Stakeholder Costs and Benefits of Distributed Energy Resources on Distribution Networks

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Abstract

Distributed energy resources (DER), such as rooftop solar and combined heat and power (CHP), create a unique opportunity to reduce transmission and distribution network capacity requirements, decrease electrical losses, and potentially improve reliability, resiliency, and other operating metrics. This dissertation examines how DER benefit different stakeholders in the electric power sector: DER owners, ratepayers, utilities, and society. In Chapter 2, we investigate how increasing commercial CHP system peak penetrations may affect net emissions, the distribution network, and total system energy costs. We find that small commercial CHP, due to low and inconsistent heat loads, can increase emissions relative to the bulk grid. We suggest policy options to encourage CHP operation during times of high heat loads. In Chapter 3, we develop metrics based on existing best utility practices that characterize how much solar can reduce peak demand on distribution network feeders. We conclude that solar can act as a capacity resource, but the size of the resource depends on the geographic region. Energy storage or an allowance for occasional overloading within a transformer's tolerance can increase the capacity resource of solar. Chapter 4 is a value of solar and rate impact study for the Pennsylvania Public Utility Commission (PUC). The Pennsylvania PUC can use it to decide whether the environmental benefits of solar are worth the relatively small rate impact caused by rooftop solar. In Chapter 5, we assess the ability of rooftop solar and storage to reduce peak loads and defer distribution capacity projects in the PECO service territory. We find that targeted placement of solar can increase the total deferral value up to fourfold, but capacity deferral opportunities are rare and large administrative efforts to manage deferral projects, such as markets, are probably not warranted.

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Chapter 1: Overview and Motivation

In the United States, there are a variety of pathways-permutations of electrical grid configurations and generation options-available to generate cleaner power, reduce health damaging emissions, and decrease our carbon footprint. In one pathway, renewable energy is concentrated in resource rich locations; the transmission network is reinforced and expanded to smooth variability and bring power from remote locations to end-use consumption. Another pathway and the focus of this dissertation is the development of high quantities of distributed energy resources (DER) on electrical distribution networks, close to end-use consumption. DER can be any technology on electrical distribution networks that generate power (e.g. solar photovoltaics, combined heat and power, diesel generation) or that manage power (e.g. energy storage, energy efficiency, demand response). DER create a unique opportunity. They bypass the transmission network, reduce the use of the distribution network, lowers electrical losses, and with the right configuration, could improve reliability, resiliency, and other operating metrics. In this dissertation we focus on the benefits and challenges of rooftop solar photovoltaics, combined heat and power owned by small commercial businesses, and energy storage. The dissertation is motivated by challenges today and in the next 5-10 years, and two themes are present throughout. First, distribution networks are complicated and heterogenous and generally, were not designed for DER. Second, many people rely on distribution networks. DER owners, utility shareholders, ratepayers, and society will pay different costs and receive different benefits from any changes to the distribution network.

The Rocky Mountain Institute (RMI) is an organization dedicated to sustainable and profitable energy innovations. It describes a “significant methodological gap” in solar benefit cost analyses due to the inherent complexity and heterogeneity of distribution networks (Rocky Mountain Institute 2013). Distribution networks vary in topology, voltage level, protection system configuration, capacity, and control equipment options, such as tap changing transformers and capacitors. Poorly developed utility feeder models and a dearth of high quality, publicly available models are a fundamental barrier for anybody trying to develop generalized conclusions and strategies for DER on distribution networks. We attempt to overcome this challenge with two data sets: a set of representative distribution networks feeders developed by the Department of Energy's Pacific Northwest National Lab (PNNL), and four distribution networks from Philadelphia's electric utility (PECO).

A lack of data, lack of high quality models, and conflicting motivations have led to dramatically different assessments of the value of DER. For example, literature reviews of the value of solar by the New York State Energy Research & Development Authority (2015) and Rocky Mountain Institute (2013) cover more than an order of magnitude, from $0.03/kWh to $0.35/kWh. While some of this variability is caused by heterogeneity in the US electric grid, some of these value of solar studies suffer from imprecise engineering estimates and the incorrect characterization of wealth transfers as savings or costs. In this dissertation we explore pragmatic methods for valuing combined heat and power, rooftop solar photovoltaics and energy storage.

In Chapter 2, we investigate how increasing commercial CHP peak penetrations[1] may affect net emissions, the distribution network, and total system energy costs. We constructed an integrated planning and operations model that maximizes owner profit through sizing and operation of CHP on a realistic distribution feeder in the Northeast. We find that a greater peak

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[1] Throughout this dissertation, we use energy penetration and peak penetration to describe DER quantities. Energy penetration is the amount of DER energy produced relative to the total energy consumption. We define, peak penetration as the DER system nominal capacity relative to peak load. Generally, we follow the convention that energy penetration is more appropriate for describing DER on the bulk electric grid, while peak penetration is more appropriate when describing DER on distribution network feeders.

penetration of CHP reduces both total system energy costs and network congestion. Commercial buildings often have low and inconsistent heat loads. In the Northeast, power transmitted over transmission networks is relatively clean, and a 5% peak penetration of small commercially owned CHP would increase CO_2 emissions by 2%. Low emission CHP installations can be encouraged with incentives that promote CHP operation only during times of high heat loads. In contrast, natural gas rate discounts, a common incentive for industrial CHP in some states, can encourage CHP operation during low heat loads and thus increase emissions.

In Chapter 3, we examine whether rooftop solar can reliably reduce loading on distribution network feeders and define this load reduction as the Distribution-Effective Load Carrying Capability (D-ELCC). The D-ELCC is a fundamental metric for estimating the value that solar has for reducing load and avoiding capacity investments on distribution networks. Denholm et al. of the National Renewable Energy Lab (NREL) write that "utilities may be reluctant to reduce feeder capacity with PV because of concerns about high loads during periods of low solar output" (2014). Our analysis includes several features designed to quantify the D-ELCC and overcome utility reluctance. First, we use 23 prototypical feeders (the PNNL taxonomy) in 6 locations in the United States, two real PECO feeders, and 19 years of weather data to simulate load and solar profiles. Second, we develop two D-ELCC metrics that are based on utility standards and practices. Our "worst-case D-ELCC" is based on the worst-case loading over all years and solar penetrations. We find the worst-case D-ELCC is above 40% at low penetrations for 19 of the 23 feeders examined. Utility engineers often use statistical weather normalization and transformer aging criteria to plan for capacity, both of which allow a small amount of overloading risk. When these planning criteria are used with solar and transformer aging is fixed at pre-solar levels, we find that the effective capacity of solar is consistently higher than found under worst-case load conditions. We call this the transformer aging D-ELCC. Alternatively, relatively small amounts of energy storage used with solar can achieve high effective capacities without any overloading events. We find that pairing PV with a one hour duration battery rated at 5% of the feeder peak loads could achieve an effective capacity of 50% or more for all feeders when the peak load penetration of solar is at or below 20%. As a point of comparison, we found that New York Feeder R2-12.47-3 at a 20% solar peak penetration of its 1 MW peak, had a worst-case D-ELCC of only 10%, due to cloudy conditions in the region, but had a transformer aging D-ELCC of 56% because some overloading was allowed, and could achieve a 50% D-ELCC without any overloading with 50 kWh of energy storage.

Chapter 4 is a value of solar and rate impact study in for the Pennsylvania Public Utility Commission. Central to the study is a utility financial model that estimates how the average customer ‘all-in-rate’ (i.e. the volumetric rate based on the total revenue requirement and kWh sales of all customer classes), will change for different energy penetrations of solar in the PECO service territory if Pennsylvania continues offering net energy metering (NEM) rates.

We estimate the value of solar (VOS) in the PECO service territory to be \$0.086±0.006/kWh for a 5% penetration of solar rolled out from 2020-2030 with random placement on distribution feeders. This estimate for the VOS is below our estimate of \$0.118/kWh for PECO’s all-in-rate[2] so if Pennsylvania continues with net energy metering, lost revenue will exceed avoided costs and there will likely be a small, 0.9%, increase in rates over a time horizon from 2020-2040. We find that solar’s effect on PECO’s business is small due to recent Pennsylvania policies, such as the Fully Projected Future Test Year and Revenue per Customer decoupling.

In chapter 4, we also estimate avoided T&D capacity expenses assuming that solar is not targeted at overloaded sections of the T&D network. The combination of solar’s slow rollout, the relative infrequency of overloaded networks, and the untargeted placement of solar results in a

[2] The all-in-rate is different than the rate paid for by residential customers. It is the total revenue requirement for all customers divided by the kWh sales for all customers.

low T&D VOS, a small effect on rates, and minimal impact on PECO's business model.

By displacing fossil fuel generation and reducing criteria pollutant emissions, solar avoids health damages and premature loss of life. These environmental benefits of solar are not included in our model because they do not affect rates, but from a societal perspective have a high value in Pennsylvania due to the state's relatively high proportion of coal and natural gas fired power. Perez et al. (2012) estimate the value of solar at $0.05-0.12/kWh in Pennsylvania. This chapter can be used by the Pennsylvania PUC to decide whether these large environmental benefits are worth the small rate impact caused by solar.

In Chapter 5, we assess the ability of rooftop solar and storage to reduce peak loads and defer distribution capacity projects in the PECO service territory. We find that solar may modestly reduce rates and that the value of solar at 5% energy penetration can be increased up to fourfold if solar is targeted at overloaded locations. Targeted placement of solar, a higher effective capacity using energy storage, a 30% hosting capacity and 10% growth-related capex could reduce the rate increase (described in Chapter 4) to 0.4% and generate $55MM of deferral value over the same 20-year time horizon. We conclude that capacity deferral with solar should be included in PECO's planning process but that large administrative efforts to manage deferral projects, such as markets, are probably not warranted.

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Chapter 2: Are high penetrations of commercial cogeneration good for society?[3]

Abstract

Low natural gas prices, market reports and evidence from New York State suggest that the number of commercial combined heat and power (CHP) installations in the United States will increase by 2-9% annually over the next decade. We investigate how increasing commercial CHP penetrations may affect net emissions, the distribution network, and total system energy costs. We constructed an integrated planning and operations model that maximizes owner profit through sizing and operation of CHP on a realistic distribution feeder in New York. We find that a greater penetration of CHP reduces both total system energy costs and network congestion. Commercial buildings often have low and inconsistent heat loads, which can cause low fuel utilization efficiencies, low CHP rates-of-return and diminishing avoided emissions as CHP penetration increases. In the northeast, without policy intervention, a 5% penetration of small commercially owned CHP would increase CO_2 emissions by 2% relative to the bulk power grid. Low emission CHP installations can be encouraged with incentives that promote CHP operation only during times of high heat loads. Time-varying rates, such as time-of-day and seasonal rates, are one option and were shown to reduce customer emissions without reducing profits. In contrast, natural gas rate discounts, a common incentive for industrial CHP in some states, can encourage CHP operation during low heat loads and thus increase emissions.

2.1 Introduction

Combined heat and power (CHP) systems can achieve higher fuel utilization efficiencies

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than conventional power plants. CHP contributes approximately 7% of US generation capacity with 97% of this capacity found in the electrical power and industrial sectors (EIA 2012). Low natural gas prices may encourage more commercial CHP in commercial and institutional settings. Schools, hospitals, nursing homes, laundromats (i.e. a self-service laundry), prisons, swimming pools and other buildings with hot water needs are likely to benefit from commercial CHP (Flin 2010) (U.S. EPA 2014). Already, the majority of CHP sizes in New York are less than 1 MWe (U.S. Department of Energy 2019) (Supporting Material, Figure 2-16) and US market forecasts predict annual growth rates of between 2-9% or about 15-70 GWe over the next five years (Technavio 2015) (Navigant Resarch 2015) (EIA 2016). If these forecasts are accurate, CHP may have a large effect on the environment and on electric distribution grids.

Research on high penetrations of CHP in commercial buildings is limited. There is considerable research examining the economic feasibility and optimal sizing of CHP (King and Morgan 2006) (Siler-Evans, Morgan and Azevedo 2011) (Flores, Brendan and Brouwer 2014), but this work often focuses on universities and hospitals rather than on small commercial buildings such as strip malls. Studying these smaller commercial buildings is important because they tend to have large daytime heat loads only in the winter and low heat loads during other times, but CHP could still be attractive for these customers at low natural gas prices. Variable commercial building heat loads may lead to wasted heat and low fuel utilization efficiencies if the CHP is operated during times of low heat loads (Barbieri, Melino and Morini 2012) (Smith, Mago and Fumo 2013) (Mago, Chamra and Hueffed 2009).

To mitigate the problem of wasted heat, Smith et al. (2013) recommend oversizing water tanks (where space permits) to allow more heat storage and consequent emission reductions. Mago et al. (2009) suggest operating CHP at small offices only during office hours. These authors did not, however, assess the capability of commercial CHP to reduce regional emissions in high penetration scenarios. Lane Clark & Peacock (2014), for example, have shown that industrial cogeneration may produce higher emissions than the bulk grid in Great Britain by 2030. Even though the overall fuel efficiency for heat and power can be high, small CHP have electrical efficiencies as low as 25%, so CHP placed at buildings with low heat loads could produce higher emissions than the bulk power grid. Finally, we are not aware of any research that examines the effect of commercial CHP on the local distribution network. Commercial CHP operation is dependent on building heat loads and will have a unique effect on the network losses, congestion and power flows. We examine stakeholder costs and benefits, emissions, and network effects of high penetrations of commercial CHP. Because the details and emission consequences of how commercial CHP is operated may also be dependent on who owns the CHP, we compare utility and customer ownership.

We have constructed an integrated planning and operations model that maximizes owner profit through sizing and operation of commercial CHP on a realistic distribution feeder in New York. In the following section we describe our model. Customer and utility ownership models are used to explore how the benefits of CHP vary. We then discuss results that show that CHP in commercial buildings reduces electric distribution system costs but that policies aimed at reducing emissions should encourage CHP operation only during times of high heat loads. Finally, time varying rates, such as time-of-day and season rates, are demonstrated as one option for reducing emissions.

2.2 Combined heat and power model

Our model compares the CHP benefits accrued when operated by a utility and by a customer. These ownership models reflect current opposing viewpoints on who should own distributed energy resources (DER). For example, the American Council for an Energy Efficient Economy (ACEEE) has recently reported on the benefits of utility owned CHP (Chittum and Farley 2013) while the New York Reforming Energy Vision (REV) process currently prohibits utility ownership of DER (Opalka and Heidorn 2015).

An overview of the model is shown in Figure 2-1 and details are in the modeling section of the Supplementary Materials. A radial distribution feeder is modeled with hourly time-varying electrical and heat loads; these are derived from the GridLab-D feeder taxonomy (K. P. Schneider, et al. 2008) and the US Department of Energy (DOE) commercial reference building model (DOE Office of Energy Efficiency and Renewable Energy 2016) (EERE 2015) respectively. CHP that are installed at commercial buildings on the feeder can be used to supplement grid power and heat from pre-existing boilers (Supplementary Materials Figure 2-9) and thus avoid energy costs, but at the expense of additional capital and operations & maintenance (O&M) costs. So, the model places CHP in commercial buildings only if the resulting cash flow yields a rate-of-return greater than 10%. The units are sized to maximize the net present value (Supplementary Materials Figure 2-10). Next, the CHP are operated for one year (using observed heat loads and power prices) and the economic, environmental, and network benefits are computed. The primary difference between the owners is that customer owners are subject to retail tariffs and a demand charge. The utility is modeled as an investor owned deregulated utility that buys power on the wholesale market at time-varying locational marginal prices (LMPs), but the model could also be generalized to vertically integrated utilities. Additionally, the utility must offer the customer a power purchase agreement (PPA) to compensate for the opportunity cost foregone by not renting the space the CHP occupies; the utility can afford to do this because CHP reduces the utility's wholesale power purchase costs. We define a PPA similarly to the SolarCity PPA, where the customer earns a fixed rate for each kWh produced by the CHP. All modeling parameters were based on representative values from the northeastern United States (Supplementary Materials, Input Section).

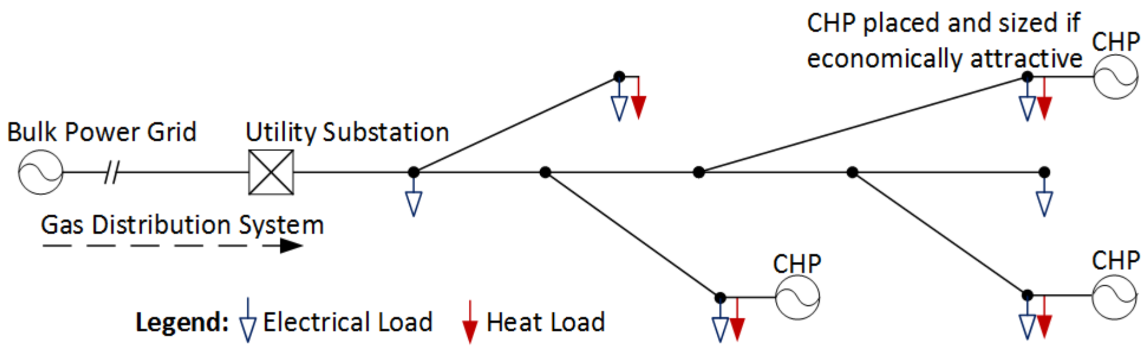

Figure 2-1: A simplified version of the integrated planning and operations model is shown. Economically attractive CHP are placed on a distribution feeder with time varying electrical and heating loads. The CHP are operated by a customer, subject to a flat tariff, and a utility subject to time varying locational marginal prices. The effect of each owner's planning and operating strategy on the CHP economics, environmental benefits and network benefits are recorded and compared. Statistics for the full model are shown in **Table 2-8** of the Supplementary Materials. The full model has over 700 nodes and a lower penetration of CHP than shown here.

Annual metrics for the distribution network effects, relative CHP emissions, and allocation of economic benefits were collected. Distribution network effects were examined through the loading on all the network components such as transformers. We used regional marginal emission factors (MEFs) for the bulk power generation grid to compare the CHP emissions with marginal emissions on the bulk power grid. The MEFs estimate the emissions of the power plants that the CHP are most likely to replace at the time of day and year the CHP is producing power. We used three metrics for the allocation of economic benefits: System savings compare the cost of energy (i.e. LMP) and transmission & distribution (T&D) costs needed to deliver power to the loads against the cost of delivering that power with CHP (including fuel, O&M, and capital expenses). Customer savings depend on the ownership model and describes the final reduction in the customers' bills accounting for tariff structure (e.g. the energy charge and demand charges), capital costs, O&M costs, and power purchase agreement. Utility savings also depend on the ownership model, and compares avoided LMP costs, with loss of revenue through PPA costs, reduced demand charges, capital costs, O&M costs, and lost sales. Details are in Metrics Section of the Supplementary Materials.

2.3 Results

We find that the benefits of commercial CHP depend on the penetration level and how the CHP fleets are operated. Customer ownership leads to a higher CHP penetration, which has benefits for the grid. However, lower CHP penetration and less CHP operation at night and in the summer leads to lower relative CO_2 and NO_x emissions in the utility ownership scenario.

We first discuss in what kinds of buildings CHP is profitable under the two ownership models. In our model, customer CHP owners install more CHP than utility owners on a greater variety of buildings (Table 2-1). The reason for the difference is that customers benefit from reduced demand charges under both ownership models and utilities must share revenue through a PPA.

Table 2-1: Planning Results. Customer CHP owners install more CHP on a greater number and variety of buildings.

Owner	Commercial Buildings																	Penetration	Total (kWe)
		Large Office	Supermarket	Primary School	Secondary School	Strip Mall	Warehouse	Quick Service Rest.	Stand-Alone Retail	Small Office	Hospital	Medium Office	Full Service Rest.	Small Hotel	Midrise Apt	Outpatient	Large Hotel		
Customer	Total [kWe]	513	76	62	600	69	85	0	94	7	425	2	0	30	15	50	250	13.4%	2278
Utility	Total [kWe]	10	25	0	20	0	45	0	0	0	135	0	0	20	0	85	250	3.4%	590

In many cases it is not necessary for the utility to offer a PPA, because the customer's avoided demand charges are greater than the opportunity cost foregone by not renting the space the CHP occupies. Figure 2-22 of the Supplementary Materials shows the range of PPAs that the utility could offer to the host customer of each load.

