and the extra revenues recovered either through a monthly charge or a volumetric rate), both have real-time prices and the combined effect of the distribution peak demand charge and the residual cost recovery can therefore be derived by comparing against outcomes under the RTP tariff. Furthermore, the difference between the two cost-reflective tariffs can be attributed to the difference in residual cost recovery, i.e., either through an increase in the volumetric rate or a fixed monthly charge.

## 3.1 Flat tariff

In 2016, the majority of residential customers in the ComEd service territory had a flat volumetric rate that did not vary over the course of the day. We therefore assume that all customers in our sample were on the basic residential service rate schedule as presented in Table 6.[19]

[19] The ComEd load data do not indicate which rate schedule each customer was on in 2016.

TABLE 6

**Basic residential service in 2016 for "single family no electric heat" customer class — business as usual scenario**

| Tariff portion | Price | Resulting fixed variable aggregate tariff structure | |
|---|---|---|---|
| Customer charge | $10.53/month | Fixed rate | $14.89/month |
| Standard metering charge | $4.36/month | Variable rate | $0.11/kWh |
| Distribution facilities charge | $0.03156/kWh | | |
| Electricity supply charge (summer) | $0.05799/kWh | | |
| Electricity supply charge (winter) | $0.05865/kWh | | |
| IL electricity distribution charge | $0.00116/kWh | | |
| Transmission services charge | $0.01122/kWh | | |
| Environmental cost recovery adjustment | $0.00038/kWh | | |
| Energy efficiency programs | $0.00345/kWh | | |

We used this flat rate as our business as usual (BAU) scenario to calibrate the preference parameters for the utility function in the DR-DRE 2.0 model. However, this BAU volumetric supply charge of approximately 6 cents/kWh is higher than a direct pass-through of supply (i.e., variable generation) costs: the (load weighted) average supply price in 2016 was 2.9 cents/kWh, indicating a markup of approximately 3 cents/kWh. It is possible that this markup may at least partially be recovering the costs of installed generation capacity charges from PJM as well as a hedging premium in long-term supply contracts, but ComEd does not document this in its embedded cost of service study. Thus, in order to ensure that the tariffs are revenue neutral, we replace the 2016 supply charges with those generated by the ED model in our flat-rate scenario. We thus calculate a flat rate based on the load-weighted average price dictated by the ED model. The resulting volumetric supply rate is 2.7 cents/kWh. Thus, none of our rates include a volumetric markup.[20] To recover the PJM installed generation capacity costs as described in Table 4, we include a monthly demand charge that is the same across all tariff design scenarios. (Keeping this charge unchanged across scenarios makes any differences in results across rates

[20] It is possible that if more cost-reflective rates became the norm, then they would all have the markup. However, as existing ComEd TOU and RTP rates do not have this markup, we remove it from all rates.

not attributable to the installed generation capacity charge — this is desirable because it is not the main focus of our study.)

For the flat tariff scenario, we use the charges in Table 6, with the exception of the calculation of the supply and capacity charges as just described.

## 3.2 Time-of-use (TOU) tariff

Following ComEd's 2019 Residential Time of Use Pricing Pilot,[21] we develop a similar TOU tariff, which varies the supply portion over the time of day. To identify peak and off-peak hours, we looked at historical prices and loads (pre-2016), and identified that the maximum peak revenues would have been collected at 5 p.m. and the minimum at 3 a.m. Thus, we choose a four-hour super-peak window around the maximum peak, and a six-hour off-peak window around the minimum, resulting in the same peak windows as ComEd's 2019 TOU rate.

To identify the rates within the three peak periods, we follow ComEd's methodology formula, which is described in the 2019 Residential Time of Use Pricing Pilot Filing,[22] but instead use 2016 historical real-time prices and loads.[23]

TABLE 7

### Time-of-use tariff supply charges

| Period | Time of day | Summer price (¢/kWh) | Non-summer price (¢/kWh) |
|---|---|---|---|
| Super-peak | 3–7 p.m. | 6.61 | 5.54 |
| Shoulder | 6 a.m.–3 p.m.,<br>7 p.m.–12 a.m. | 3.74 | 3.46 |
| Off-peak | 12–6 a.m. | 1.89 | 2.23 |

[21] See https://www.comed.com/SiteCollectionDocuments/MyAccount/MyBillUsage/CurrentRates/75_Rate_RTOUPP.pdf.
[22] Ibid.
[23] ComEd provides historical load profiles beginning in April 2009 on their website, which provides an average profile for each delivery class. We use the residential profile for our analysis, for all dates prior to 2016, accessed July 24, 2019, https://www.comed.com/MyAccount/MyService/Pages/ARCHIVE/HistoricalLoadProfiles.aspx.

To be consistent across all tariffs, we impose the same monthly demand charge to recover the marginal PJM generation capacity costs as in the flat tariff, and include in the volumetric rate the distributional facilities charges[24] and volumetric taxes/fees as defined in Table 6.

## 3.3 Critical peak price (CPP) tariff

For this tariff, we identify the top 10 hottest days of the year and assume that these will be the critical peak event days. We implement a CPP during the peak hours of the day as identified in the TOU rate (3–7 p.m.). These 10 hottest days (as shown in Figure A1 in Appendix A, blue bars) are also very much correlated with high-demand and high-price times. To ensure a high ratio between peak and off-peak prices, and following what other utilities have done for CPP prices,[25] we impose a price ratio of 10:1 on supply prices, where the price in the off-peak period is $0.024/kWh and the critical peak price is $0.24/kWh. These values were created based on the hourly prices generated by our ED model. The formula we use to calculate the off-peak price is as follows:

$$Non\ critical\ peak\ price = \frac{Total\ supply\ cost}{(10 * Af * LoadCPT + Af * LoadNPT)}$$

where:

Af= Adjustment factor (1.08)

LoadCPT = Load during critical peak hours (3–7 p.m. on 10 hottest days)

LoadNPT = Load during non-critical peak hours

Total supply cost = $\sum_{n=1}^{8760}(ComEdLoad_n * \ ED\ real\ time\ price_n)$

The capacity demand charge and volumetric adders are included in the same way as in the TOU and flat tariffs.