We next discuss network energy losses, thermal violations (i.e. equipment overloading) and voltage violations (e.g. over voltages) for each ownership model (Supplementary Materials, Metrics Section). Resistive energy losses in the distribution network equipment account for approximately 1% of network demand without CHP and were reduced to 0.9% and 0.8% under utility and customer ownership, respectively. If these losses are monetized using the New York 2014 LMPs, savings would be $6-8/kWe-year, a small amount relative to CHP capital costs

(~2%). The distribution network in this analysis is representative of many Northeastern feeders and is loaded to 60% of its capacity. It is likely that greater value could be obtained from reduced losses through CHP placed on more heavily loaded feeders.

System benefits can also be produced by CHP that defers capital investments needed for the distribution network infrastructure. On networks with more congestion or high load growth, customer ownership would be more effective than utility ownership in deferring capacity investments (Supplementary Materials Figure 2-23). We did not observe thermal violations or voltage violations that were caused or reduced by the commercial CHP.

A potential challenge with using commercial CHP to defer capacity investments for electrical distribution networks is that congestion will be shifted from the electricity network to the gas distribution network. Commercial CHP increased the yearly natural gas consumption for the sum of the buildings by 46% and 400% under the utility and customer ownership scenario, respectively. Thus, high penetration commercial CHP scenarios are likely to require capacity investments in natural gas distribution infrastructure. These new capacity investments, however, may not raise customer natural gas distribution rates since the CHP fleets increased natural gas load factors from 11% to 15% and 36% under customer and utility ownership, respectively.

2.4 Emissions

The relative CO_2, SO_2 and NO_x emissions of each CHP owner compared to the NPCC bulk power grid are shown in Figure 2-2. CHP decreases CO_2 and SO_2 emissions, but NO_x emissions increase. We find that utility owned CHP CO_2 and NO_x emissions are lower than those of customer owned CHP, despite having less installed CHP capacity. There are two reasons that the customer owned fleet of CHP has higher emissions. First, the customer owner is subject to a flat electricity tariff and operates the CHP more than the utility owner does during the night when heat loads are low and excess heat is wasted. This behavior is illustrated in

Figure 2-3 for a supermarket. The utility sees lower LMPs at night, so will turn the CHP off at night and waste less heat. For similar reasons, the customer owner will operate the CHP more during the summer when heat loads are low. Buildings that have consistent heat loads, like hospitals, are less sensitive to time-varying rates and show less variation in emissions between owners.

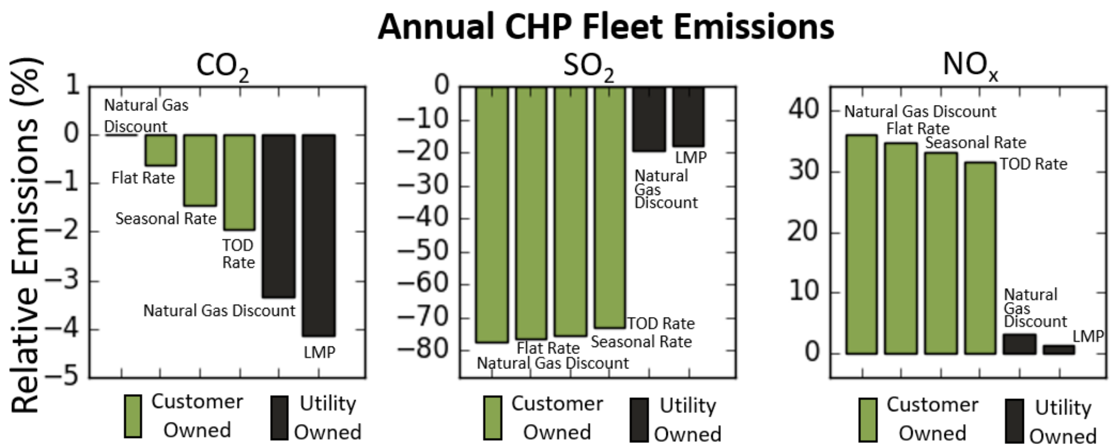

Figure 2-2. Utility and customer CHP emissions relative to the NPCC bulk power grid. Utility owned CHP reduces CO_2 and NO_x emissions more than customer owned CHP despite having less installed CHP capacity. Customer owned CHP emissions are higher because the customer's flat rate incentivizes continuous operation even when heat loads are low, and because the customer fleet contains more CHP with higher emissions. Time-varying rates, shown in the Time-of-Day (TOD) and Seasonal Rate scenario, reduce customer emissions by incentivizing the owner to reduce CHP operation during times of high heat loads. In contrast, a natural gas discount will encourage more operation of the CHP and increases emissions

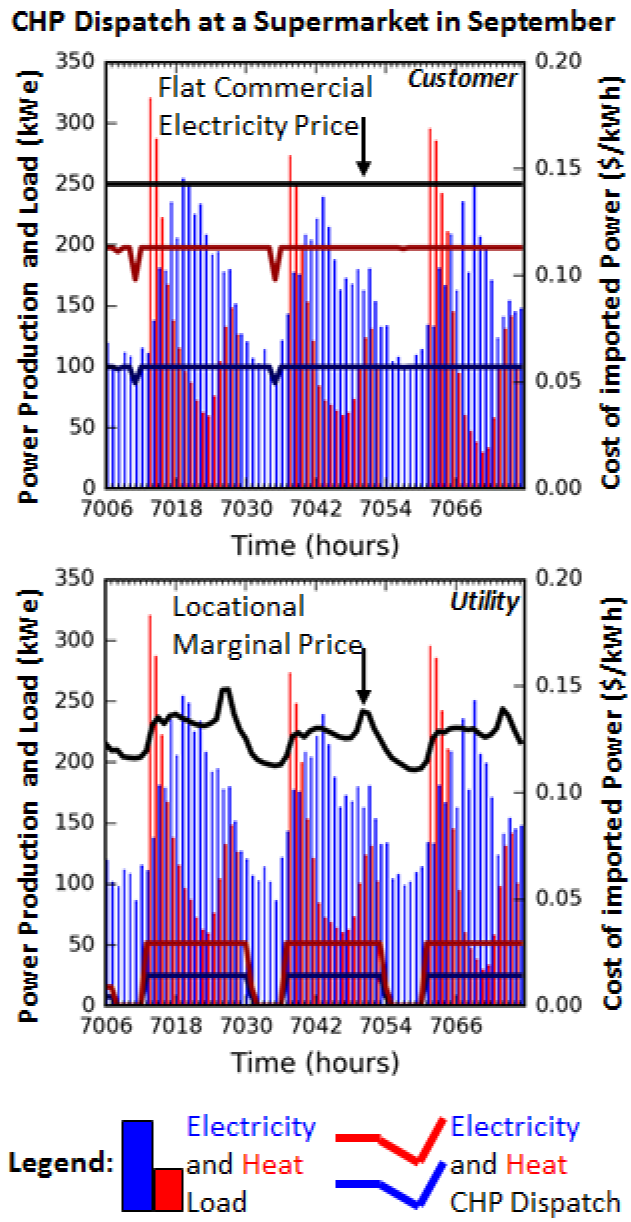

Figure 2-3. Utility and customer CHP dispatch. A supermarket has large heat loads in the day and very low heat loads during the night. The customer owner will continue to operate the CHP at night, but the utility which sees lower LMPs at night, will turn the CHP off. This results in lower overall emissions from the utility. Generally, dispatch is very sensitive to the heat load and price. Because time-varying rates tend to be small when loads are small, the utility dispatches CHP in a manner that follows the heat load more often.

The second reason that customer CHP ownership produces higher relative emissions is that the customer owned fleet has both larger and more CHP at buildings with higher relative emissions. Large offices with CHP produce more emissions than if powered from the bulk power grid (Figure 2-4), and more commercial CHP capacity is profitable at large offices in the customer ownership scenario (Table 2-1). Taken together, this suggests that higher penetrations of commercial CHP may yield higher relative emissions as CHP is placed at more buildings with variable heat loads. We examine this possiblity further in the sensitivity analysis.

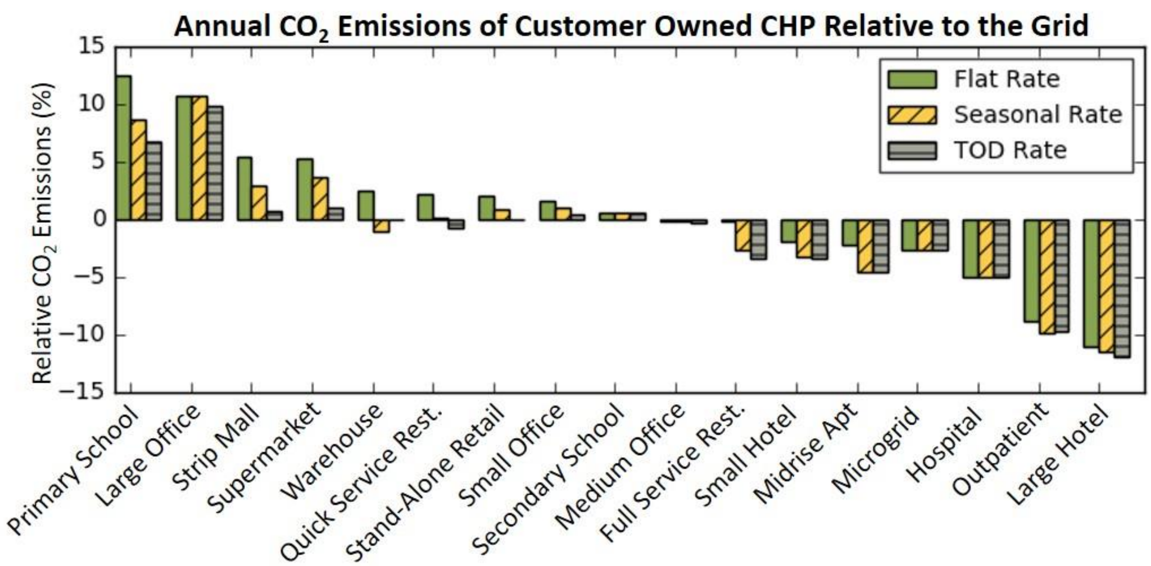

Figure 2-4. Customer owned CHP CO_2 emissions for representative buildings. Seasonal and Time-of-day (TOD) rates reduce customer CO_2 emissions. CO2, SO_2 and NO_x building level emissions are shown for the full fleet in the Supplementary Materials, **Figure 2-24**. The microgrid is composed of one warehouse and one secondary school.

A more general way to assess the potential of CHP to reduce emissions is by directly comparing marginal emission factors and CHP emissions (Supplementary Materials Figure 2-19, where marginal emission factors are shown for the NPCC reliability region in the summer, winter, and shoulder months). CHP emissions are also shown, but have a range that depends on how much boiler heating is avoided. Commercial CHP, for example, can reduce CO_2 emissions if heat is not wasted. SO_2 reductions are certain, because natural gas contains very little sulphur. NO_x emissions depend greatly on both the CHP and boiler emission technology.

In our analysis, we assume a best-case scenario for CHP with low NO_x CHP operation and boilers that do not control NO_x emissions. Despite this assumption, NO_x emissions from uncontrolled boilers are still about ¼ the magnitude of low-NO_x CHP. Because boiler NO_x emissions are relatively low, heat generated from CHP is less effective at reducing NO_x emissions (Figure 2-2).

Figure 2-19 of the Supplementary Materials can be used to estimate the ability of CHP to reduce emissions in locations other than New York. Regions with high percentages of coal powered generation, such as MRO, will benefit from high penetrations of commercial CHP.

2.5 Potential emission reduction policies

As previously discussed, CHP is profitable for some commercial buildings with variable heat loads; in such installations some emissions can increase. Emission controls placed on commercial CHP and boilers would have a large effect on the relative NO_x emissons. Selective Catalytic Reduction (SCR) can reduce CHP NO_x emissions by 95% (EPA 2015) and would ensure NO_x reductions similar to that of SO_2 for commercial CHP. However, SCR would add about \$150-\$700/kWe to the CHP capital cost (approximately 6-27%, respectively) (EPA 2015). On the other hand, improved emission controls can reduce heating system boiler emissions by approximately 70% (EPA 1998), but would significantly reduce the ability of commercial CHP to avoid NOx emissions. We find it is unlikely that commercial CHP owners would install these emission controls because yearly emissions do not qualify most buildings for EPA regulation (e.g. as a ‘major source’ of emissions).

We examine the possibility of using time-of-day rates and seasonal rates to reduce CHP emissions. We constructed hypothetic rates centered on the NYSEG commercial customer rate and designed the rates to discourage CHP operation during times of low heat loads. A time-of-day tariff of \$0.121/kWh during the night and \$0.165 during the day and a seasonal summer rate of \$0.128/kWh and a winter rate of \$0.158/kWh were used. Figure 2-2 and Figure 2-4 show that emission reductions are achieved for the CHP fleet and for individual buildings when customers are subject to time-varying rates. The emission reductions are achieved because the time-of-day rate discourages CHP operation and therefore, wasted heat during the night when commercial buildings have low heat loads. Similarly, the seasonal rate avoids wasted heat during the summer.

We found that time-varying rates can achieve emission reductions without reducing the economic value of customer-owned CHP, but customer-owned CHP can also lead to high utility losses and possible rate increases for ratepayers. Figure 2-5 shows that the system, customer, and utility savings remain similar if the customer has time-varying rates. However, utility losses are also high under all customer ownership scenarios because the utility loses revenue from reduced demand charges and reduced energy sales that embody the sunk costs of the distribution system infrastructure. Macroeconomic demand supply models have been used on the bulk power grid to quantify the short-term price reductions and jobs associated with industrial cogeneration (Baer, Brown and Kim 2015). Work is needed that expands on Baer, Brown and Kim (2015) and compares the value of reduced energy costs and reduced long term infrastructure requirements with the short-term cost shifts needed to pay for stranded assets.

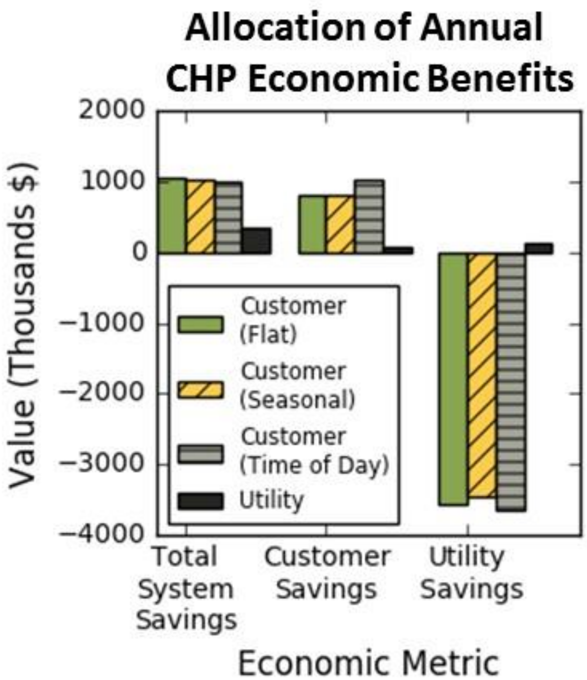

Figure 2-5. Allocation of CHP Savings for the base case and time-varying rates. Total system savings are positive for both owners indicating that the capital costs and energy costs of delivering power with CHP are cheaper than the grid. The high utility losses reflect lost energy sales and sunk distribution infrastructure costs. Time-varying rates do not have a large effect on customer or utility savings suggesting that time-varying rates can achieve emission reductions without negatively affecting the CHP payback period.

Microgrids are sometimes discussed as another option for reducing emissions (DOE 2012), but we did not observe consistent emission reductions from microgrids. As shown in Figure 2-4 and Figure 2-30 of the Supplementary Materials, microgrids composed of a warehouse and secondary school tend to produce lower emissions than if CHP were placed at those loads separately. The opposite is true for microgrids composed of a quick-service restaurant and strip mall. Microgrids may be more effective if emission reductions are included in the CHP sizing objective functions. Also, microgrids composed of many buildings could take advantage of the increasing electrical efficiencies and decreasing heat-to-power ratios of larger sized CHP (Supplementary Materials Figure 2-14). However, despite these improvements, commercial building microgrids will still tend to produce wasted heat because many commercial buildings have highly correlated heat loads (Supplementary Materials Figure 2-31).

Hot water absorption chillers use heat energy to cool buildings and are another option to use waste heat from CHP. We believe more research is needed on absorption chillers, but high capital costs, maintenance challenges, inconstant cooling loads, and low coefficients of performance currently limit their economic feasibility.

In some states, natural gas discounts are used to encourage CHP. New Jersey Natural Gas, for example, offers natural gas discounts of up to 50% to residential and commercial customers that install CHP (New Jersey Natural Gas 2016). We applied a natural gas discount of $2/MCF ($1.9/GJ) to the CHP fleet in Table 2-1 and examined the effect of this discount on the CHP fleet emissions, shown in Figure 2-2. The natural gas discount increases CO_2 and NO_x emissions because it encourages operation of the CHP even during times of low-heat loads. This result is further discussed in the following section.

2.6 Sensitivity analysis

We examined the robustness of the ability of time-varying rates to reduce emissions. In Figure 2-2 and Figure 2-4, we showed that time-varying rates cause utility owned CHP to turn off when heat loads are low, resulting in higher overall fuel utilization efficiencies. An important question is to what extent time-varying rates will be effective at reducing emissions in states that have different electricity and natural gas prices. For example, we also showed in Figure 2-2 that a natural gas discount would increase both customer and utility CHP fleet emissions, thus reducing the ability of time-varying rates to reduce emissions. Similarly, a greater reliance on natural gas fired generation could lead to more closely coupled electricity and natural gas prices and make CHP operations less economical. A simple visual tool is needed to estimate how these future scenarios can affect CHP emissions.

Figure 2-6 can be used to predict how time-varying rates and varying spark spreads will affect CHP emissions. It shows dispatch regions for a 10 kWe and 500 kWe CHP over a range of natural gas and electricity prices. These regions approximate how electricity and gas prices affect CHP dispatch under different loading scenarios. CHP units are not dispatched in the black region. In the green regions, CHP are dispatched only if a heat and electric load are present. In the yellow region, CHP are dispatched even when only the electric load is present. The customer owner's dispatch behavior, presented earlier for New York State with electricity and natural gas at $0.143/kWh (OpenEI 2015) and $8.3/MCF ($7.9/GJ) (EIA 2013), falls in the yellow region. The average utility electricity and natural gas prices also fall within the yellow region, but it is subject to a time varying LMP and thus often falls within the green region. Also, low LMPs tend to occur when commercial heat loads are low, so utilities fall within the green region when it is possible to achieve higher efficiencies. In contrast, the customers in the New York State have a flat rate, so they are consistently in the yellow dispatch region, and operate the CHP less efficiently. CHP larger than 10kWe have smaller green regions and will be less sensitive to time-varying rates, as shown in Figure 6 for a 500 kWe CHP.