[24] The one exception is in the cost-reflective rate, which imposes a demand charge for the distribution costs rather than the flat volumetric distribution facilities charge.
[25] See Fenrick et al. (2014) for a review of critical peak pricing rates across multiple utilities.

In our CPP scenario we implicitly assume that the utility informs the customer through an email, phone or text notification that the following day will be a high-priced day. Thus, there is a clear signal to the customer that they can respond to.[26]

## 3.4 Real-time price (RTP) tariff

Following ComEd's 2016 Basic Electric Service Hourly (BESH) Pricing Tariff,[27] we maintain the distribution portion of the bill fixed, except for the customer charge, which was slightly higher for those customers ($10.92), and charge customers the hourly supply prices based on our ED model's 2016 real-time prices.[28] Table 8 shows summary statistics of observed hourly prices and those estimated by the ED model for the entire year, and the correlations across the datasets. This table demonstrates that the ED model produces prices that are very much in line with the observed prices, with 0.88 correlation.

TABLE 8

### Hourly electricity prices

| | Economic dispatch hourly prices ($/MWh) | PJM day-ahead hourly prices ($/MWh) |
|---|---|---|
| Mean | 25.8 | 26.1 |
| Standard deviation | 11.8 | 14.5 |
| 50th percentile | 24.1 | 23.4 |
| Correlation | 0.88 | |

The capacity demand charge and volumetric adders are included in the RTP tariff in the same way as in the CPP, TOU and flat tariffs.

[26] In practice, the utility may not accurately predict the 10 hottest days of the year, but for modeling purposes we assume perfect foresight. Furthermore, in practice, utilities choose CPP days when they expect very high demand from an upcoming hot day. Thus, it is likely that many of the days we chose would also have been chosen by the utility.
[27] See https://www.comed.com/SiteCollectionDocuments/MyAccount/MyBillUsage/CurrentRates/05_RateBESH.pdf.
[28] Following ComEd's methodology for passing through real-time prices to customers, these need to be adjusted by the base uncollectible cost factor (SBUF), the incremental supply uncollectible cost factor (ISUF) and the distribution loss factor (DLF) (see Rate BESH Tariff Filing). In 2016, ISUF was 0.99, SBUF 1.02 and DLF 0.0636.

## 3.5 Cost-reflective rate — fixed monthly charge (CRRf) tariff

ComEd's tariffs all present a volumetric rate for distribution cost recovery, yet these types of tariffs do not reflect the structure of the costs associated with delivering electricity to customers. Thus, we develop a cost-reflective rate that assigns costs to the tariff based on cost causation from information pulled from the 2015 ComEd ECOSS.

The first part of the tariff is a fixed charge, to collect costs that do not vary over time or demand — for example, customer-specific charges due to metering, billing and so on. From the cost of service study, we use the costs associated with what is described as customer-related and metering services, and identify the fixed charge to be $15.24.

The second part of the tariff is a distribution system demand charge, to collect costs that vary with coincident peak demand. To estimate the size of this charge, we run US-RNM as described in the previous section; this produces the long-run marginal cost, which is defined as the slope of the curve ($40/kW-year) in Figure 4. We apply this charge as a coincident critical peak demand charge on the top 10 peak hours of the year; the resulting distribution demand charge is thus $4/kW applied 10 hours per year (see Figure A1 in Appendix A for the days of the year with demand charges). Similar to the CPP tariff scenario, we assume that the utility will announce that the following day will be a high-priced day, such that the customer is able to respond. Although the utility may not know a priori which 10 hours will be the hottest in the year, our modeling assumes perfect foresight and that the utility was able to predict accurately the hottest hours of the year and signal this information to the customer.

The supply portion of the cost-reflective tariff consists of an hourly rate as defined by 2016 ED-modeled real-time prices. The PJM generation capacity demand charge is applied in the same way as the other tariffs.

Finally, we calculate all residual required distribution network revenues from the ComEd cost of service study after applying the fixed charge and distribution demand charge to customer demands. In a truly cost-reflective tariff, the residual revenues should be recovered through a fixed monthly charge, such as to not distort incentives. Thus, our cost-reflective tariff divides the residual revenues by the number of customers to attain the residual monthly charge.

## 3.6 Cost-reflective rate — volumetric charge (CRRv) tariff

As an alternative to the cost-reflective tariff described above, we create a slightly different tariff, changing how the utility recovers the residual revenues. Instead of applying the residual revenues as a fixed charge, we calculate a flat volumetric distribution charge by dividing the residual revenues by total kWhs demanded over the course of the year. Thus, the tariff will have five parts: a fixed charge, a volumetric rate that doesn't vary over time, a distribution network capacity-coincident critical peak demand charge, a generation capacity demand charge, and a real-time price.

# 4. Results

The results of our tariff scenario runs for each of our 45 representative customers include information on both adoption of DERs (including the size of the DER) as well as load shape. Below, we summarize some of our main findings related to adoption of DER, how these vary across clusters, and how the underlying tariff and level of DER technology costs affect these adoption rates.

## 4.1 Effect on rooftop PV adoption

Our model demonstrates that there are two major economic drivers for investment in rooftop PV: total upfront cost and the payment per kWh of PV generation. The results show that under current rooftop PV investment costs (including the 30% investment tax credit), no clusters will invest in PV, regardless of the underlying electricity tariff. This is likely due to a combination of factors, including low solar irradiation in Chicago, but also because the high upfront costs and low volumetric supply prices that are prevalent in the ComEd service territory reduce the incentive to invest under NEM (where the customer implicitly gets paid the volumetric price in the relevant hour for the PV-produced electricity). To that end, we run some sensitivity analyses to identify the effect of the two economic incentives: volumetric prices and upfront capital costs.