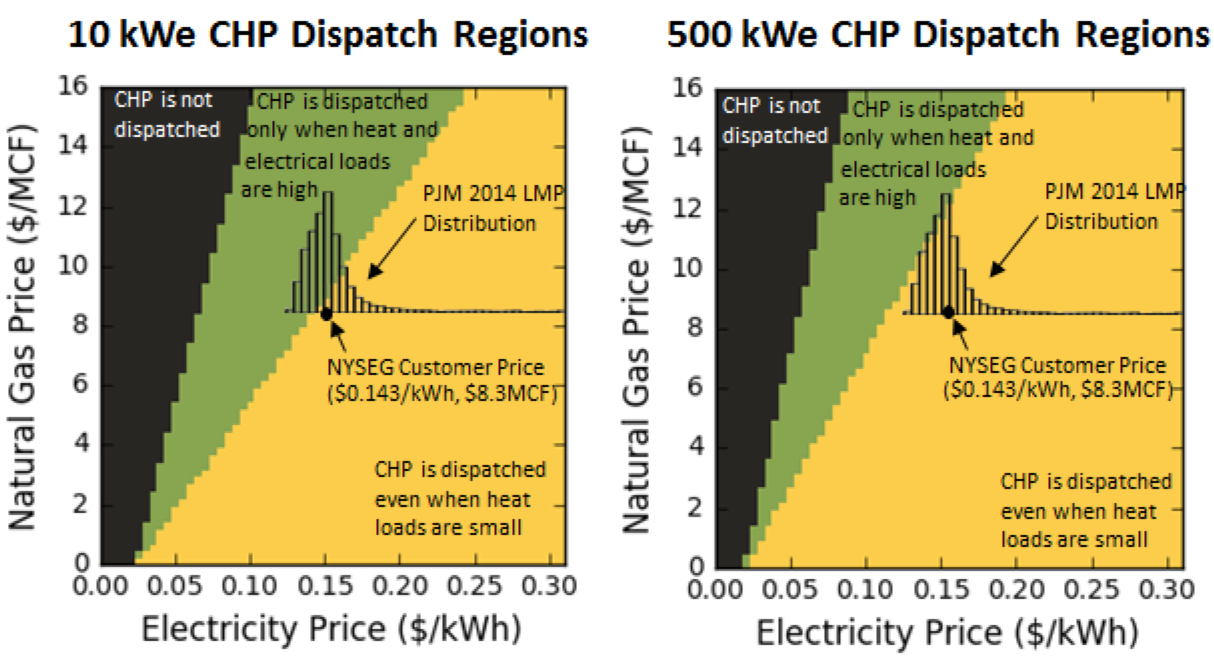

Figure 2-6. Sensitivity of dispatch of a 10kWe and 500kWe CHP to natural gas and electricity prices. CHP are not turned on in the black region. In the green region, CHP are only turned on if a heat and electric load is present. In the yellow region, CHP are dispatched at times even when only electric load is present. Dispatch in the green zone is likely to reduce emissions. Dispatch in the yellow zone may not reduce emissions if CHP heat production does not offset building heat load. For small CHP the customer owner's dispatch behavior, presented earlier, with electricity and natural gas at $0.143/kWh and $8.3/MCF ($7.9/GJ) falls in the yellow region. And, the utility is subject to a time varying LMP and so, it often falls within the green region, leading to lower utility emissions. Larger CHP becomes less sensitive to these effects, so time-varying rates will not be effective at reducing large CHP emissions.

As the penetration of commercial CHP increases, the emission benefits associated with CHP diminish. Figure 2-2 shows that the smaller utility owned fleet of CHP produces fewer relative emissions than the larger customer owned fleet. The larger customer fleet has more emissions because it has more CHP at buildings with higher relative emissions. This relationship is further examined in Figure 2-7. A range of CHP penetration scenarios for small CHP (<100 kWe) was created by varying the capital cost and discount rate of the CHP investments. As the economic conditions became more favorable to commercial CHP, penetrations increased, but the relative emissions also increased. Time-varying locational marginal prices caused the utility owned fleet to produce lower emissions than the customer owned fleet for similar penetration levels. In contrast, the owner emissions of larger CHP (>100kWe) are unaffected by penetration level and time-varying rates (see Figure 2-7, where the CHP fleet penetration correspond to the following scenarios moving from left to right: 30% Increase in CHP Capital Costs, 30% Increase in Discount Rate, Base Case, 30% Decrease in Discount Rate, 30% Decrease in CHP Capital Costs, 50% Decrease in Capital Costs and Discount Rate).

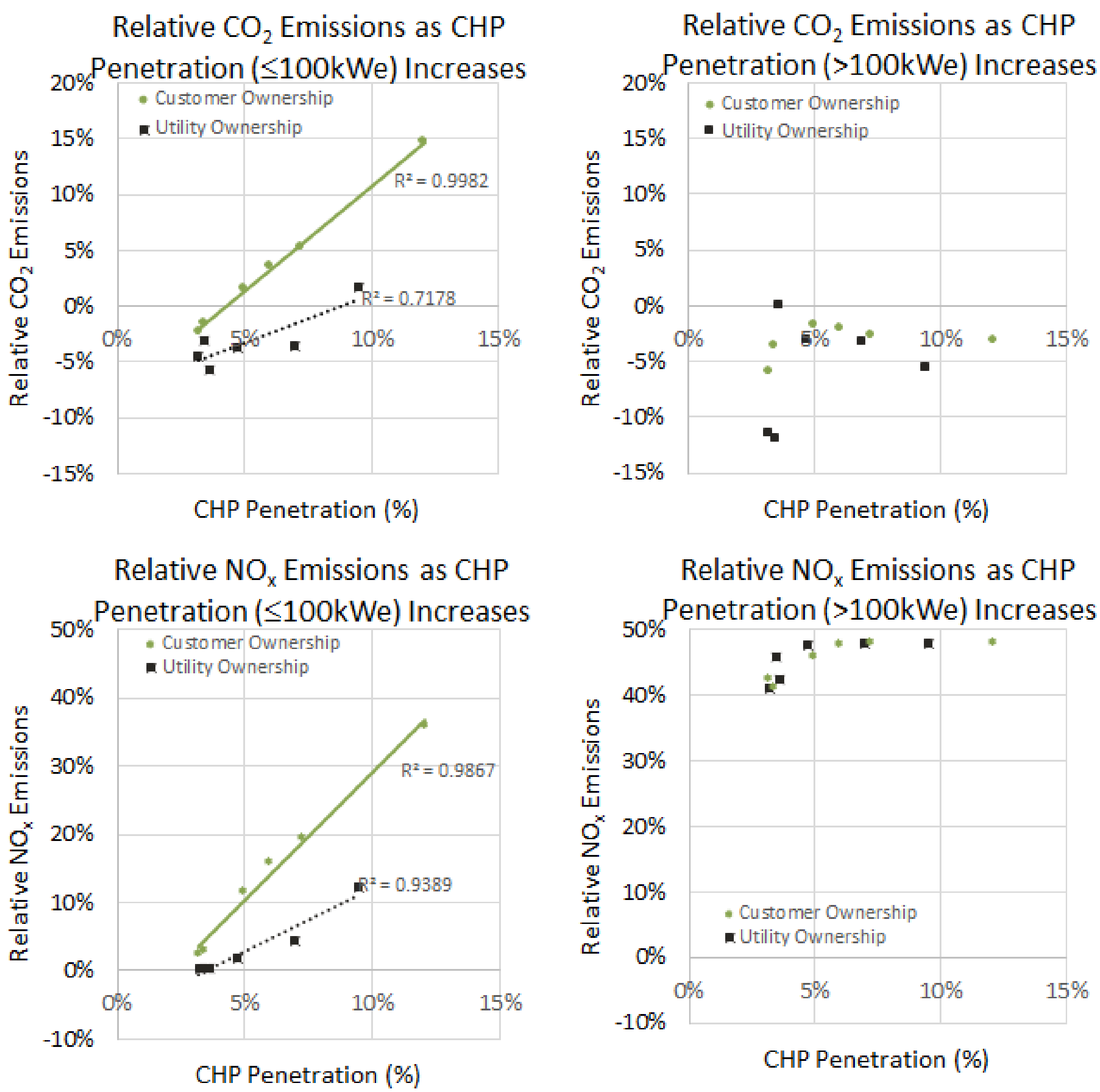

Figure 2-7. Comparison of utility-owned CHP (subject to locational marginal prices) with customer-owned CHP (a non-varying flat rate). Utility locational marginal prices cause lower emissions than customer owned CHP subject to a non-varying retail rate. Emissions increase as the penetration of small CHP (< 100 kWe) increase but time-varying locational marginal prices are effective at reducing these emissions for the utility. Emissions do not increase for large CHP (>100 kWe) and time-varying rates are ineffective at reducing emissions.

The emission and economic benefits of CHP were simulated for the years 2010 through 2014 to determine if the corresponding natural gas prices, electricity prices and marginal emission factors would affect the relative emissions or economic benefits of CHP fleets. The results are shown in Figure 2-25 and Figure 2-29 of the Supplementary Materials and are consistent with the 2014 results. Customer CHP fleet emissions are generally higher than utility emissions, and the economic benefits are allocated similarly for most years.

2.7 Conclusion and policy implications

We constructed an integrated planning and operations model that maximizes owner profit through optimal sizing and operation of commercial CHP on a realistic distribution feeder in New York. Using customer and utility ownership models we found that a greater penetration of CHP reduces network congestion and total system costs. Our results agree with previous findings that large CHP will reduce emissions and that policies encouraging large CHP will reduce system wide emissions (Brown, Cox and Baer 2013). Commercial CHP, however, will not always reduce emissions if large amounts of wasted heat are produced, as summarized in Figure 2-8 for the New York Clean Power Plan targets. Both commercial buildings produce emissions much higher than their technical potential, and only the outpatient facility is able to help New York meet its emission target.

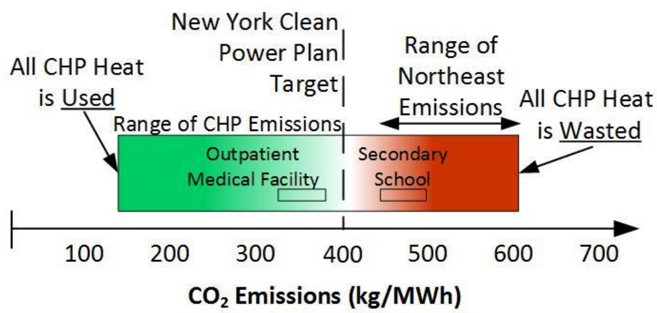

Figure 2-8. Commercial CHP produce higher emissions because the heat they produce cannot always be used. In some cases, this wasted heat will prevent commercial CHP installations from helping New York meet their Clean Power Plan Target. Outpatient medical facilities have more consistent heat loads than secondary schools, and their emissions are lower than current northeast emissions and the clean power plan target. Secondary school emissions are low relative to the current bulk grid but would not help New York meet the clean power plan target. Both commercial buildings produce emissions much higher than their technical potential.

Based on our results, we offer the following considerations to help policy makers maximize the benefits of CHP in commercial buildings.

Commercial CHP will reduce system costs. The capital, O&M, and energy costs of commercial CHP the lower than the capital, O&M, and energy costs of the grid. Overall, this will produce system savings, but there is likely to be a debate over who should be able to own commercial CHP and benefit from these savings. In particular, customer ownership has higher system savings but causes the utility to lose revenue. This loss of revenue will likely cause higher rates.

There are advantages of utility owned CHP. In addition to the benefits reported by the ACEEE (Chittum and Farley 2013), utility owned CHP avoids customer cost shifts. It may also be easier to regulate utility owned CHP emissions and to encourage operation that does not waste heat. Giving these findings, New York may want to reconsider its policy on utility CHP ownership.

Commercial CHP will reduce distribution network congestion and losses. On highly congested networks, commercial CHP may be an effective way to defer capacity investments.

Commercial CHP will reduce emissions less as penetrations increase. Commercial buildings vary in the quantity and consistency of their heat loads. Favorable economic conditions, such as a natural gas discount or a high electricity price relative to that of natural gas, may result in CHP at these buildings. SO_2 emissions decrease when CHP is installed, but CO_2 emission rates depend on the head load of the building. Local emissions could also violate limits in nonattainment regions, despite regional emission improvements (Brown, Cox and Baer 2013). In our New York model, we found large emission reductions for some buildings that have consistent heat loads, such as large hotels. However, the emission of some other building types, such as large offices, are sometimes larger than the bulk power grid emissions in the northeast because their inconsistent heat loads do not take advantage of the potential reductions due to CHP. A consequence of this finding is that high incentives for commercial

CHP can have diminishing environmental benefits. In short, while commercial CHP are likely to be effective at reducing emissions in emission intensive regions, such as the Midwest where marginal emissions range from 600-1000 kg/MWh, high penetrations of commercial CHP may not be effective at reducing emission in the northeast.

Policies aimed at reducing emissions should encourage small commercial CHP operation only during times of high heat loads. Time varying rates can be used to encourage CHP dispatch only when heat loads are high. We showed that time-of-day rates and seasonal rates reduce customer owned CHP emissions and do not reduce customer rates-of-return. A carbon price would also be effective, but the costs of monitoring may be prohibitive for small CHP. Incentives that reduce capital costs such as accelerated depreciation or an investment tax credit, are also an option where regional grid emissions are high. Reduced capital costs will neither encourage nor discourage CHP dispatch during times of high heat loads. In contrast, natural gas rate discounts, a common incentive for industrial CHP in some states, can encourage CHP operation during low heat loads and increase relative emissions. Similarly, as with industrial cogeneration (Lane Clark & Peacock 2014) a production tax credit may cause small commercial CHP to produce higher relative emissions.

2.8 References

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2.9 Supporting Materials

2.9.1 Modeling

Network Model

We used Pacific Northwest National Laboratory's (PNNL) GridLab-D solver and distribution feeder taxonomy for representative distribution feeder models and for all distribution powerflow simulations. GridLab-D is a distribution time-series AC powerflow solver produced by PNNL (PNNL 2015). The feeder taxonomy, created by Schneider et al., (2008) is a set of 24 prototype non-urban, radial feeder models from varying climate and demographic regions with residential and commercial static loads. To develop the feeder taxonomy, hierarchical clustering was performed by Schneider et al. on a set of 575 feeders[4] to determine common feeder features. (2008) The feeder taxonomy prototypes were based on these common features (2008).

In our model, the static load sources in the feeder taxonomy models were replaced with time-varying heat and electric loads. Time-varying electrical loads were first produced by Hoke et al. (Hoke, et al. 2013) [5] to study the maximum penetration of solar photovoltaics on distribution feeders[6]. To include heating loads, some time-varying electrical loads were replaced with commercial building electrical and heat loads. The electrical and heat loads were originally created as part of the *Commercial Reference Building Model of National Building Stock* for different regions in the United States (NREL 2011)[7]. These heat loads are shown for each building type in the summer and winter in Figure 2-11 and Figure 2-12. The commercial building loads were scaled to ensure that peak loading conditions remained the same as the GridLab-D feeder taxonomy. These buildings represent approximately two-third of the US commercial building stock. The percentage of each building type is based on the 2003 Commercial Building Energy Consumption survey (EIA 2003).

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[4] The feeders were provided by 17 investor owned (IOU), rural electric authority (REA), public utility districts (PUD) and municipality utilities.

[5] To create the dynamic load dataset, a commercial and residential load dataset was acquired from a utility in geographic regions corresponding to the taxonomy regions. These were then scaled by transformer capacity and a feeder wide factor that kept power flows within violation ranges. Finally, some guassian noise was added to the loads.

[6] The electrical loads are available at https://catalog.data.gov/dataset/randomized-hourly-load-data-for-use-with-taxonomy-distribution-feeders-88065

[7] The commercial building loads are available at https://catalog.data.gov/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-state-1d21c

Table 2-2 shows each commercial building type and the approximate proportion assumed to be on each feeder. Building loads were placed on pre-existing loads that minimized the norm of the difference between the electrical peak load, minimum load, and load factor. The final heat and electrical power load are scaled so that the total electrical energy consumption over the year remains the same. Figure 2-13 shows one example of each building's matched load, the scaled load, and the original time varying GridLab-D taxonomy load. The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) climate region 6 was used. Climate region 6 has a cold climate and is typical of the northeastern and north central portions of the US (AHRAE 2004).

CHP Model

We use natural gas fired reciprocating engine CHP in our model. According to Flin (2010) CHP systems are generally cost effective when there is a need to upgrade an existing heating system and can be used to supplement a boiler. Diesel-fired CHP are not used in our model because diesel's higher emissions typically limit its operating hours to backup applications (U.S. EPA 2015) and because natural gas is the most common form of fuel for CHP (EIA 2012). The full combined heat and power system is shown in Figure 2-2. The commercial building can purchase power from the distribution network or can produce its own power. Heat can be produced by the boiler or the CHP.

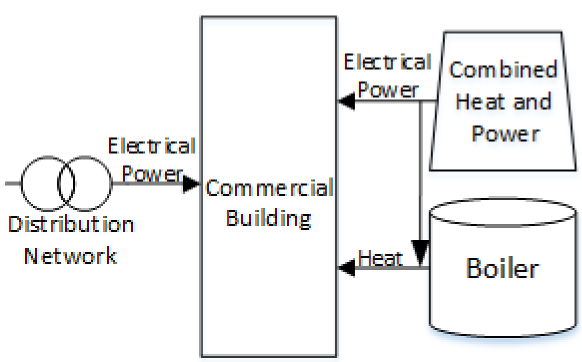


Figure 2-9: Energy options for the commercial building. Electrical power comes from the grid or from the CHP. Heat can come from the boiler or the CHP. The lowest cost source of heat and electrical power is used to meet demand at

each hour. CHP dispatch decisions also have environmental and network consequences, but these are not considered in the dispatch objective function.

CHP Type, Sizing and Placement

Natural gas, reciprocating engine CHP are placed on a load if they earn a rate-of-return greater than 10% and if their payback period is less than the equipment lifetime. If multiple CHP sizes meet these criteria, the CHP size with the maximum NPV is used. Revenues are based on one year of loading conditions and each owner's tariff structure. The CHP selection objective function is shown in Figure 2-10.

<u>CHP Selection Objective Function</u>

For all commercial loads, select the size that will,

Minimize:

NPV (Grid Costs +
Boiler Energy Costs +
CHP Energy Costs +
CHP capital costs +
Annual O&M costs)

Subject to:

Energy purchased, generated = demand
CHP stays within operational limits
Rate of return > 10%
Payback period is within CHP lifetime

Figure 2-10: CHP selection objective function. The CHP size with the lowest capital costs, O&M costs, and energy costs is used. CHP are not placed on the commercial load if the rates-of-return are less than 10%.

CHP are considered in sizes of 1 kW and higher. According to the EPA (U.S. EPA 2015) CHP are available in sizes ranging from 10kW to over 18 MW, but we have found CHP as low as 1 kW (Lempereur and Tesoriero 2008). Reciprocating engines are used because they are well suited for optimized dispatch. In comparison to microturbines and fuel cells, they are better at following load, have faster startup capabilities and have been used for peak shaving (Flin 2010) (U.S. EPA 2015). CHP parameters were extrapolated from DER-CAM, a software tool produced by Lawrence Berkeley National Lab and from the EPA's 2015 CHP Characterization

(U.S. EPA 2015). Both sets of parameters are determined with an industry expert survey. Capital costs include engineering fees and labor. A fixed linear efficiency is used for each CHP. The DER-CAM CHP parameters are shown in Table 2-3 for a 1121 kW, 250 kW and 75 kW CHP. The extrapolated CHP capital costs, O&M, efficiencies, and heat-to-power ratios are shown in Figure 2-14.

The CHP sizes used in our model range from 1kW to 1000kW, but the most common size was less than 75 kW, and less than the CHP sizes characterized by DER-CAM or the EPA. Our main concern was that we were underestimating the capital costs for small commercial CHP and overestimating penetration levels. To the best of our knowledge, industry surveys do not exist for small CHP, but we were able to obtain a quote on the internet site Alibaba. The quote was for a 10kW natural gas CHP generator. The capital cost quoted was $1000/kW, and slightly less than the capital cost for a 100kW given by the EPA (U.S. EPA 2015) at $1400/kW. From this, we conclude that our linear extrapolating capital costs for small CHP is reasonable.