Regarding the volumetric rates, we run the simulation under the observed flat rates (which have a 3-cent markup on the volumetric portion) and find greater levels of adoption. Intuitively, in locations where volumetric prices are higher or in rates where more costs are recovered through the volumetric rather than the fixed portion of the rate, there would be a greater incentive to invest in PV.

We next test how the adoption rates differ under lower PV investment costs. Because we do not find adoption at current levels of PV system costs (which are net of a 30% federal subsidy on all-in costs), we run a number of simulations reducing the all-in cost of PV capacity, from 70%

(which is BAU) to 40% of current costs. These alternative cost scenarios reflect the fact that PV costs have been decreasing significantly over time and will likely continue to drop over time.

Table 9 shows the percentage of current upfront costs necessary to achieve PV investments, separated out by tariff. We also show the resulting adoption rate under the lower PV costs, and the average size of the PV system adopted (conditional on adoption).

TABLE 9

### Fraction of current PV costs required to achieve PV investment

| Rate | Alternative cost scenario (%)* | Average size of PV (kW)† | Adoption rate (% of households) |
|---|---|---|---|
| Flat | 50 | 1.9 | 85 |
| TOU | 50 | 4.2 | 100 |
| CPP | 50 | 0.3 | 28 |
| RTP | 50 | 4.2 | 100 |
| CRRv | 40 | 1.4 | 73 |
| CRRf | N/A | N/A | 0 |

* Alternative cost scenario represents the percentage of non-subsidized PV costs required for financial incentive to invest.

† Conditional on adoption.

These results demonstrate that, in order to achieve PV adoption, different tariffs will require different reductions in cost. Given the lower bundled volumetric rates under CRRf compared to RTP, the reductions need to be larger (total costs would need to be 40% of current all-in costs) in order to achieve PV adoption. With CRRf tariffs, which include a fixed charge used to recover residual costs, the bundled volumetric rate is even lower than under CRRv; thus, we find that PV costs would need to be even less than 40% of existing all-in costs in order to achieve PV adoption.[29] Furthermore, we find different size of investments across the different tariffs, with TOU and RTP leading to adoption of larger PV systems.

This demonstrates that tariffs do indeed affect PV adoption incentives, and that there is an interplay with the investment cost of the PV system, such that, under certain tariffs, the cost of PV would not have to come down as much in order to achieve greater adoption. We find that the

[29] We do not run the analysis on costs below 40% of all-in costs.

two time-variant tariffs with higher volumetric prices (TOU and RTP) lead to the greatest level of adoption and that customers also invest in larger PV systems. The reason for this is that volumetric rates are higher during the hours of the day when the PV systems generate electricity.

## 4.2 Effect on battery adoption

We find that no clusters invest in batteries under any tariff design scenario, even at 10% of current capital costs. This is likely due to the fact that the price differences across time-periods in the volumetric rate are not large enough to make it profitable for the customer to invest in a battery in order to arbitrage.[30]

To further explore the decision to invest in batteries, we conduct three sensitivity analyses. First, we adjust the upfront capital cost. We find that when the capital cost drops to 5% of current costs, 8% of customers will adopt under the TOU rates as described in Table 7. Our second sensitivity analysis is to make the TOU rate more extreme, whereby the super-peak charge recovers twice the system costs of the original TOU rate; we label this TOU2. The new TOU prices are listed in Table 10.

[30] Importantly, our demand charge rates are not modeled in the same way as most commonly imposed demand charges, which charge customers for their monthly peak demand, either coincident or non-coincident with pre-set hours of the day. Instead, our demand charges are backward looking, which means that they are imposed only on a few hours of the year. It's possible that with a TOU demand charge, which charges customers for their monthly maximum peak demand during peak hours of the day, the arbitrage signal would be high enough to make battery investment profitable. However, given modeling restrictions, we do not model this sort of demand charge.

TABLE 10

### TOU2 supply prices

| Period | Price, summer (¢/kWh) | Price, winter (¢/kWh) |
|---|---|---|
| Super-peak price | 7.92 | 7.03 |
| Shoulder price | 3.33 | 3.08 |
| Off-peak price | 1.68 | 1.98 |

As can be seen in Table 10, the price is 1.3–1.5 cents/kWh higher during the super-peak period by (depending on the season) relative to our previously defined TOU rate, and lower by 0.21–0.42 cents/kWh in the off-peak hours (depending on season and time of day). Under this tariff, with a greater peak to off-peak ratio, we find that adoption of batteries increases to 44% under the 5% upfront battery cost scenario.

Finally, we conduct a third sensitivity analysis, related to removing NEM. Combined with a flat volumetric rate, NEM allows the consumer to use the grid as a battery and removes the arbitrage potential that batteries can provide to the household. Instead of paying customers the hourly retail rate (as in NEM), we instead impose a flat export price, whereby the customers will receive the yearly average ED supply price as an export (2.58 cents/kWh). This reflects real-world situations where NEM has been replaced by an export price that reflects the utility's avoided hourly cost (i.e., the supply cost; see Revesz and Unel 2017 for examples of where this has been implemented). Under the no-NEM scenario, we see battery adoption when the upfront cost is 10% of the current cost, with both TOU and TOU2 rates.

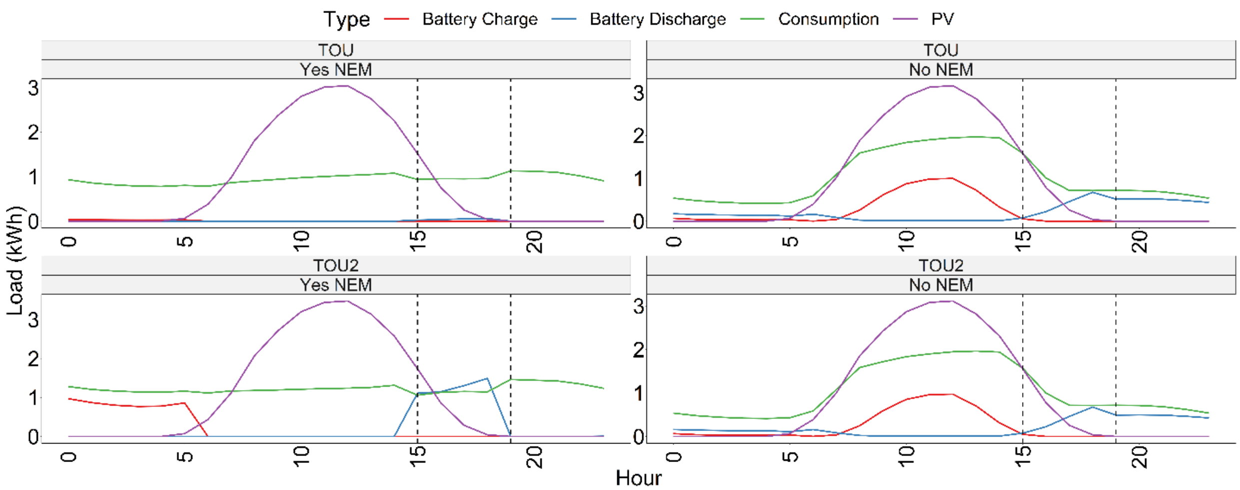
*Table 11*

### Results with no NEM

| Rate | PV cost (%) | Battery cost (%) | PV adoption (%) | Battery adoption (%) | Net load (kWh) | PV size (kW) | Battery size (kW) |
|---|---|---|---|---|---|---|---|
| TOU | 10 | 5 | 100 | 100 | 1,154 | 5.2 | 2.3 |
| TOU | 10 | 10 | 100 | 99 | 1,887 | 5.2 | 0.8 |
| TOU | 50 | 50 | 69.5 | 0 | 5,300 | 1 | 0 |
| TOU2 | 10 | 5 | 100 | 100 | 1,154 | 5.2 | 2.3 |
| TOU2 | 10 | 10 | 100 | 98.8 | 1,937 | 5.2 | 0.8 |
| TOU2 | 50 | 50 | 69.4 | 0 | 5,371 | 0.9 | 0 |

FIGURE 5

## Loads under NEM and no-NEM scenarios




The changes to loads, PV generation and battery charging under NEM and no-NEM scenarios, and at less than 5% of upfront battery costs, are also presented graphically in Figure 5. The consumption line shows total thermal and non-thermal loads demanded by the household. The figure shows that with NEM, batteries are adopted only under the TOU2 rate, and they are charged only during off-peak hours (12–6 a.m.). When we remove NEM, battery charging takes place during solar hours, as customers use the excess generation from their PV systems rather than exporting to the grid.

Thus, we provide evidence that the incentive to invest in batteries increases under significantly lower upfront costs, more extreme price ratios in TOU or a lower flat price on exports to the grid. These findings indicate that the incentive to invest in batteries is likely to be strengthened over time. For example, battery costs have come down significantly over the past decade and are expected to continue to do so (Henze 2019). Furthermore, utilities may begin to implement both TOU rates with higher ratios (given the observed higher reductions in peak demand under higher price ratios; see Lessem et al. 2017), as well as actively identifying alternatives to NEM (see, for example, Revesz and Unel 2017 for a discussion of the regulatory trends moving toward NEM alternatives). Thus, these trends highlight that battery adoption may become more profitable over time.

## 4.3 Effect on electric heat pump adoption

The model chooses between investing in an electric heat pump and a gas heater given the underlying costs and tariffs. We find that the gas heater is chosen almost always, except under the CRRf tariff. This is because the volumetric rate is quite low under this tariff, making the investment in electric heating much more profitable for the consumer.

However, we find that almost 20% of households do not invest in an electric heat pump, even under CRRf. Those who do so are larger households with an average yearly load and maximum demands that are twice as large as those of customers who choose not to invest. This is intuitive, as large customers have a greater incentive to offset a larger heating need by choosing a cheaper fuel-cost option, and the upfront capital cost of a heat pump makes up a relatively smaller share of total costs.

It is important to point out that although nobody invests in PV under CRRf, the tariff does provide the incentive to invest in another clean technology — namely, heat pumps. This is an important finding, since the building sector contributes significantly to carbon dioxide emissions in the US (almost 9% of the US total greenhouse gas emissions in 2015; Leung 2018), and thus electrifying this fossil-fuel-based heating system may help to provide large environmental benefits once the US electricity mix becomes cleaner.

## 4.4 Effects on natural gas distributed generator adoption

We do not see adoption of natural gas distributed generators under any tariff. Part of this is due to our assumption that the customer will not receive payments for exports to the grid; rather, the benefit of this investment comes from avoiding using grid electricity during periods with high demand charges and/or volumetric rates. However, even for cost-reflective tariffs that have significant demand charges during certain hours of the year, investing in these systems is not profitable due to the high upfront costs of a DG system

Importantly, our simulations do not model other benefits associated with these types of DG investments, such as reliability benefits and black start capability. Although this is generally the reason these systems are adopted in the residential sector, our model is unable to capture these alternative benefits, and thus likely underestimates the incentive of households to invest in this technology.