Ownership Model

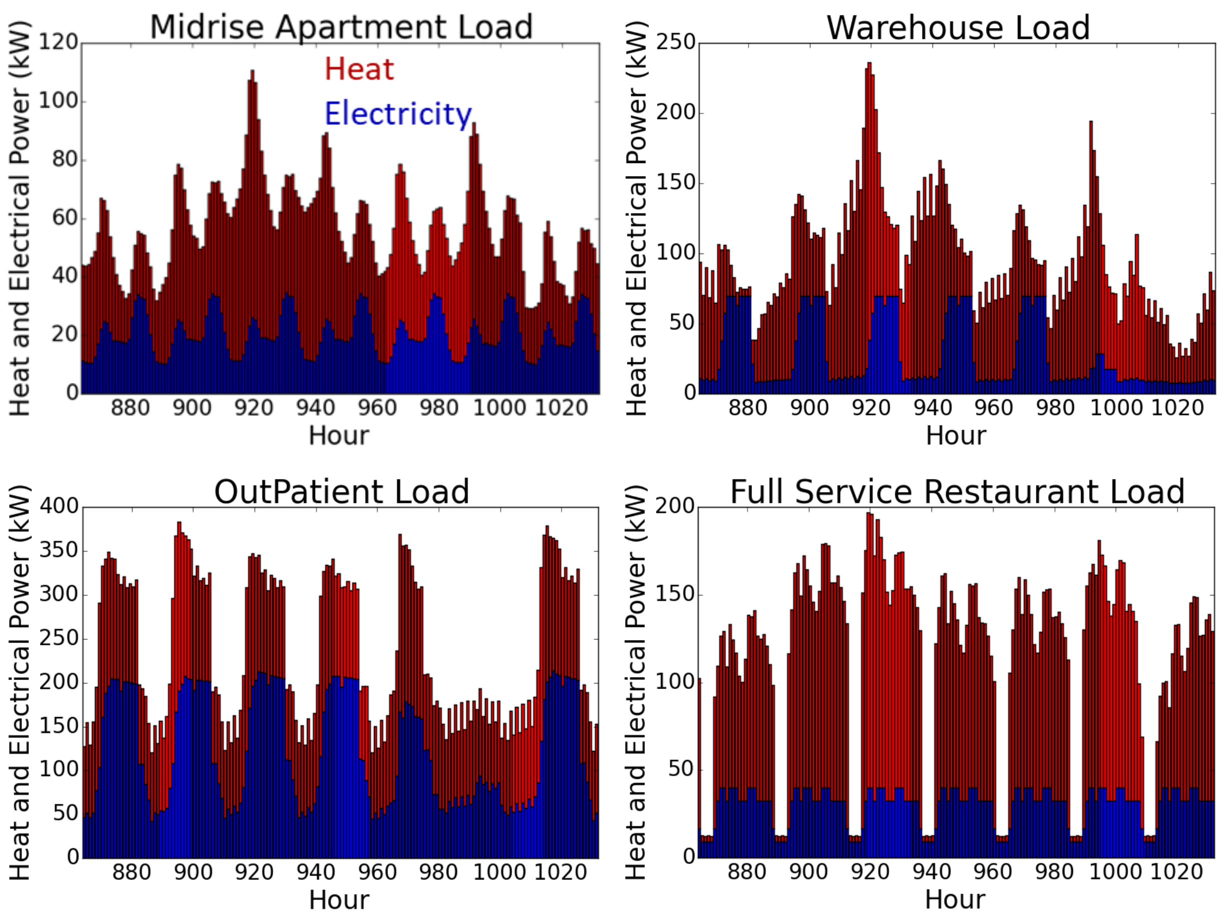
In recent years, a debate has emerged over who should own distributed energy resources (DER), such as CHP, and profit from their benefits. Utilities argue that market participation will allow them to fulfill their traditional obligations in serving unserved customers (Lacey 2015). NYSERDA (2010) adds that utility ownership may be beneficial because utilities can readily access customer information and technical information, avoid duplicative services, and improve customer service quality through differentiated service options associated with DER. The Edison Electric Institute (EEI, the trade group for investor-owned electric utilities) has argued for a “level playing field” for utilities and new DER market entrants, and it warns of potential grid safety, reliability, and customer cross-subsidies-to the disadvantage of low-income customers- without sufficient involvement from utilities (Craver 2013). In a series of white papers, the American Council for an Energy-Efficient Economy (ACEEE) argues that there are societal benefits of utility CHP ownership (Chittum and Farley 2013). They say that utilities may be better equipped to capture the environmental benefits of CHP, to participate in ancillary markets, and to manage long term investments (Chittum and Farley 2013). However, third parties, fearful of utility market advantages, argue that utility involvement will inhibit competition, (NYSERDA 2010) (Lacey 2015), and we will lose an opportunity to invigorate a stagnate industry (King and Morgan 2003).

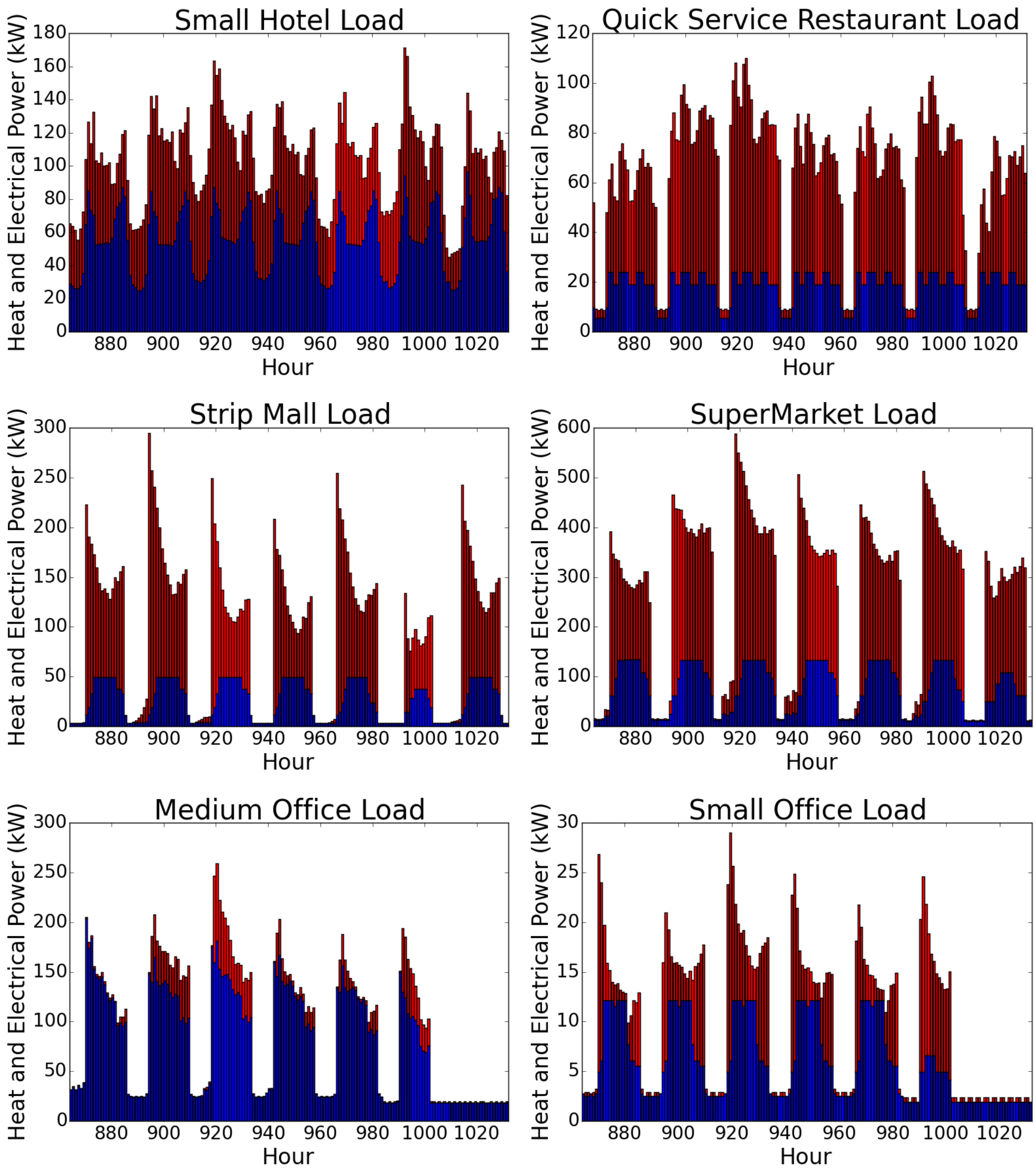
Private customer and utility owned CHP operating strategies are both modeled. In the private customer ownership model, the owner is assumed to be a customer of the utility with a flat rate that does not vary hourly or seasonally[8]. The customer operators attempt to minimize their costs over the year by producing power when grid costs exceed generation costs. In this model, it is assumed that each customer operates independently. The objective function for the private customer ownership model is shown in Table 2-4. The first term describes customer payments to the utility for power demand less generated power. The second term describes the cost of power production less the reduced heating bill from offset boiler demand. The objective function is constrained by the generation operational limits. Scenarios were created where power exports are not permitted and where power is exported and compensated at the retail rate.

In the utility ownership model, the utility attempts to maximize its profit. The objective function is shown in Table 2-5. The first term describes revenue earned by the utility from dispatching CHP at customer sites. The revenue is based on the standard utility tariff less the value of the customer's PPA when CHP is dispatched. In the second term, heat revenue is earned at the customer's avoided heating cost. The third term describes the utility's cost of

[8] Generally, small residential and commercial customers prefer static rates. Discussions between the authors and industry stakeholders have suggested that this also appears to be true for commercial customers with CHP.

buying power from the wholesale market and of generating power. Scenarios were created where power exports are not permitted and where power is exported and compensated at the wholesale rate (including transmission costs). Demand charges are not included in the objective function but are considered indirectly during the planning stage. Additionally, the utility must offer a power purchase agreement (PPA) to the customer to compensate for the opportunity cost foregone by not renting the space the CHP occupies. We assume that the PPA will be different and based on the economics of each CHP location. Each customer is offered the smallest PPA that overcomes their opportunity cost.




Small Hotel Load
Quick Service Restaurant Load
Strip Mall Load
SuperMarket Load
Medium Office Load
Small Office Load
Heat and Electrical Power (kW)
Hour
880 900 920 940 960 980 1000 1020

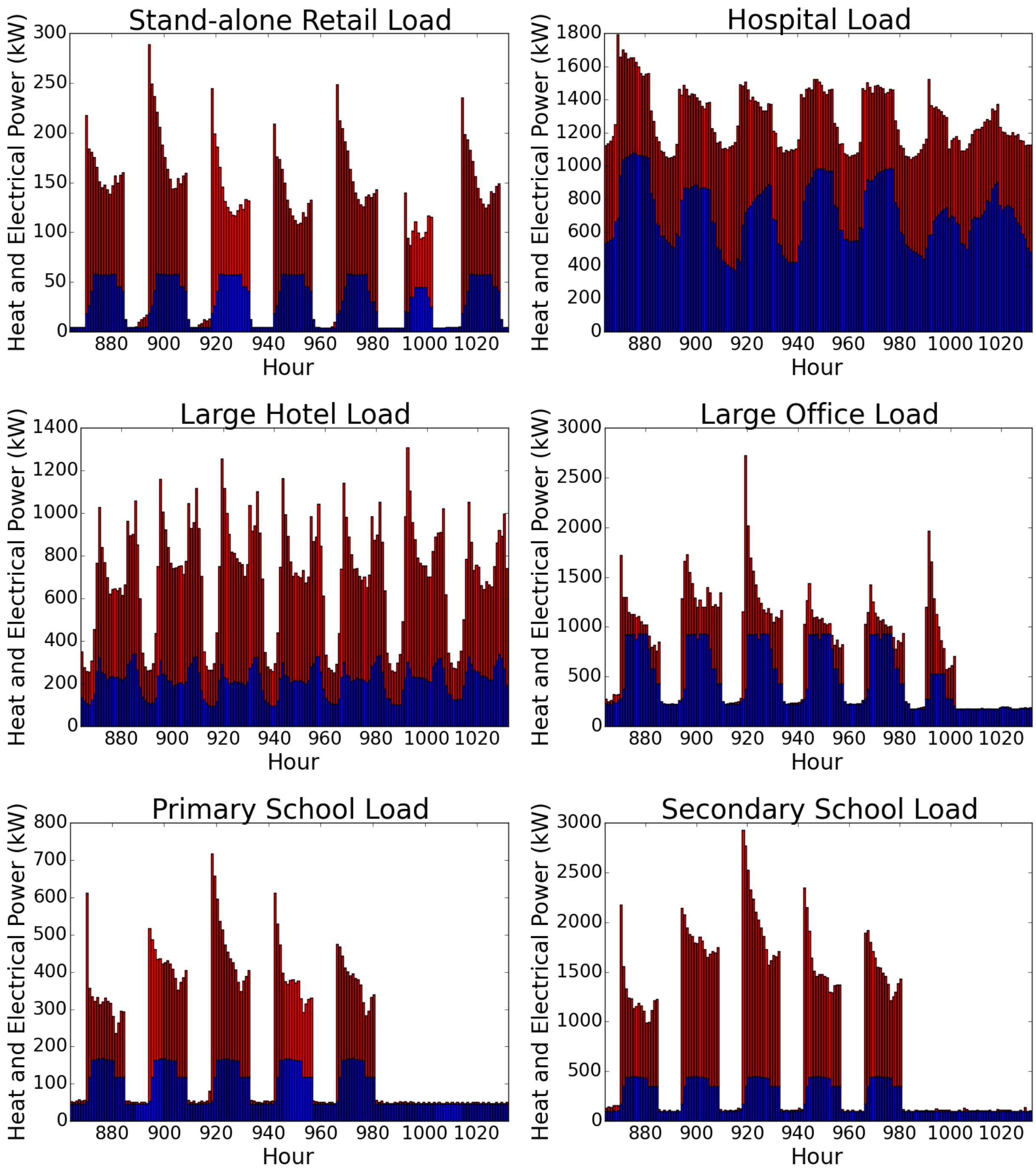
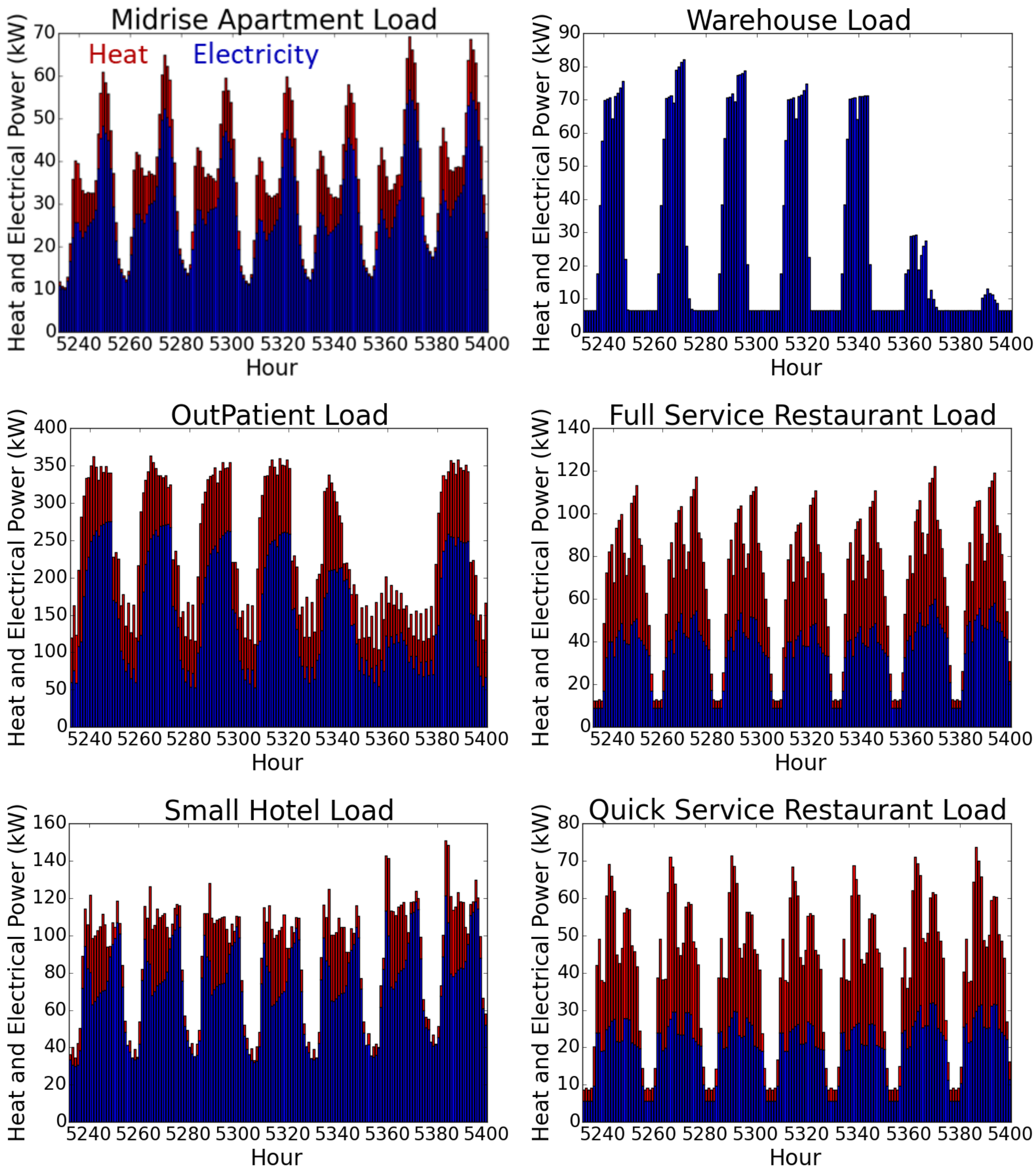
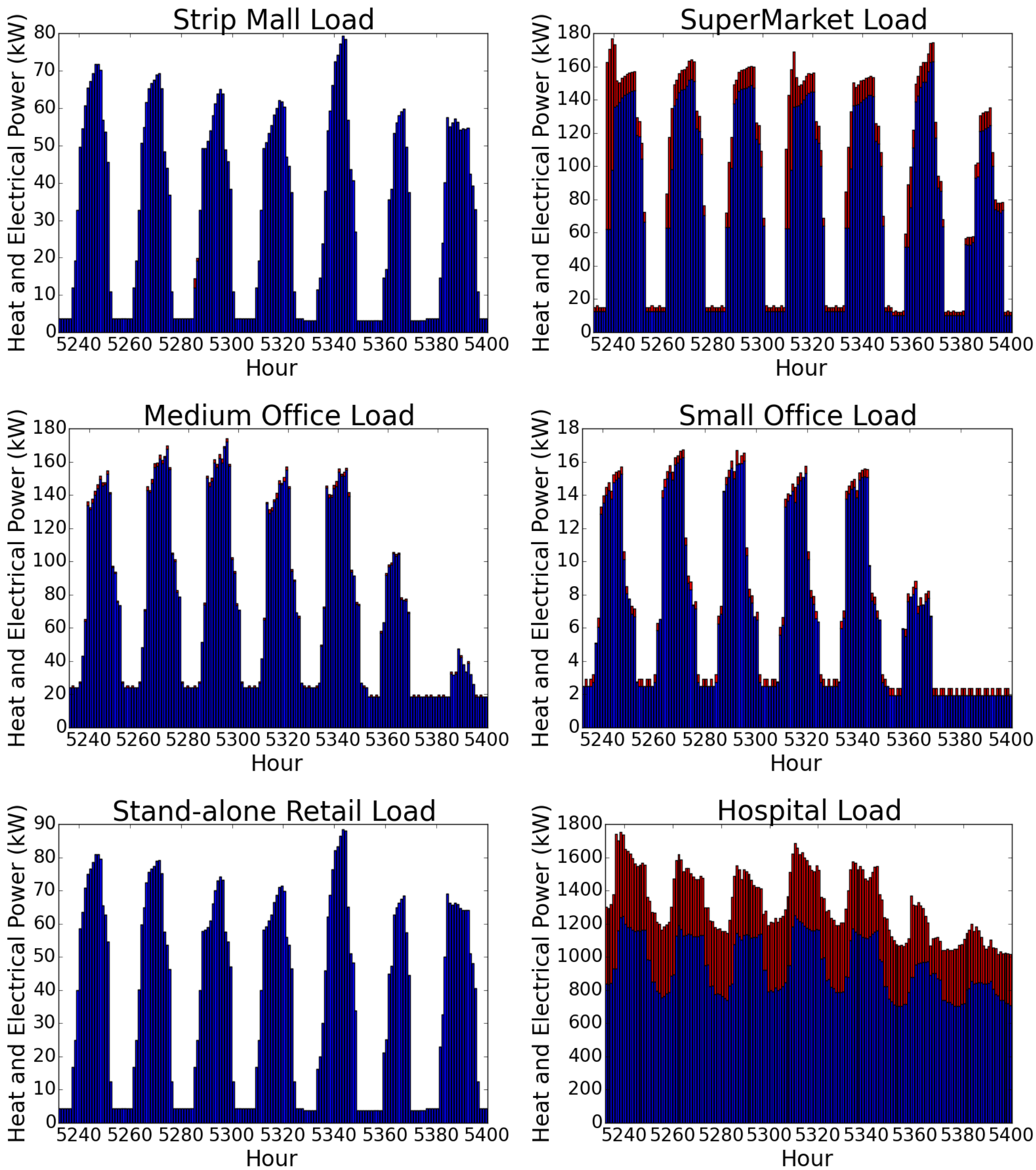


Figure 2-11: Building heat (red) and electric (blue) loads during the winter. One week in February is shown.