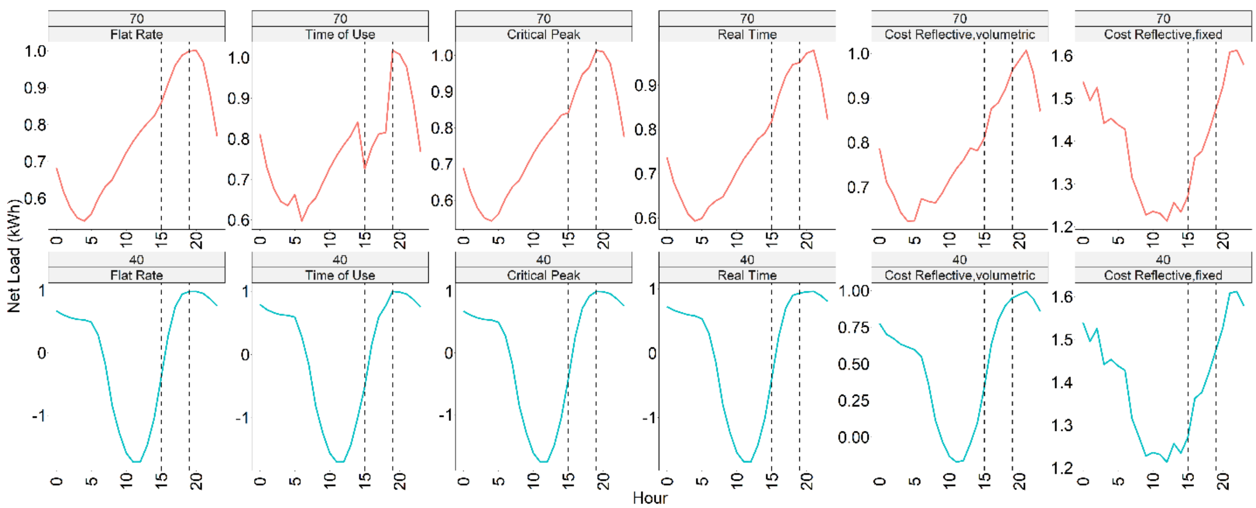
## 4.5 Combined effect on distribution system long-run costs

Moving from a flat tariff to a more time-variant, cost-reflective tariff causes two different effects: a consumption shift, and an incentive to invest in DERs. With respect to the consumption pattern shift, customers may change their demand in response to the new, underlying prices under a new tariff. In a scenario where nobody invests in PV or batteries, the overall effect is exclusively from this consumption.

Figure 6 shows how average yearly loads change under different tariffs and PV cost assumptions. The top row shows the average yearly loads under BAU costs of PV, which includes the 30% investment tax credit (thus, it is listed as 70% cost). The bottom row shows the average yearly loads under a scenario in which the upfront cost of PV is lower, specifically at 40%.

FIGURE 6

**Average yearly loads under different tariffs and PV cost assumptions**




Note: the top row shows the loads under BAU PV cost scenarios (70% of current investment cost with a federal tax credit); the bottom row shows the results under a lower-cost scenario (specifically, 40% of current non-subsidized PV costs).

These figures show graphically the impact of the interaction of PV investment with the tariff. In the BAU PV cost-assumption scenario — in which we find that, given high upfront costs, nobody invests in PV, batteries or DG[31] — tariffs that incorporate some form of peak-time pricing (i.e., TOU and CPP) lead to reductions in demand during the set peak hours.

[31] Investments in heat pumps are made under CRRf, but because this investment is not optional, we assume that the no-investment case includes the ability to have a heat pump.

When customers begin to invest in PV because of reductions in cost (bottom panel of Figure 6), we see that net demand bottoms out during sunny hours.

Both of these effects — reductions in peak demand due to peak prices and reductions in net demand due to PV exports — will have an impact on distribution system network costs. However, the ability of these shifts in consumption to affect distribution system costs depends on to what extent that shift reduces maximum coincident peak demands. Any reduction in *maximum coincident peak demand* (as defined by the consumption during the 10 hours of the year with the highest peak demand) between the flat tariff and all other tariff scenarios is the benefit to the distribution system of moving toward a more cost-reflective tariff. Table 12 below details the (cluster-size weighted) average change in coincident max demands when moving from a flat tariff to all other tariffs. We then multiply the change in maximum coincident peak demand by the long-run marginal cost and by the number of households in our sample in order to calculate the avoided cost on the distribution system. [32] We also present this avoided cost in terms of $/kWh avoided in the final column of the table; to put this into context, consumption from single-family homes in the ComEd service territory in 2016 cost the grid $0.035/kWh[33].

[32] This implies an assumption that all households face the same rate.
[33] To reach this $/kWh cost, we divide the total 2016 embedded cost of service for single-family homes by the total kWhs they consumed in 2016.

TABLE 12

### Effect on distribution system from moving from a flat tariff

| Tariff | Average reduction in coincident maximum demands (kW) relative to flat tariff | Avoided cost on the distribution system from consumption pattern changes ($) | $/kWh avoided |
|---|---|---|---|
| TOU | 0.21 | 366,000 | 0.001 |
| CPP | 0.23 | 400,000 | 0.001 |
| RTP | 0.11 | 191,000 | 0.000 |
| CRRv | 1.53 | 2,709,000 | 0.009 |
| CRRf | 1.55 | 2,741,000 | 0.010 |

As can be seen in Table 12, all time-variant tariffs produce reductions in average maximum coincident peak demands relative to a flat tariff, even without PV investment. The largest benefits in terms of shifted consumption come from implementing the cost-reflective tariffs, as these are the ones that provide the largest incentives for households to reduce their coincident demand, given the imposition of a distribution critical peak demand charge.

Investment in DERs will also affect coincident maximum demands, although under current DER cost assumptions we do not see investments (other than in heat pumps under CRRf). However, when DER costs are much lower, investments are made. Thus, in Table 13 we detail the change in average coincident maximum demands, by tariff, between a BAU cost scenario and a 40% cost scenario. In this 40% cost scenario, investments in PV are made by almost all clusters (see Appendix C), except in the case of CRRv (where only 73% of clusters invest) and CRRf (where no clusters invest). We then calculate the effect on distribution system costs in the same way as in Table 12. As can be seen in this table, the $/kWh avoided can be up to seven times larger for certain tariffs than when there is no investment in PV (as shown in Table 12).

TABLE 13

**Effect on distribution system from investing in PV under 40% all-in PV cost**

| Tariff | Average reduction in coincident maximum demands (kW) from investment | Avoided costs on the distribution system from PV investment | Total avoided costs ($) | $/kWh avoided from load shifting and pv investment |
|---|---|---|---|---|
| Flat rate | 0.91 | $1,608,000 | 1,608,000 | 0.005 |
| TOU | 0.88 | $1,561,000 | 1,927,000 | 0.006 |
| CPP | 0.92 | $1,622,000 | 2,022,000 | 0.007 |
| RTP | 0.88 | $1,553,000 | 1,744,000 | 0.006 |
| CRRv | 0.34 | $600,000 | 3,309,000 | 0.012 |
| CRRf | — | — | 2,741,000 | 0.005 |

These reductions in coincident peak demand compare outcomes with and without DER investment under the same tariff scenario. Thus, the total effect on avoided distribution system costs from investing in DERs *and* moving away from a flat tariff is the sum of the results from the second columns in Tables 12 and 13.

Most tariffs produce similar additional avoided distribution system costs from DER investment, although CPP results in the largest avoided costs. The smallest additional effect from DER investment comes from the cost-reflective tariffs, due to the fact that there is less investment in CRRv (and none in CRRf). The overall benefits are largest under the most cost-reflective tariffs.

The benefits are large for a region comprising three zip codes, but it is important to note — as can be seen by comparing Tables 12 and 13 — that the largest benefits in avoided system costs are achieved by moving from a flat rate to a cost-reflective tariff, rather than from DER investment. Furthermore, we do not consider any increased system costs due to potential distribution capacity investments needed to support the presence of new rooftop PV; depending on the concentration of PV systems in a specific area, these investments may be quite large. Thus, these avoided cost estimates indicate only some of the benefits investments in PV could provide, without quantifying any of the potential associated distribution system cost increases. Nevertheless, unless these unquantified distribution system costs of PV integration are large, these reductions in avoided system costs could ultimately result in decreased electricity tariffs in the long run, as revenue requirements drop as a result of reduced investment needs.

# 5. Discussion and conclusion

In this paper, we use an economics-engineering simulation model to analyze the effects of more granular and time-variant residential electricity tariffs on changes in electricity demand and investment in DERs. We analyze tariffs from the least to the most granular in terms of time variation, including TOU, CPP and RTP rates, as well as creating two cost-reflective tariffs based on ComEd's embedded cost of service studies.

We run these six different tariff design scenarios for each of our 45 representative customers, in addition to varying our assumptions on DER investment costs. First, we assume current all-in costs for DERs, including the 30% US investment tax credit on rooftop PV and battery storage.

Under the BAU PV cost scenario, we find that investments in rooftop PV, batteries and natural gas distributed generators are not privately optimal. However, we quantify an important reduction in peak demands through moving away from a flat tariff and towards more time-variant, cost-reflective tariffs, thereby significantly reducing long-run distribution costs. We find that the largest gain in avoided distribution system costs is achieved with cost-reflective tariffs, which include a distribution critical peak demand charge that is applied only on the highest cost hours of the year. We also find that the cost-reflective tariff with the lowest volumetric rate results in the adoption of heat pumps. This result illustrates that cost-reflective electricity tariffs can be an important driver of beneficial electrification in the building sector and thereby contribute to reductions in carbon dioxide emissions — especially as the US electricity mix becomes cleaner over time.

When considering lower costs for DER technologies, we find that PV costs would have to be approximately 50% of current investment costs (thus, a 20% reduction after the investment tax credit) to achieve investments across all tariffs with the exception of the cost-reflective tariffs, which require even greater reductions in PV costs to make the investment profitable to households. This is due to the fact that both of these tariffs recover distribution costs in a non-volumetric manner, thereby reducing the volumetric rate and the potential revenues from PV exports to the grid. We find that TOU and RTP tariffs require the lowest reduction in costs (50%) to ensure 100% investment in rooftop PV across all our representative customers.

With respect to battery investments, we find that the incentive to invest in this technology is increased by massive reductions in battery upfront costs (to 5% or 10% the current costs), the removal of NEM, and a steeper price difference during peak and off-peak hours.

A limitation of this analysis is that it takes electricity use and consumption preferences in the Chicago area in 2016 as a point of departure. The electricity system of the future will, through electrification of the heating and transport sector, need to accommodate new electricity services and end uses not considered here, such as electric vehicle (EV) charging. Another related dimension to consider in future research is the decoupling of electricity consumption and energy services that could be made available by battery and thermal storage in vehicles and buildings.

Our findings indicate that more granular time-variant rates and cost-reflective rates can help reduce coincident peak demand and associated distribution system costs, but that they are unlikely to lead to widespread DER deployment given current DER technology costs and the electricity and gas prices considered here for our Chicago study area.[34] Our findings therefore also highlight the need to consider region-specific costs and conditions when analyzing the effects of electricity tariff reform, as well as future energy services such as widespread EV charging.

[34] As electricity prices increase, the financial case for investing in PV also grows. This implies that in states such as California and Hawaii, where the retail rate is significantly high, the likelihood of investing is much larger; this has played out in California, where with up to almost 45% of all homes have rooftop PV (Gavop 2019).