Midrise Apartment Load
Heat
Electricity
Heat and Electrical Power (kW)
0 10 20 30 40 50 60 70
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
Warehouse Load
Heat and Electrical Power (kW)
0 10 20 30 40 50 60 70 80 90
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
OutPatient Load
Heat and Electrical Power (kW)
0 50 100 150 200 250 300 350 400
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
Full Service Restaurant Load
Heat and Electrical Power (kW)
0 20 40 60 80 100 120 140
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
Small Hotel Load
Heat and Electrical Power (kW)
0 20 40 60 80 100 120 140 160
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
Quick Service Restaurant Load
Heat and Electrical Power (kW)
0 10 20 30 40 50 60 70 80
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour


Strip Mall Load
Heat and Electrical Power (kW)
0 10 20 30 40 50 60 70 80
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
SuperMarket Load
Heat and Electrical Power (kW)
0 20 40 60 80 100 120 140 160 180
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
Medium Office Load
Heat and Electrical Power (kW)
0 20 40 60 80 100 120 140 160 180
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
Small Office Load
Heat and Electrical Power (kW)
0 2 4 6 8 10 12 14 16 18
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
Stand-alone Retail Load
Heat and Electrical Power (kW)
0 10 20 30 40 50 60 70 80 90
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour
Hospital Load
Heat and Electrical Power (kW)
0 200 400 600 800 1000 1200 1400 1600 1800
5240 5260 5280 5300 5320 5340 5360 5380 5400
Hour

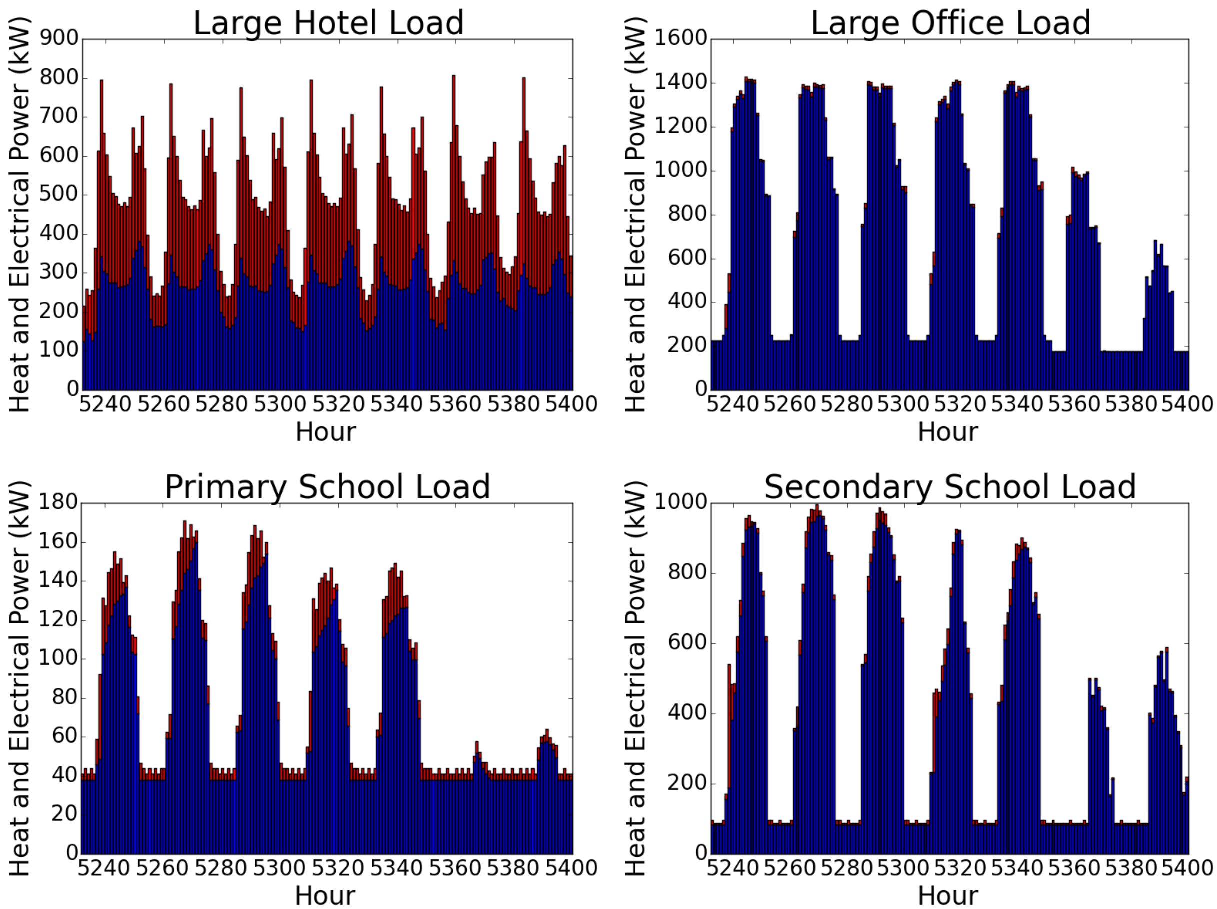
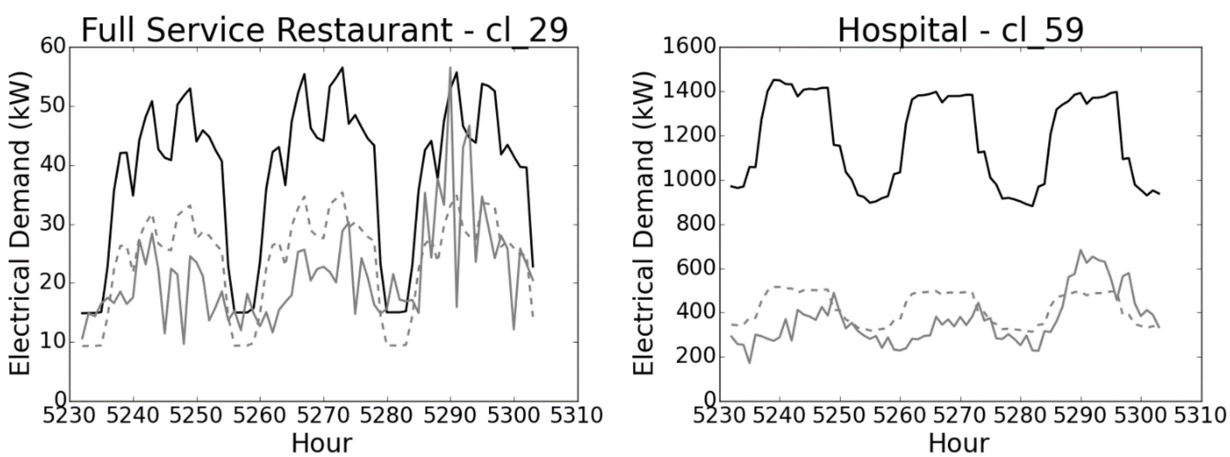
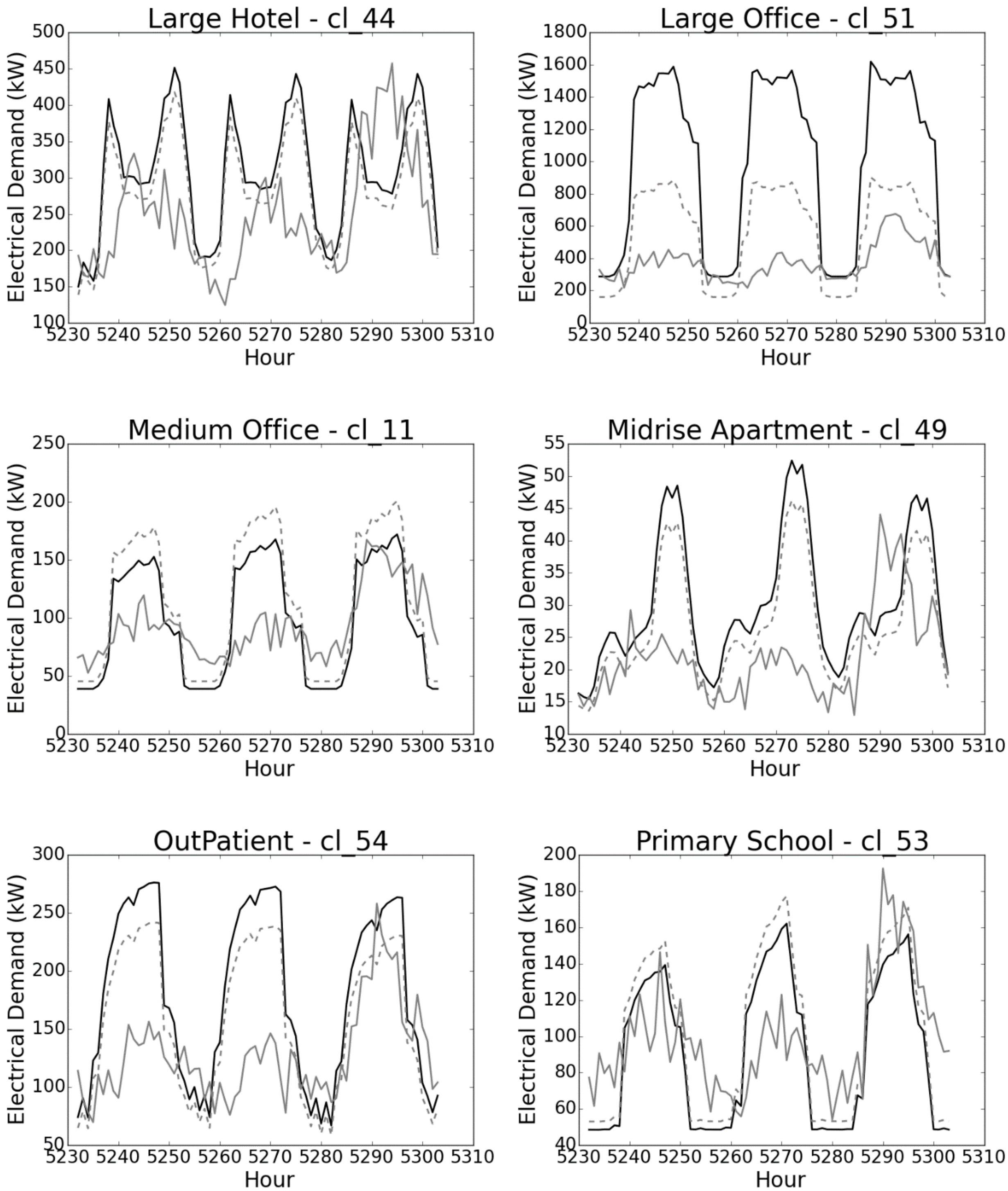


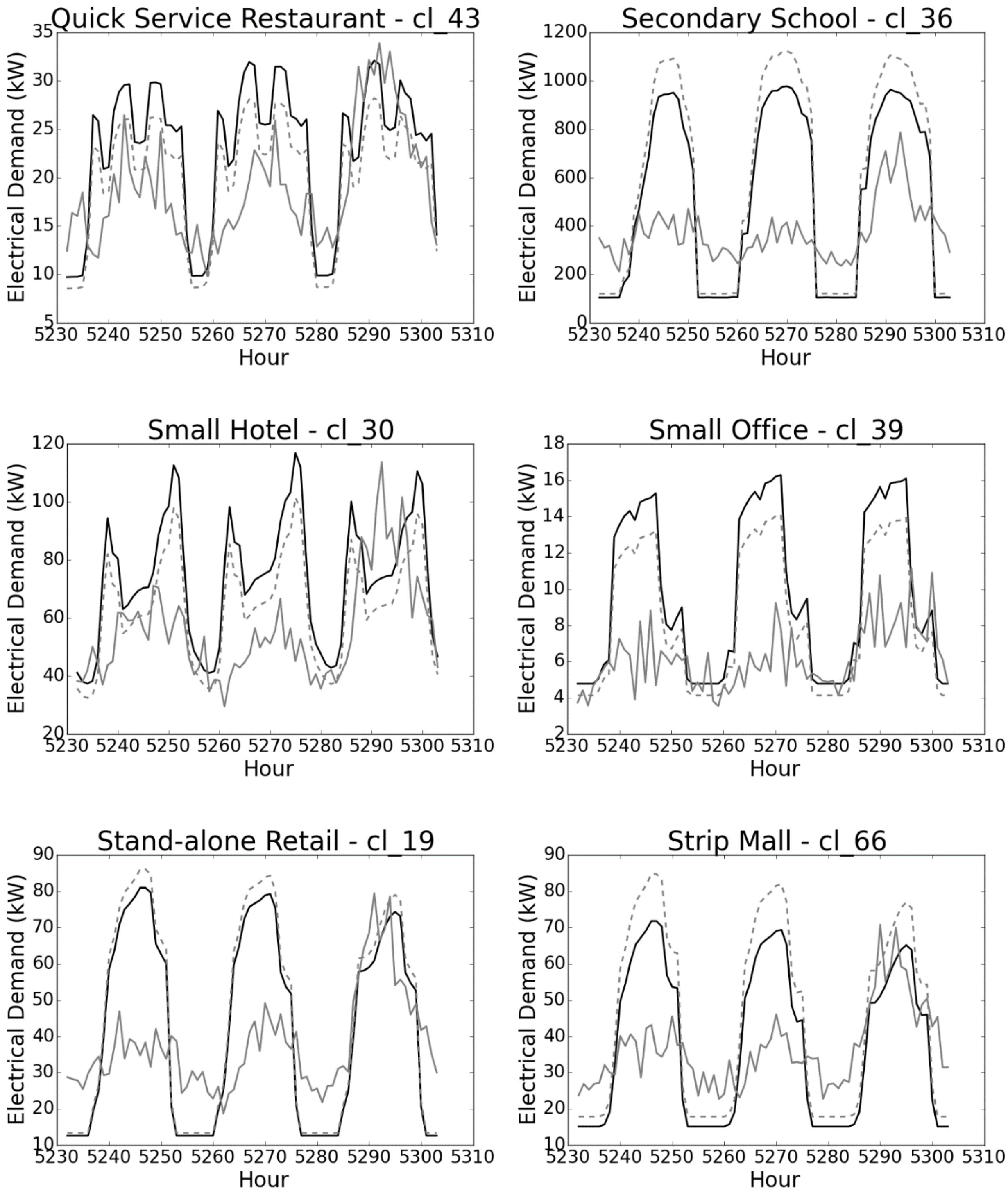
Figure 2-12: Building heat (red) and electric (blue) loads during the summer. One week in July is shown.

Table 2-2: Commercial building types and quantity. The commercial buildings shown represent approximately two-thirds of the US commercial building stock and are used to determine heat and electrical loads for the feeder, as provided by NREL **(NREL 2011)**. The percent quantity found on each feeder is based on of the DOE's 2003 commercial building energy survey **(EIA 2003)**.

Commercial Building Type	Feeder Quantity (%)
Small Office	9
Warehouse	9
Stand-Alone Retail	7
Strip Mall	7
Medium Office	6
Primary School	6
Large Office	4
Hospital	4
Outpatient Healthcare	3
Secondary School	2
Full Service Restaurant	2
Small Hotel	2
Large Hotel	2
Midrise Apartment	1
Quick Service Restaurant	1
Supermarket	1




Large Hotel - cl_44
Large Office - cl_51
Medium Office - cl_11
Midrise Apartment - cl_49
OutPatient - cl_54
Primary School - cl_53
Electrical Demand (kW)
Hour


Quick Service Restaurant - cl_43
Secondary School - cl_36
Small Hotel - cl_30
Small Office - cl_39
Stand-alone Retail - cl_19
Strip Mall - cl_66
Electrical Demand (kW)
Hour

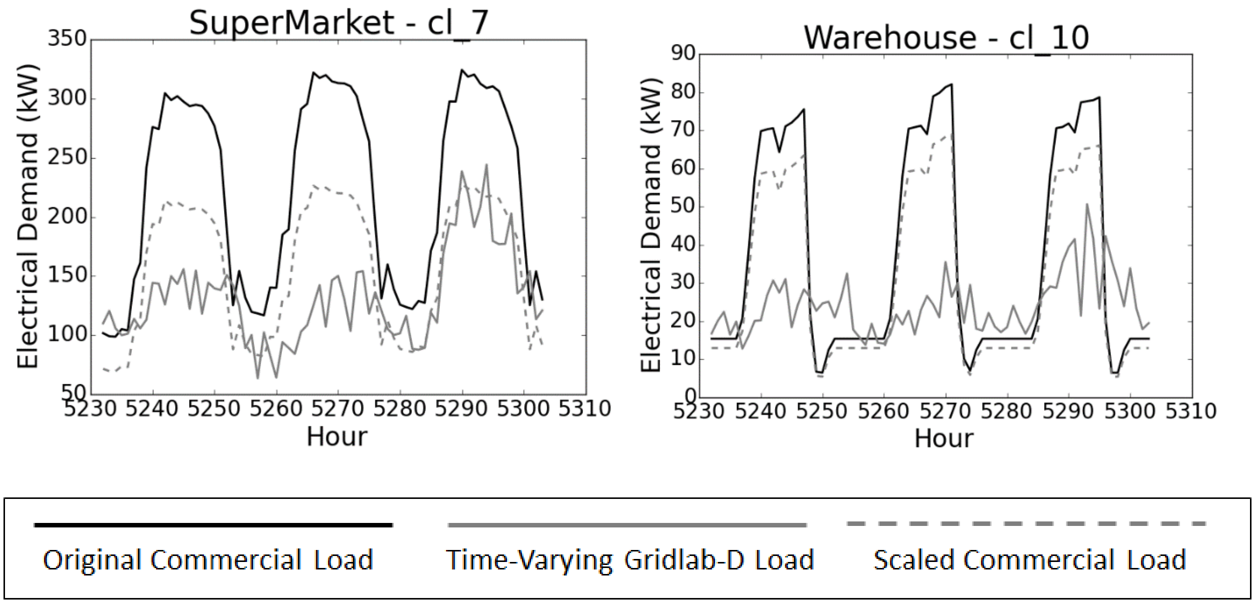


Figure 2-13: Matched electrical loads are shown for the three days in July. The electrical commercial building loads are matched to the GridLab-D loads and used to replace these GridLab-D loads so that commercial building heat loads can be introduced to the model. The matching algorithm uses the set of loads with the minimum norm of the difference between peak load, minimum load, and load factor. The building loads were then scaled so that the total yearly energy consumption was the same as the GridLab-D load. Large discrepancies between the scaled commercial load and GridLab-D load are caused by seasonal differences in the load profiles and the limited number of commercial GridLab-D loads to match.

Table 2-3: DER-CAM CHP Technology Options LBNL **(Lawrence Berkeley National Laboratory 2015)** and the EPA. **(U.S. EPA 2015)** Internal Combustion Engines with Heat Exchangers for collecting hot water are considered for placement on the commercial loads. CHP parameters are extrapolated from these values.