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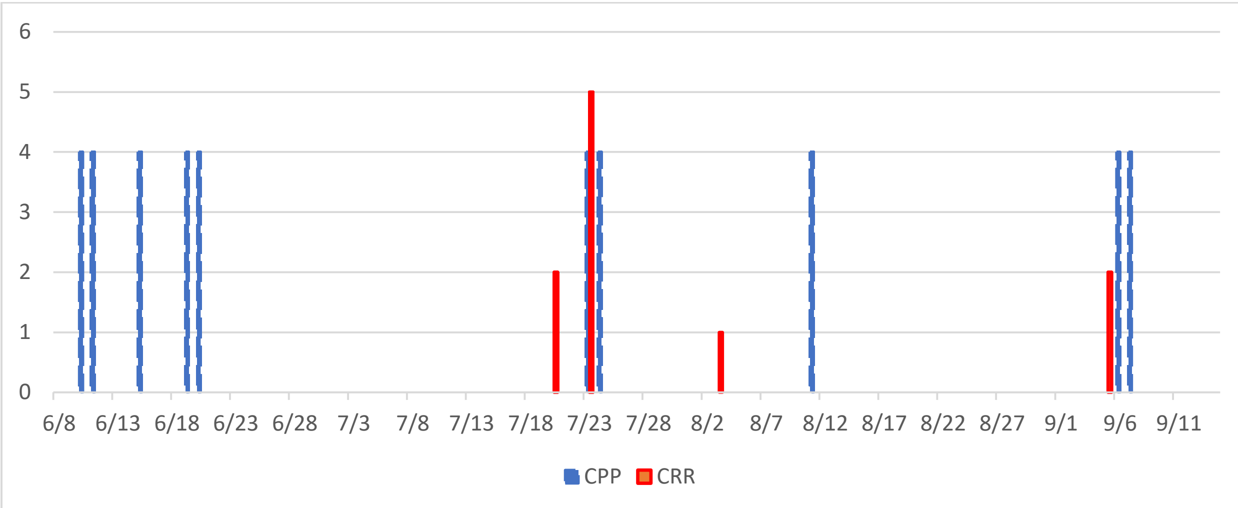
# Appendix A: Tariff scenarios

| Tariff | Fixed charge ($/month) | Volumetric charges ($/kWh) | Demand charge ($/kW) | Peak periods |
|---|---|---|---|---|
| Flat rate | 14.89 | 0.075 | 4.21 (Jan–May)<br>3.12 (Jun–Dec) | N/A |
| TOU | 14.89 | 0.07–0.11 (depending on time of day and season) | 4.21 (Jan–May)<br>3.12 (Jun–Dec) | Super-peak: 3–7 p.m.<br>Off-peak:12–6 a.m.<br>Shoulder: 6 a.m.–3 p.m., 7 p.m.–12 a.m. |
| CPP | 14.89 | 0.072–0.287 (depending on time of day) | 4.21 (Jan–May)<br>3.12 (Jun–Dec) | 3–7 p.m. on top 10 hottest days of the year |
| RTP | 15.28 | Real-time price for supply | 4.21 (Jan–May)<br>3.12 (Jun–Dec) | N/A |
| CRRf | 33.18 | Real-time price for supply | $4/kW applied on top 10 peak hours of the year;<br>4.21 (Jan–May)<br>3.12 (Jun–Dec) | Variable peak hours of year/month |
| CRRv | 15.24 | Real-time price for supply + $0.024/kWh | $4/kW applied on top 10 peak hours of the year;<br>4.21 (Jan–May)<br>3.12 (Jun–Dec) | Variable peak hours of year/month |

FIGURE A1

**Number of high-priced hours per day across the year (CPP and CRR)**



# Appendix B: Clusters

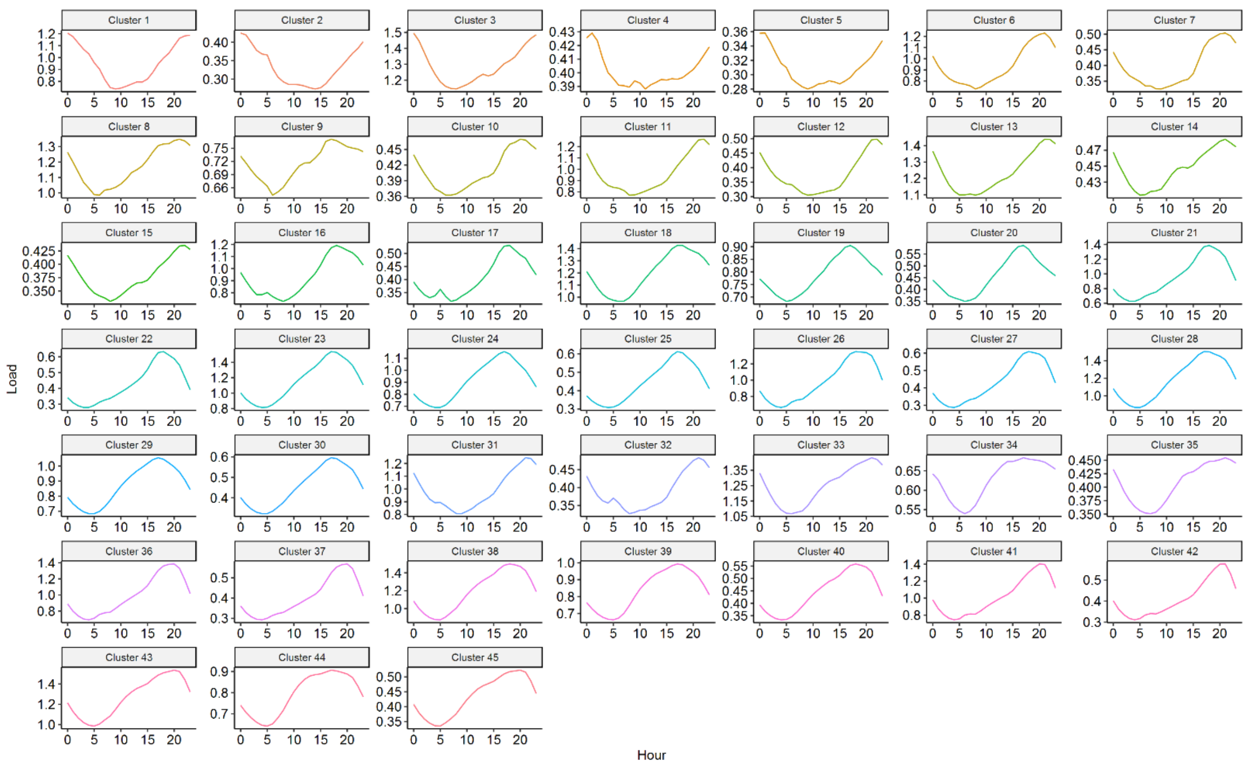
| Cluster description | No. of households |
|---|---|
| Summer off-peak, winter off-peak, cluster 1 | 51 |
| Summer off-peak, winter off-peak, cluster 2 | 81 |
| Summer off-peak, winter off-peak, cluster 3 | 42 |
| Summer off-peak, winter off-peak, cluster 4 | 60 |
| Summer off-peak, winter off-peak, cluster 5 | 38 |
| Summer off-peak, winter peak, cluster 1 | 95 |
| Summer off-peak, winter peak, cluster 2 | 101 |
| Summer off-peak, winter peak, cluster 3 | 50 |
| Summer off-peak, winter peak, cluster 4 | 63 |
| Summer off-peak, winter peak, cluster 5 | 27 |
| Summer off-peak, winter shoulder, cluster 1 | 320 |
| Summer off-peak, winter shoulder, cluster 2 | 301 |
| Summer off-peak, winter shoulder, cluster 3 | 192 |
| Summer off-peak, winter shoulder, cluster 4 | 167 |
| Summer off-peak, winter shoulder, cluster 5 | 82 |
| Summer peak, winter off-peak, cluster 1 | 243 |
| Summer peak, winter off-peak, cluster 2 | 127 |
| Summer peak, winter off-peak, cluster 3 | 186 |
| Summer peak, winter off-peak, cluster 4 | 101 |
| Summer peak, winter off-peak, cluster 5 | 53 |
| Summer peak, winter peak, cluster 1 | 2976 |
| Summer peak, winter peak, cluster 2 | 2038 |
| Summer peak, winter peak, cluster 3 | 1844 |
| Summer peak, winter peak, cluster 4 | 1218 |
| Summer peak, winter peak, cluster 5 | 535 |
| Summer peak, winter shoulder, cluster 1 | 4655 |
| Summer peak, winter shoulder, cluster 2 | 2573 |
| Summer peak, winter shoulder, cluster 3 | 2486 |
| Summer peak, winter shoulder, cluster 4 | 1528 |
| Summer peak, winter shoulder, cluster 5 | 611 |
| Summer shoulder, winter off-peak, cluster 1 | 266 |
| Summer shoulder, winter off-peak, cluster 2 | 181 |
| Summer shoulder, winter off-peak, cluster 3 | 198 |
| Summer shoulder, winter off-peak, cluster 4 | 131 |
| Summer shoulder, winter off-peak, cluster 5 | 86 |
| Summer shoulder, winter peak, cluster 1 | 2262 |

| | |
|---|---|
| Summer shoulder, winter peak, cluster 2 | 1578 |
| Summer shoulder, winter peak, cluster 3 | 1180 |
| Summer shoulder, winter peak, cluster 4 | 843 |
| Summer shoulder, winter peak, cluster 5 | 343 |
| Summer shoulder, winter shoulder, cluster 1 | 5902 |
| Summer shoulder, winter shoulder, cluster 2 | 3615 |
| Summer shoulder, winter shoulder, cluster 3 | 2452 |
| Summer shoulder, winter shoulder, cluster 4 | 1563 |
| Summer shoulder winter shoulder cluster 5 | 741 |

Figure B1 presents the yearly loads for all 45 clusters, demonstrating variability in timing of the peak load, as well as magnitude of total loads.

FIGURE B1

## Yearly average load shape by cluster



# Appendix C: Investments in DERs by cost of PV

| Tariff | Share of current CAPEX | Mean energy bill | PV adoption rate | Mean PV size (kW) | Mean total net load | Heat pump adoption rate | Mean heat pump size (kW) |
|---|---|---|---|---|---|---|---|
| BAU flat rate | 70% | $ 1,028 | 0% | N/A | 6,685 | 0% | N/A |
| | 60% | $ 1,028 | 0% | N/A | 6,685 | 0% | N/A |
| | 50% | $ 795 | 85% | 1.9 | 3,711 | 0% | N/A |
| | 40% | $ 512 | 100% | 4.3 | -53 | 0% | N/A |
| Time of use | 70% | $ 1,095 | 0% | N/A | 6,733 | 0% | N/A |
| | 60% | $ 1,095 | 0% | N/A | 6,733 | 0% | N/A |
| | 50% | $ 513 | 100% | 4.2 | 94 | 0% | N/A |
| | 40% | $ 513 | 100% | 4.2 | 92 | 0% | N/A |
| Critical peak price | 70% | $ 1,016 | 0% | N/A | 6,707 | 0% | N/A |
| | 60% | $ 1,016 | 0% | N/A | 6,707 | 0% | N/A |
| | 50% | $ 975 | 28% | 0.3 | 6,176 | 0% | N/A |
| | 40% | $ 512 | 100% | 4.3 | -110 | 0% | N/A |
| Real-time price | 70% | $ 1,034 | 0% | N/A | 6,721 | 0% | N/A |
| | 60% | $ 1,034 | 0% | N/A | 6,721 | 0% | N/A |
| | 50% | $ 517 | 100% | 4.2 | 183 | 0% | N/A |
| | 40% | $ 517 | 100% | 4.2 | 181 | 0% | N/A |
| Cost-reflective rate — fixed monthly charge | 70% | $ 894 | 0% | N/A | 6,871 | 0% | N/A |
| | 60% | $ 894 | 0% | N/A | 6,871 | 0% | N/A |
| | 50% | $ 894 | 0% | N/A | 6,871 | 0% | N/A |
| | 40% | $ 737 | 73% | 1.6 | 4,370 | 0% | N/A |
| Cost reflective rate — volumetric charge | 70% | $ 798 | 0% | N/A | 12,242 | 83% | 5103 |
| | 60% | $ 798 | 0% | N/A | 12,242 | 83% | 5103 |
| | 50% | $ 798 | 0% | N/A | 12,242 | 83% | 5103 |
| | 40% | $ 798 | 0% | N/A | 12,242 | 83% | 5103 |