CHP Technology Options					
Max Power (kW)	Lifetime (years)	Capital Cost ($/kW)	Variable O&M ($/kWh)	Full Load Efficiency	Heat to Power Ratio
75	15	2880	0.0255	0.26	2.0
250	15	2614	0.025	0.27	1.82
1121	15	2366	0.019	0.368	1.12

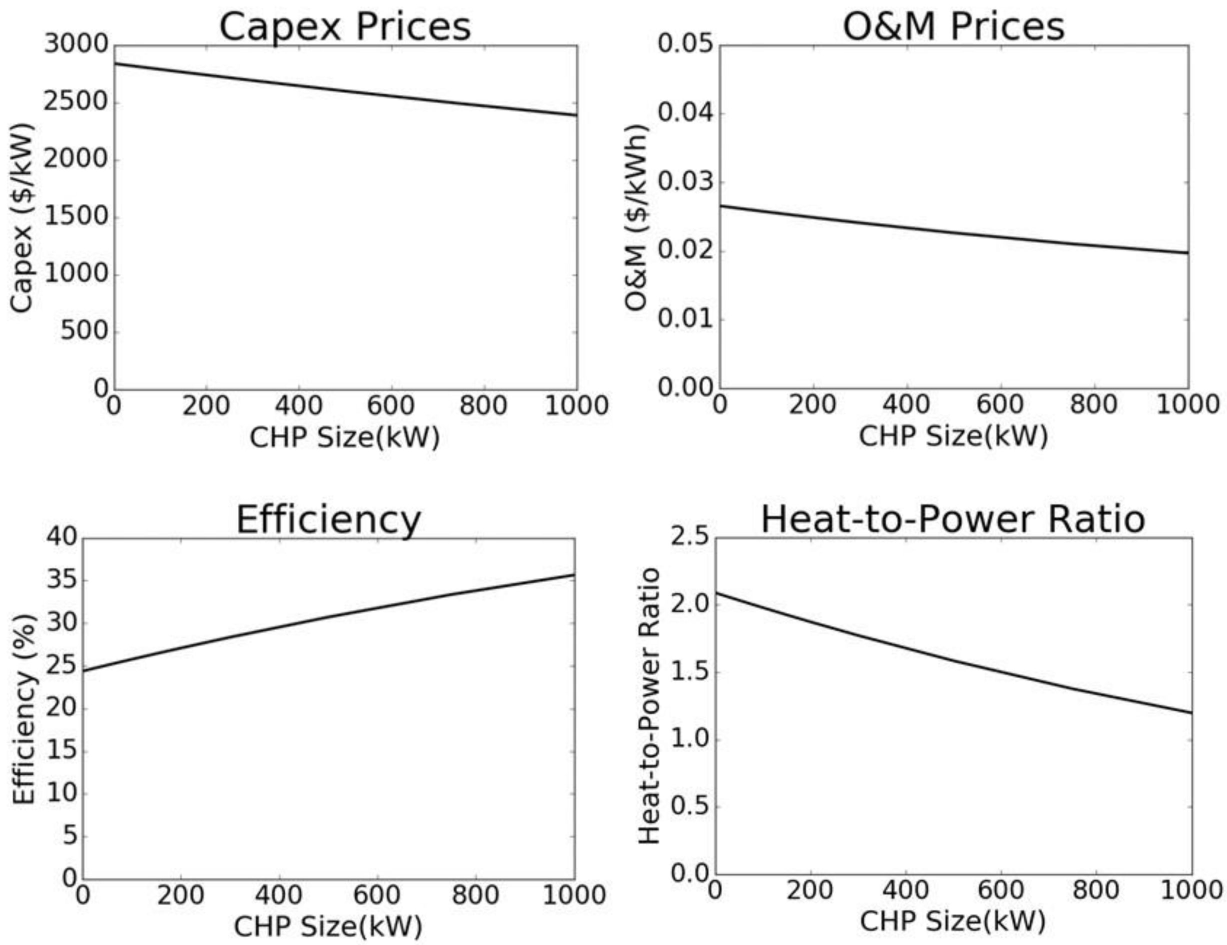


Figure 2-14: CHP Capital prices, O&M prices, and efficiency as a function of CHP Size.

Table 2-4: Private Customer Ownership Hourly Dispatch Model. The first term describes customer payments to the utility for power demand less generated power and shed load. The second term describes the cost of power production less the reduced heating bill from offset boiler demand. The objective function is constrained by the generation operational limits. Demand charges are not included in the objective function but are considered indirectly during the planning stage.

Objective	**Owner**	**Market**	**Input**	**Control Variable**
Minimize Cost over all hours(t)	<u>Private Operation</u> Prosumer with one generator	Deregulated	α=heat to power ratio of CHP plant η_{boiler} = efficiency of the boiler $\eta_e(S_{e,t})$=efficiency of fuel conversion to electrical power as a function of the electrical power delivered D_{max} = Customer's maximum demand in a month $L_{e,t}$ = Hourly Metered Electrical Load $L_{h,t}$ = Hourly Metered Heat Load P_d = The utility demand charge $P_{e,retail}$ = Retail utility price per kWh. P_{ng}=price of natural gas in $/ MMBtu $S_{h,t}$ = The heat power delivered by the generator (depends on $S_{e,t}$)	$S_{e,t}$ = The complex electrical power delivered by the generator

$$\min_{\forall\, hours,t} \begin{array}{l} \left[P_{e,retail} * \left(L_{e,t} - S_{e,t}\right)\right] \\ + \left[\dfrac{S_{e,t}}{\eta_e\left(S_{e,t}\right)} * P_{ng} - \min \begin{cases} S_{e,t} * \alpha * \dfrac{P_{ng}}{\eta_{boiler}}, & S_{e,t} * \alpha \leq L_{h,t} \\ L_{h,t} * \dfrac{P_{ng}}{\eta_{boiler}}, & S_{e,t} * \alpha > L_{h,t} \end{cases}\right] \end{array}$$

Minimize the cost of buying power from the utility.

Minimize the cost of natural gas needed to run the CHP and the boiler. The CHP does not offset natural gas costs if heat demand is already met.

$$s.t. \quad S_{e,min} \leq S_{e,t} \leq S_{e,max}$$

Each generator must operate within its limits.

Table 2-5: Utility Ownership hourly dispatch Model. The first term describes revenue earned by the utility from dispatching CHP at customer sites. The revenue is based on the standard utility tariff less the value of the customer's PPA when CHP is dispatched. The second term describes heat revenue earned at the customer's avoided heating cost. The third term describes the utility's cost of buying power from the wholesale market and of generating power. Power exports at the customer level are not permitted. Demand charges are not included in the objective function but are considered indirectly during the planning stage. Additionally, the utility must offer a power purchase to agreement to compensate for the opportunity cost foregone by not renting the space the CHP occupies**.**

Objective	**Owner**	**Market**	**Input**	**Control Variable**
Maximize profit over all hours(t)	Utility Operation i Customers with CHP	Deregulated	$P_{e,retail}$ = Utility retail price per kWh of electricity/heat. $P_{e,PPA}$ = the agreed PPA for electricity/heat P_{ng}=price of natural gas in $/ MMBtu $P_{m,t}$ = locational marginal price (modified) $L_{e/h,i,t}$ = Hourly metered electrical/heat Load P_d = The utility demand charge D_{max} = Customer's maximum demand in a month $\eta_e(S_{e,t})$=efficiency of fuel conversion to electrical power as a function of the electrical power delivered $S_{h,t}$ = The heat power delivered by the generator (depends on $S_{e,t}$)	$S_{e,t}$ = The complex electrical power delivered by the generator

$$\max_{\forall\, hours,t} \left[\sum_i \left(\left(P_{e,retail} - P_{e,PPA}\right) * \left(S_{e,i,t}\right) + P_{e,retail} * \left(L_{e,i,t} - S_{e,i,t}\right)\right)\right]$$

Maximize profit from CHP and retail electrical power sold to the customer. The CHP power is discounted in accordance with a PPA.

$$+\left[\sum_i \min \begin{cases} S_{e,i,t} * \alpha * \dfrac{P_{ng}}{\eta_{boiler}}, & S_{e,i,t} * \alpha \le L_{h,i,t} \\ L_{h,i,t} * \dfrac{P_{ng}}{\eta_{boiler}}, & S_{e,t} * \alpha > L_{h,t} \end{cases}\right]$$

Maximize profit from CHP and heat power sold to the customer. The CHP does not offset natural gas costs if heat demand is already met.

$$-\left[\sum_i \left(\left(L_{i,t} - S_{e,t}\right) * P_{m,t} + \frac{S_{e,t}}{\eta_e\left(S_{e,t}\right)} * P_{ng}\right)\right]$$

Minimize wholesale costs for any load that has not been offset by the CHP, and minimize natural gas costs for running the CHP.

$$s.t. \quad S_{e,min} \le S_{e,t} \le S_{e,max}$$

Each generator must operate within its limits.

$$\sum_i S_{i,t} \le feeder\ demand$$

2.9.2 Metrics

The operational strategy of each owner affects when the CHP are dispatched and therefore, will affect the network, economic, and environmental benefits associated with the CHP.

Network Metrics

The metrics used for quantifying the network benefits are network losses, equipment capacity utilization, and network violations. Network losses are the I^2R losses and are multiplied by the wholesale cost to determine the network system costs. Capacity utilization is the ratio of the maximum observed electrical power (or electrical current) to the equipment rating. Reductions in capacity utilization can be quantified in terms of their potential for capital expenditure deferrals. Similarly, a reduction in network violations also has value to the utility. Voltage violations, which we define as any deviation in voltages outside the ANSI standard (114-126 volts) (Short 2004), may require adjustments to under load tap changing transformers (ULTCs), investments in capacitors, or reconductoring distribution lines. Thermal violations (i.e. equipment overloading) may require investments in new transformers or new distribution lines. The cost of capacity for different distribution components are shown in Table 2-6.

Table 2-6: Cost of distribution components. Each ownership operating strategy will affect the network differently and may increase or reduce future network investment costs. Figure adapted from Knapp et al. **(Knapp, et al. 2000)** Original data is from Willis et al. **(Willis and Scott, Distributed Power Generation 2000)** and Burke. **(Burke 2002)** The number of significant figures have been preserved from the original sources.

<table>
<tr><th>Equipment Type</th><th colspan="3">Cost Example</th></tr>
<tr><td>Lines</td><td colspan="3">▪ $50k/mile (46 kV wooden pole subtransmission)</td></tr>
<tr><td>Feeder</td><td colspan="3">▪ $10-15 per kW-mile (12.47 kV overhead)
▪ $30-50 per kW-mile (12.47 kV underground)</td></tr>
<tr><td>Laterals</td><td colspan="3">▪ $5-15 per kW-mile (low voltage overhead)
▪ $5-15 per kW-mile (low voltage underground-direct buried)
▪ $30-100 per kW-mile (low voltage underground-ducted)</td></tr>
<tr><td rowspan="5">Single Phase Pad Mount Transformers</td><td>Capacity</td><td>12.5 kV</td><td>34.5 kV</td></tr>
<tr><td>20 kVA</td><td>$2552</td><td>$3119</td></tr>
<tr><td>50 kVA</td><td>$2986</td><td>$3931</td></tr>
<tr><td>75 kVA</td><td>$3591</td><td>$4725</td></tr>
<tr><td>100 kVA</td><td>$4972</td><td>$5728</td></tr>
<tr><td>Three Phase Pad</td><td>Capacity</td><td>12.5 kV</td><td>34.5 kV</td></tr>
</table>

Mount Transformers	75 kVA	$7,749	$10,584
	150 kVA	$9,450	$11,605
	300 kVA	$11,718	$15,574
	500 kVA	$13,608	$20,034
	750 kVA	$21,357	$21,377
	1000 kVA	$25,515	$28,824
	1500 kVA	-	$40,824
	2500 kVA	-	$50,841
Substation	▪ $3,348,000 (115/13.2 kV, 20/37.3 MVA, 4 feeder) ▪ $1,026,000 (35/12.5kV, 12/16/20 MVA, 2 feeder) ▪ $4,050,000 (115/35kV,60/112 MVA, 5 feeder) ▪ $23/kW (rural 69 kV 5MVA single transformer) ▪ $25-33/kW (138/12.47kV 80 MVA)		

Economic Metrics

The system savings, private customer savings, and utility savings were assessed for one year of operation. They are summarized below and in Figure 2-15. The system savings is identically defined for all ownership models. The private customer and utility savings change for each ownership model.

System Savings

The system savings include all savings associated with meeting end-user heat and electrical energy demand, but excludes any costs associated with reselling power. Savings include, the wholesale power purchase reductions, generation cost reductions, heating cost reductions, and T&D cost reductions. The system savings is,

$$System\ Savings = System\ Costs\ without\ CHP - System\ Costs\ with\ CHP$$

$$System\ Cost = \sum_{\forall CHP} \sum_{\forall Hours} \begin{array}{l} Net\ Load_{CHP,hour} * Modified\ LMP_{hour} \\ \quad +Generation\ Cost_{CHP,hour} \\ \quad +Heating\ Cost_{CHP,hour} \end{array}$$

The LMP is increased (modified) to equal the average commercial price of electricity, as given by the EIA, so it includes transmission and distribution costs. The net load is the original load less generation and the generation cost is defined by,

$$Generation\ Cost = \frac{Real\ Power}{Efficiency} * Cost\ of\ Natural\ Gas + O\&M\ Costs + Capex$$

Private Customer Ownership Model

When the CHP are operated by a private customer, the utility sells less power, so savings are negative. The utility loses revenue for each unit of CHP energy (less the pass-through transmission and energy costs) that is produced. Customer savings are created from avoided retail power costs less the generation cost. The customer saves money if the retail value of this power is greater than the generation cost.

$$Utility\ Savings = \left(-\sum_{\forall CHP}\sum_{\forall Hours} Power_{CHP,hour} * (Retail\ Price_{hour} - Transmission\ Cost - LMP_{hour})\right) - \sum_{\forall CHP}(Max\ Load - Max\ Net\ Load) * Demand\ Charge$$

$$Customer\ Savings = \sum_{\forall CHP}\sum_{\forall Hours} \begin{matrix} Power_{CHP,hour} * Retail\ Price_{hour} \\ -Generation\ Cost_{CHP,hour} \end{matrix} + \sum_{\forall CHP}(Max\ Load - Max\ Net\ Load) * Demand\ Charge$$

Utility Ownership Model

When the utility operates the CHP, customer and utility savings are dependent on the PPA. The PPA is the $/kWh rate paid to customers by the utility to compensate for the opportunity cost foregone by not renting the space the CHP occupies. The utility savings are defined as the difference between load acquired entirely through the wholesale market (i.e. LMP and transmission costs) and load acquired through a combination of market purchases, PPA purchases, and generation costs. The customer savings increase according to the PPA for each unit of CHP power produced and for demand charge reductions.

Utility savings are defined with a modified LMP that includes transmission costs as,

$$
\begin{aligned}
&Utility\ Savings \\
&= \sum_{\forall CHP} \sum_{\forall Hours} Load_{CHP,hour} * Modified\ LMP_{hour} \\
&- \left[\sum_{\forall CHP} \sum_{\forall Hours} Net\ Load_{CHP,hour} * Modified\ LMP_{hour} \right. \\
&+ \sum_{\forall CHP} \sum_{\forall Hours} Power_{CHP,hour} * PPA + \sum_{\forall CHP} \sum_{\forall Hours} Generation\ Cost_{CHP,hour} \\
&- \sum_{\forall CHP} \sum_{\forall Hours} Heat\ Costs_{\ CHP,hour} \\
&\left. - \sum\nolimits_{\forall CHP} (Max\ Load - Max\ Net\ Load) * Demand\ Charge \right]
\end{aligned}
$$

The customer savings are defined as,

$$
\begin{aligned}
&Customer\ Savings \\
&= \sum_{\forall CHP} \sum_{\forall Hours} Power_{CHP,hour} * PPA \\
&+ \sum\nolimits_{\forall CHP} (Max\ Load - Max\ Net\ Load) * Demand\ Charge
\end{aligned}
$$

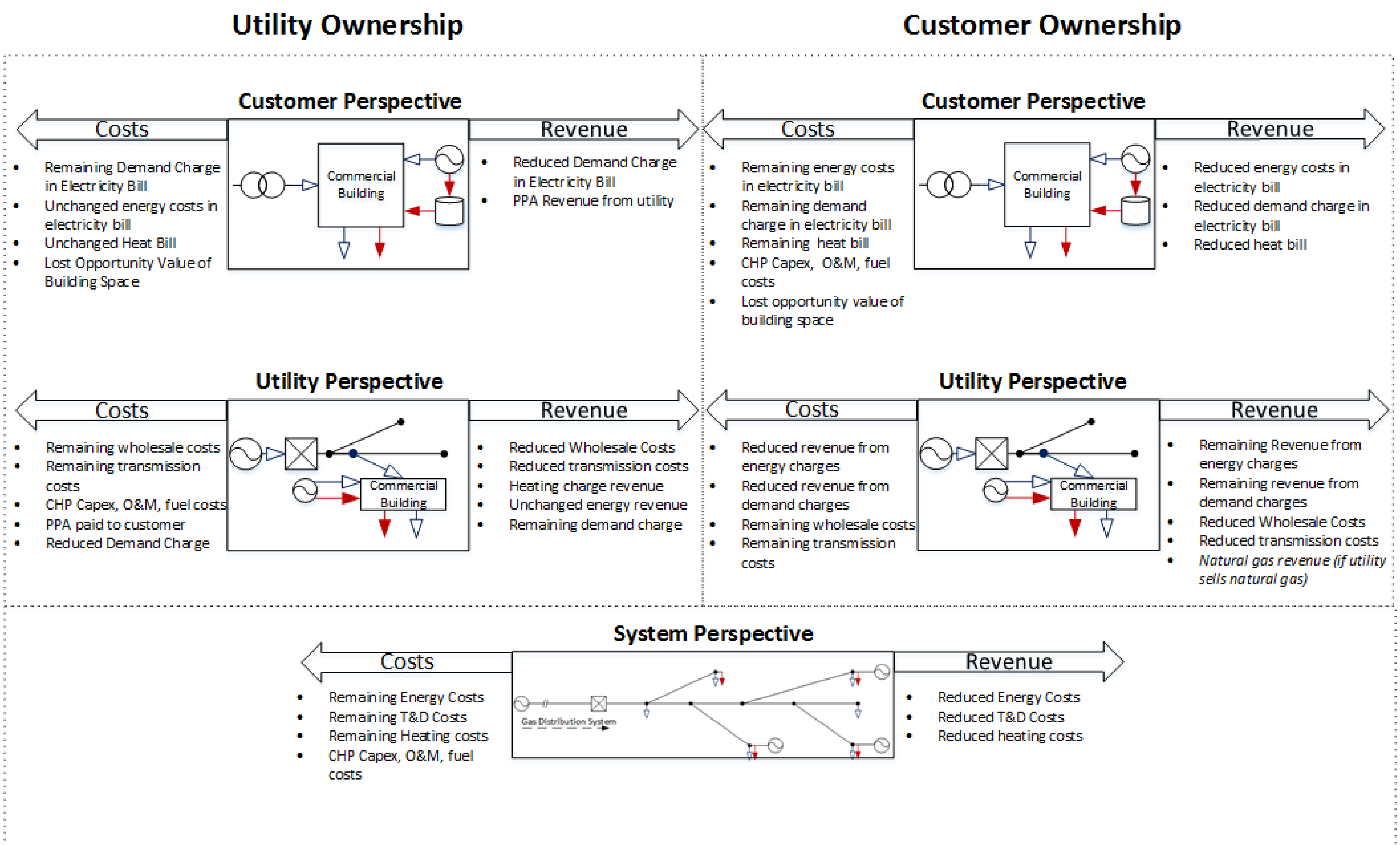


Figure 2-15: System, customer and utility costs and revenues associated with CHP. For example, under customer ownership, the utility will see reduced revenue from energy charges and demand charges. Wholesale and transmission costs will be reduced but will still remain. Revenue will still come from remaining energy sales and demand charges not met by the CHP. The utility will also see lower wholesale and transmission costs. Overall, the utility will experience losses from this arrangement, but it is possible that the utility will benefit on occasion when wholesales costs are above the retail electricity price. Utility losses will also be mitigated if the utility sells natural gas.

Environmental Metrics

The avoided CO_2, SO_2 and NO_x emissions are used to evaluate the environmental impact of each model. Avoided emissions are aggregated over one year of operation for each owner. To calculate the avoided emissions, the emissions of each owner are compared with and without the CHP. Marginal emissions were used for the bulk power grid from Siler-Evans et al. (2012), but was updated by the authors (2012) for more recent years. Low NO_x CHP emissions and uncontrolled boiler emissions were assumed.

2.9.3 Input

The benefits of CHP for each ownership model were based on New York and Northeastern input parameters. Tariffs were taken from NYSEG and NYISO. Heat loads are based on ASHRAE climate region 6. Otherwise, data is from the northeast. All data input and their sources are summarized in Table 2-7. The distribution network statistics are shown in Table 2-8 and the network feeder is shown in Figure 2-20. Emissions produced by the bulk power system and CHP are shown in Figure 2-19 and Table 2-9, respectively. The distribution of utility bulk power prices is shown in Figure 2-20. The distribution of these prices for the years 2010-2014 are shown in Figure 2-21.

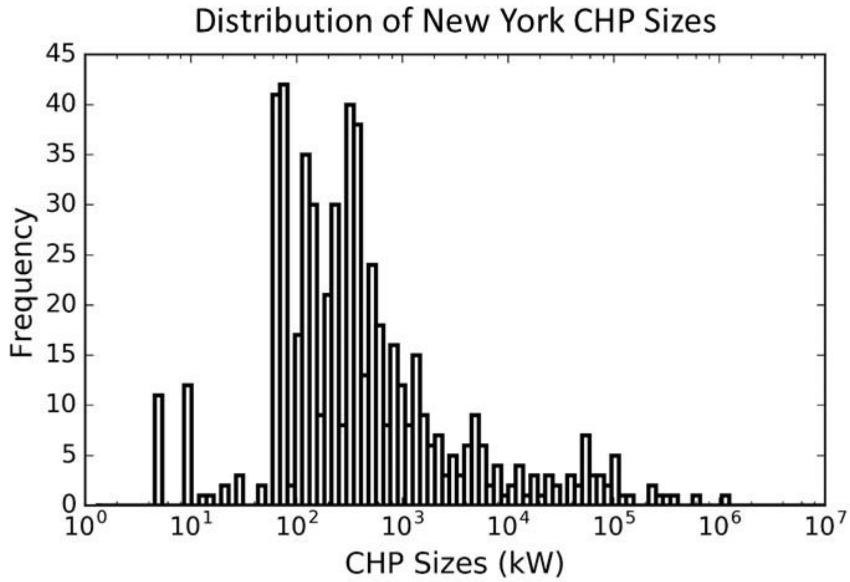


Figure 2-16: Distribution of CHP Sizes in New York **(DOE 2019)**. The majority of CHP in New York are less than 1 MW.

Table 2-7: Model input values.

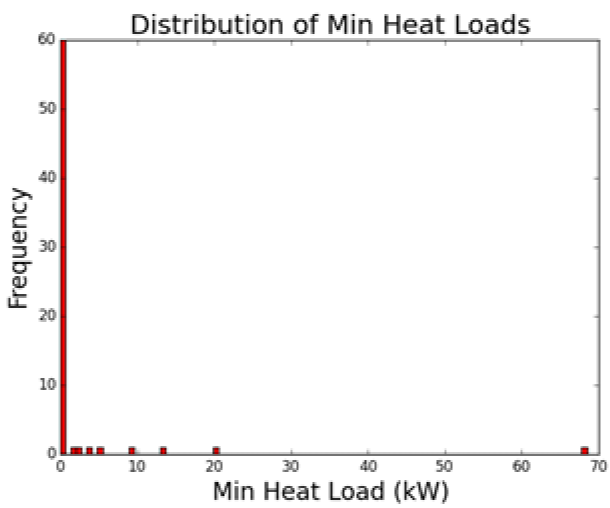
Data	Description	Value	Source(s)
Building Heating and Electric Loads	Loads are based on the DOE Commercial Reference Building Models and EnergyPlus simulation software	See Figure 2-11and Figure 2-12	(EERE 2015), (NREL 2011)
NYISO Wholesale Prices	Day-Ahead Locational Marginal Prices	Average $0.143/kWh See Figure 2-20for distribution.	(NYISO 2015)
Commercial Electricity Prices	Flat Energy Charge and Demand Charge	$0.143/kWh $8/kW	(OpenEI 2015)
US State EIA Commercial Electricity Prices	Average Commercial rate	$0.162/kWh	(EIA 2014)
Commercial Natural Gas Prices	Monthly $/MCF cost of Natural Gas in New York for commercial customers	$6-12/MCF	(EIA 2016)
Time Varying Electrical Loads	Hourly electric loads matched to PNNL Feeder Taxonomy	Figure 2-13	(Hoke, et al. 2013)
Number of each building type	Proportion of each building type that are placed on the network.	See Table 2-2	(EIA 2003)

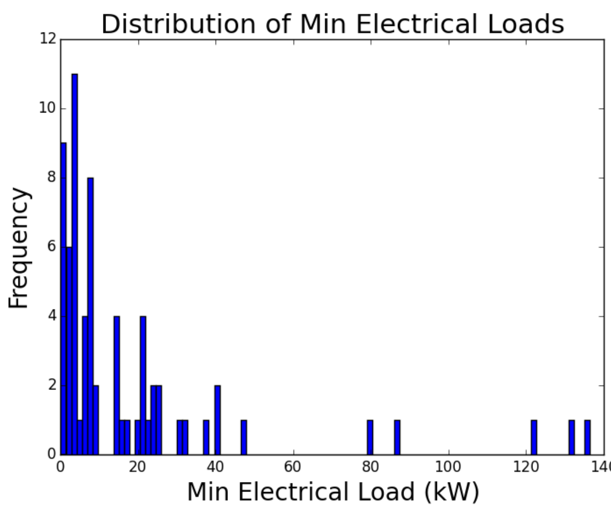
CHP Parameters	Capex, O&M, linear efficiencies for 75, 250, and 1121 kW natural gas reciprocating engines.	See Table 2-3	(Lawrence Berkeley National Laboratory 2015) *Sandbox Version (U.S. EPA 2015)
Marginal Emission Factors	NPCC marginal emission for CO2, NOx, and SO2	Figure 2-19	(Siler-Evans, Azevedo and Morgan 2012)
CHP Emissions	NOx, CO2 and SO2 emissions	Table 2-9	(U.S. EPA 2015)
Cost of Building Space	The value of building space is needed to calculate CHP host opportunity cost.	$\$25.4/ft^2$ per year Class A suburban	(Cross 2015)
Boiler Efficiency	The Annual Fuel Utilization Efficiency (AFUE) minimum requirement stated by ASHRAE 90.1-2004. This the highest efficiency used by der-cam. Decade old, but probably more representative of actual boiler stock.	0.8	(AHRAE 2004)
Boiler Emissions	CO_2, SO_2, and NOx emission of uncontrolled boilers	Table 2-9	(EPA 1998)
Effective Tax Rate	The effective tax rate is used to calculate	20%	(Small Business Administration 2009)
Depreciation	MACRS	15 Year	(IRS 2014)

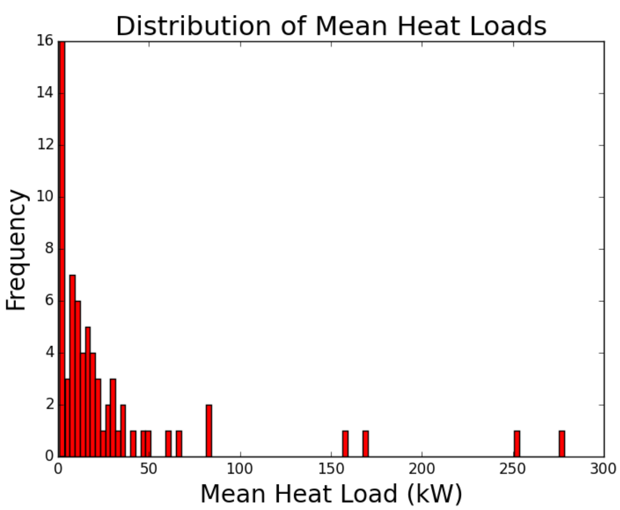
Table 2-8: Feeder Statistics for Feeder R2-25.00-1.

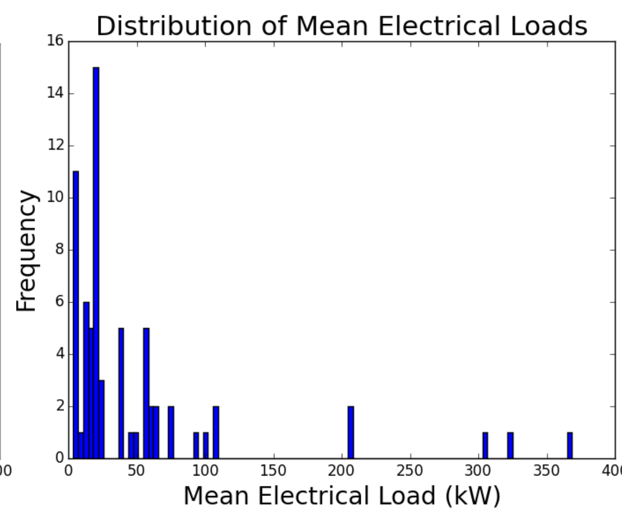
Feeder Statistics	
Description	Representative north eastern feeder situated in a moderately populated suburban area with light and moderate loading.
Components	**Number of Components**
Nodes	728
Loads	274
Regulator	1
Transformer	274

Switch	39		
Capacitor	5		
Fuse	57		
Overhead Line	146		
Triplex Line	202		
Underground Line	81		
Loading Condition	**Min**	**Mean**	**Max**
Coincident Load (kW)	5.7	10.1	16.2
Losses	0.7%	1.0%	1.1%
Load Factor	-	64%	-









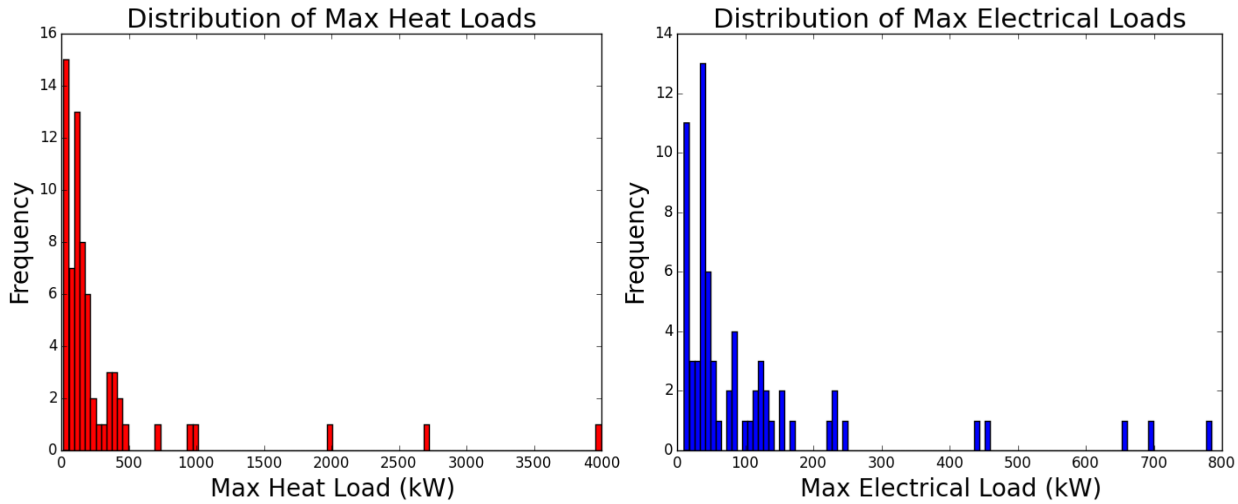


Figure 2-17: Minimum, mean, and maximum heat and electrical loads. The minimum and mean electrical loads are generally larger than the minimum and mean heat loads. CHP sizing will be constrained by the heat loads.

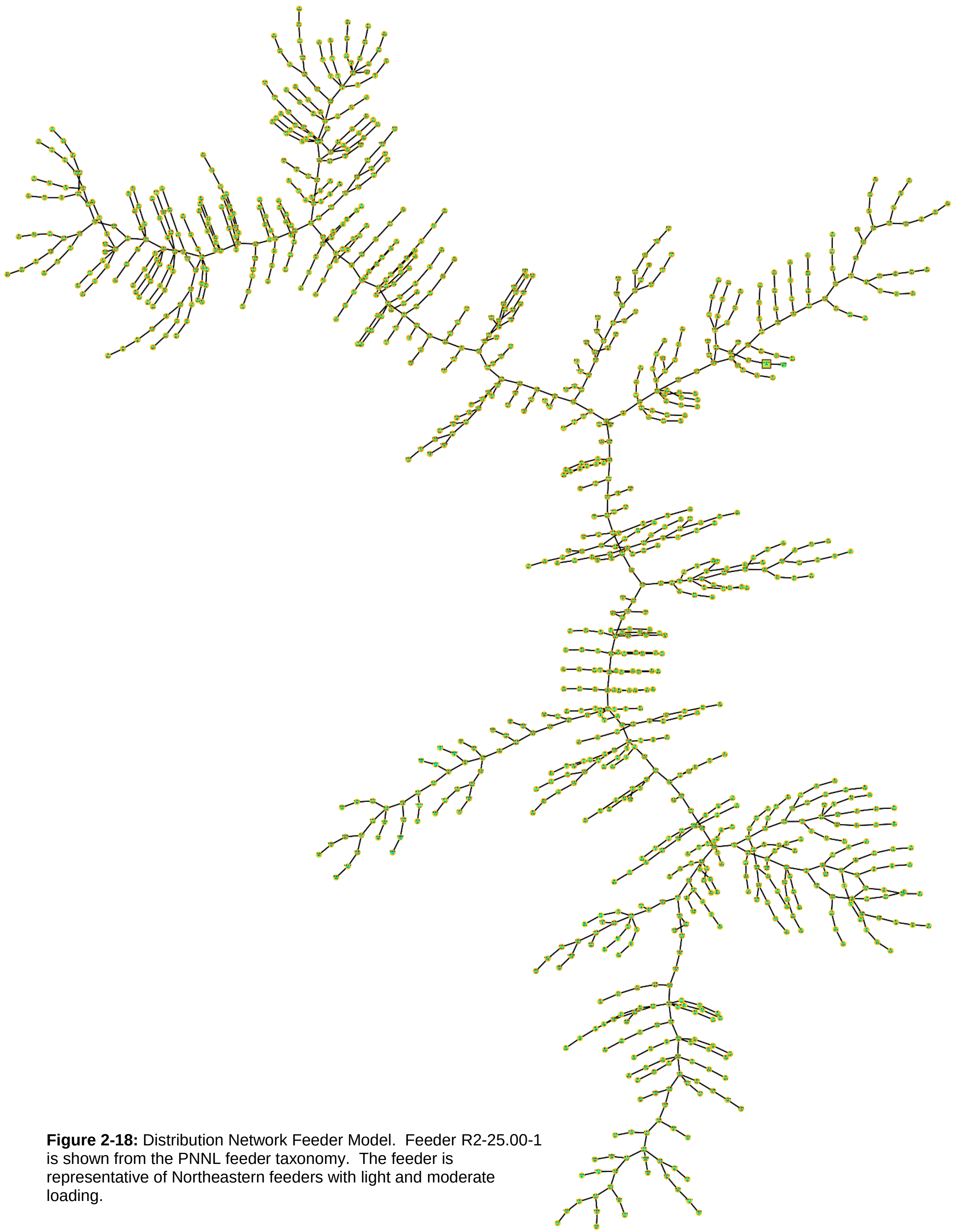
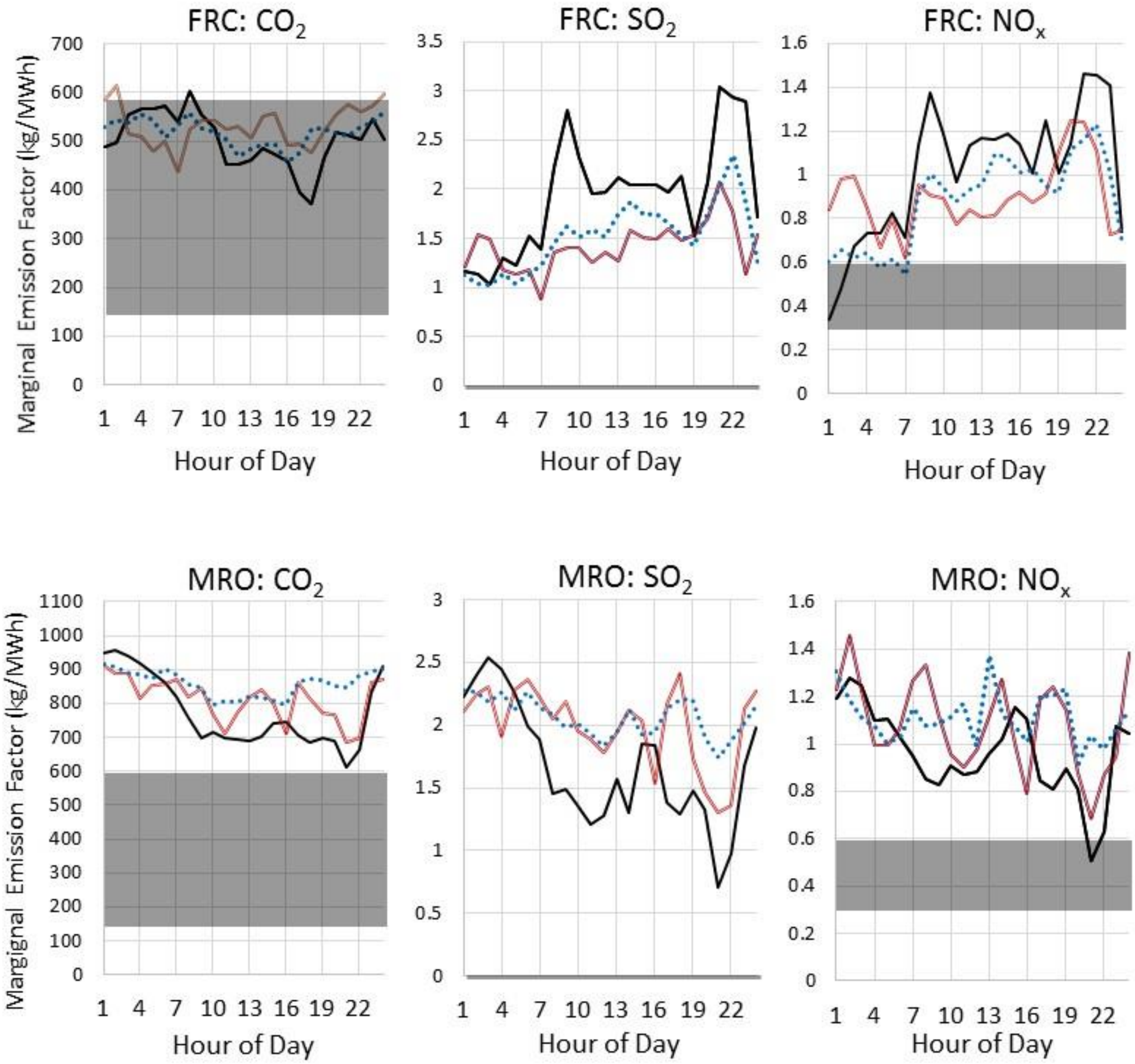
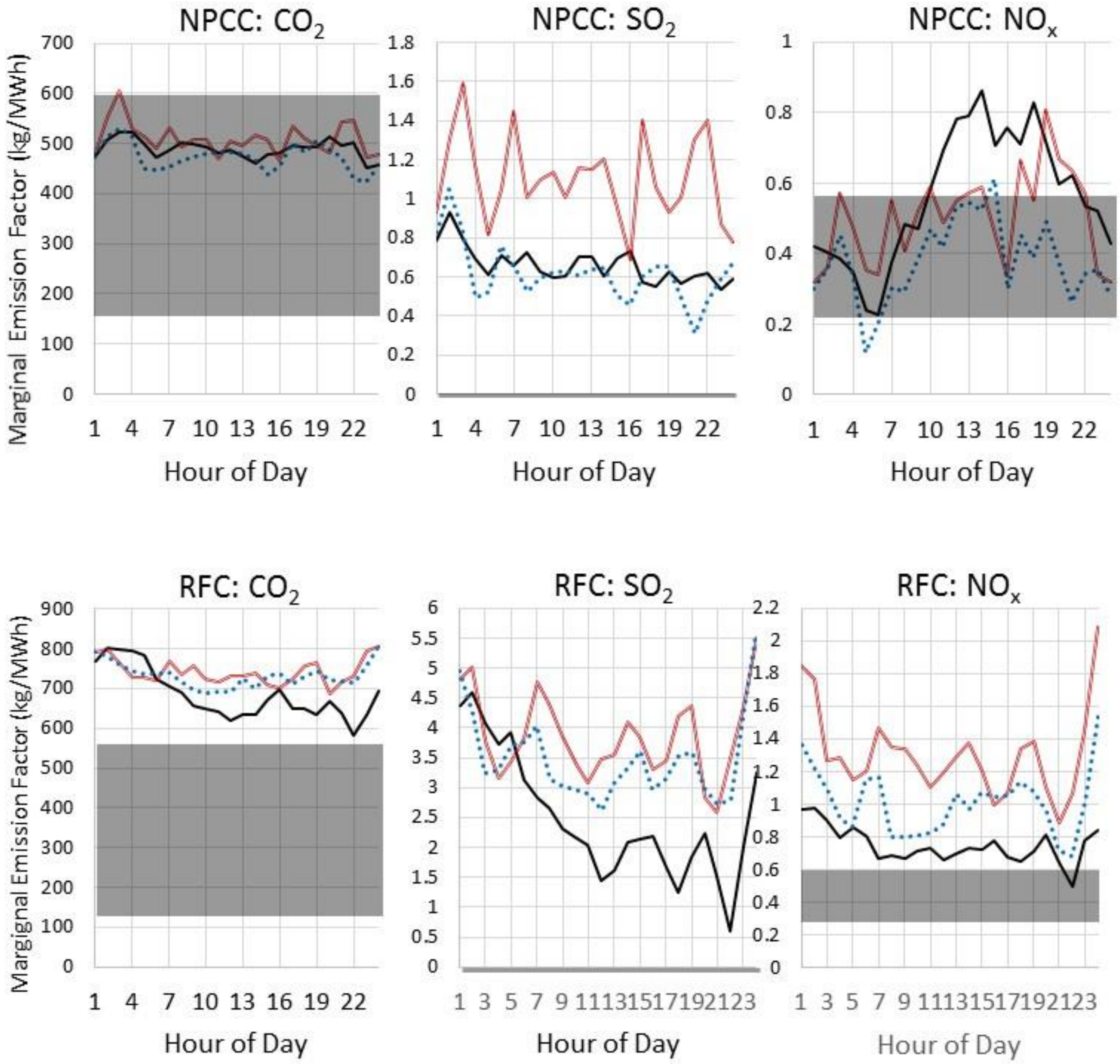
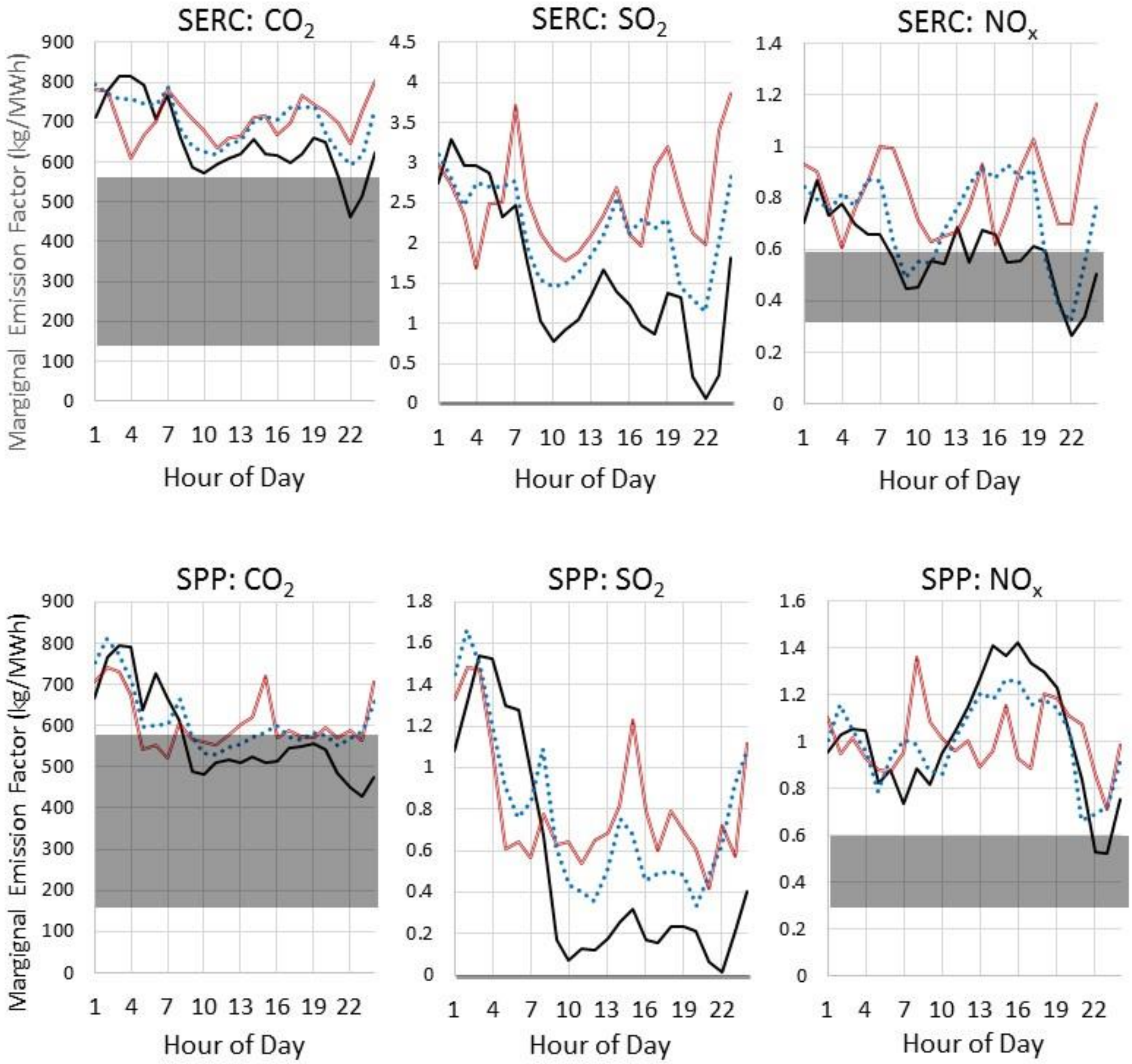


Figure 2-18: Distribution Network Feeder Model. Feeder R2-25.00-1 is shown from the PNNL feeder taxonomy. The feeder is representative of Northeastern feeders with light and moderate loading.


FRC: CO_2
FRC: SO_2
FRC: NO_x
MRO: CO_2
MRO: SO_2
MRO: NO_x
Marginal Emission Factor (kg/MWh)
Hour of Day



NPCC: CO_2
NPCC: SO_2
NPCC: NO_x
RFC: CO_2
RFC: SO_2
RFC: NO_x
Marginal Emission Factor (kg/MWh)
Margignal Emission Factor (kg/MWh)
Hour of Day


SERC: CO_2
SERC: SO_2
SERC: NO_x
SPP: CO_2
SPP: SO_2
SPP: NO_x
Margignal Emission Factor (kg/MWh)
Hour of Day
1 4 7 10 13 16 19 22

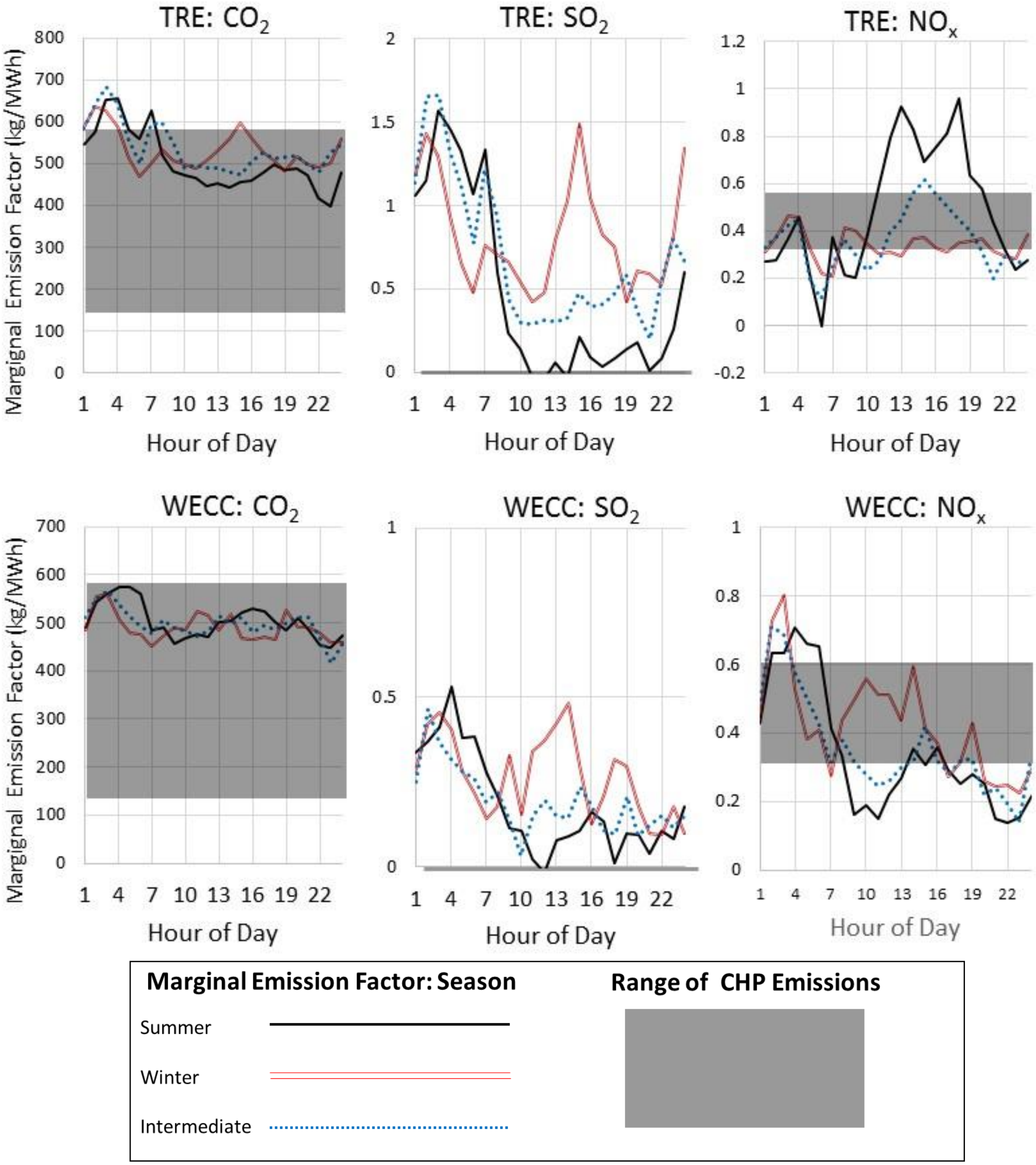


Figure 2-19: Comparison of Bulk Power Grid Marginal Emission Factors **(Siler-Evans, Azevedo and Morgan 2012)** with the range of potential CHP emissions. The marginal emission factors are shown for each reliability region, season and hour of the day. The range of CHP CO_2, SO_2, and NOx emissions is shown in the grey boxes (SO_2 emission are zero). The CHP emissions depends on how much heat load is offset. If all of the CHP heat is wasted it produces the equivalent of 600 kg CO_2/MWh, 0 kg SO_2/MWh, and 0.6 kg NOx/MWh. If all of the CHP heat is used it produces the equivalent of 150 kg CO_2/MWh, 0 kg SO_2/MWh, and 0.3 kg NOx/MWh. CHP emission are based on a 30% electrical efficiency, heat-to-power ratio of 2, and a boiler without NOx controls.

Table 2-9: CHP and Boiler Emissions.

Pollutant	CHP Emissions (kg/MWh-e)	Boiler Emissions (kg/MWh-th)
CO_2	600	225
SO_2	0.0	0.0
NO_X	0.628	0.15

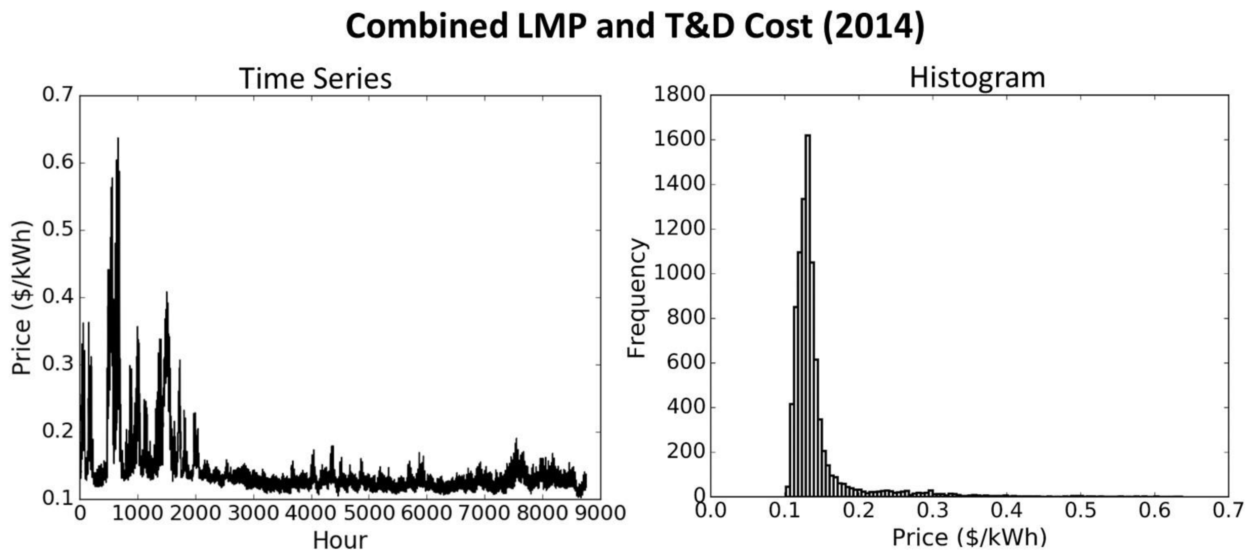


Figure 2-20: Utility cost of electricity. The time varying costs and cost histogram are shown for the year 2014.

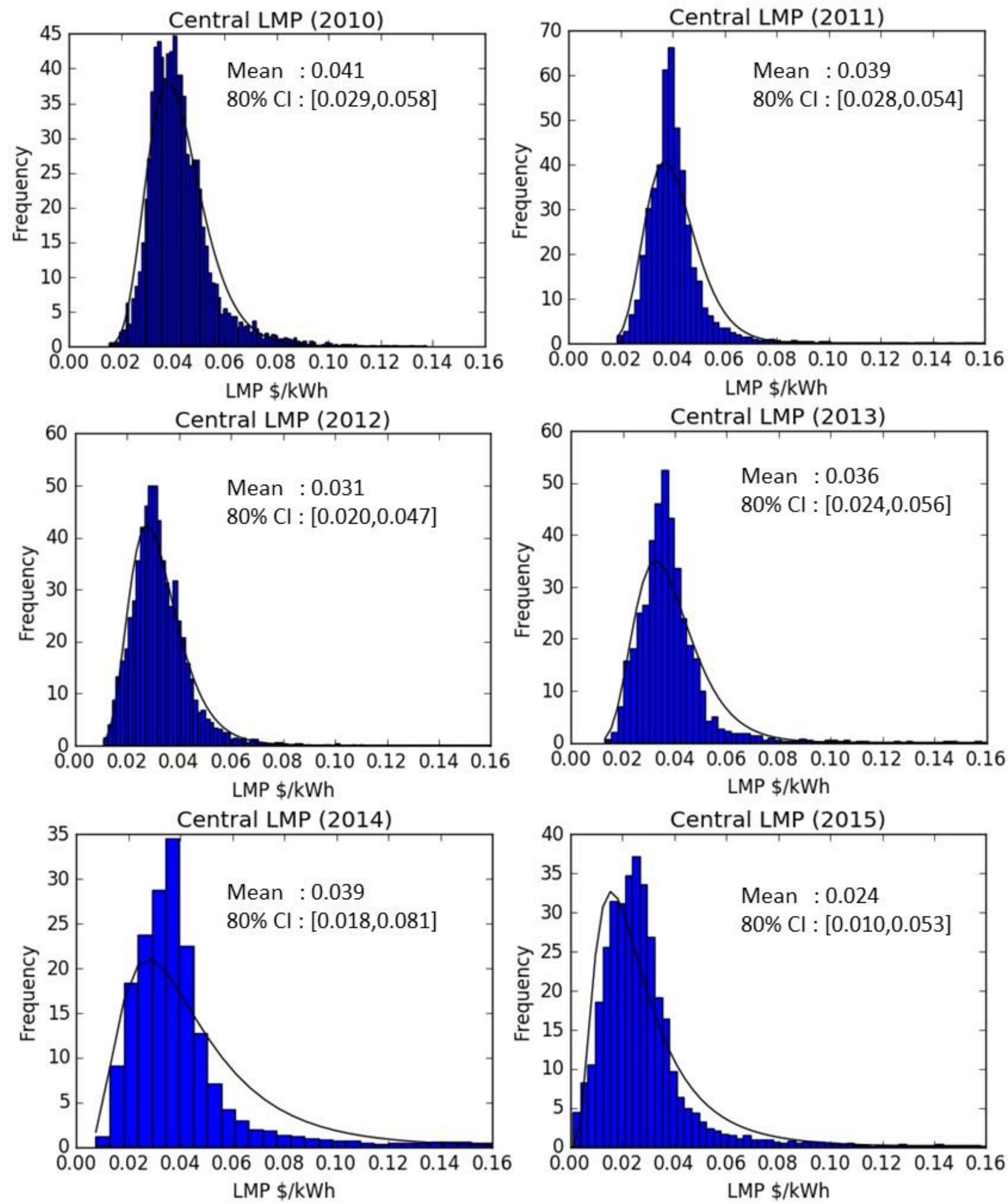


Figure 2-21: New York LMPs 2010-2015.

2.9.4 Results

Planning

The utility must offer the customer a power purchase agreement (PPA) to compensate for the opportunity cost foregone by not renting the space the CHP occupies; the utility can afford to do this because CHP reduces the utility's wholesale power purchase costs. We define a PPA similarly to the SolarCity PPA, where the customer earns a fixed rate for each kWh produced by the CHP. In many cases it is not necessary for the utility to offer a PPA, because the customer's avoided demand charges are greater than the opportunity cost foregone by not renting the space the CHP occupies. Figure 2-22 shows the range of PPAs that the utility could offer to the host customer of each load.

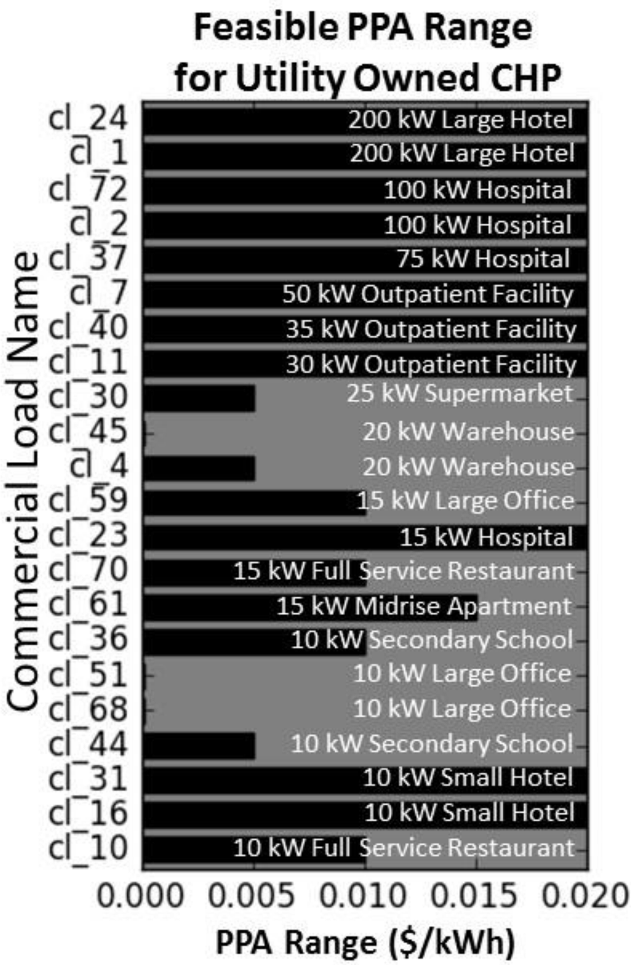
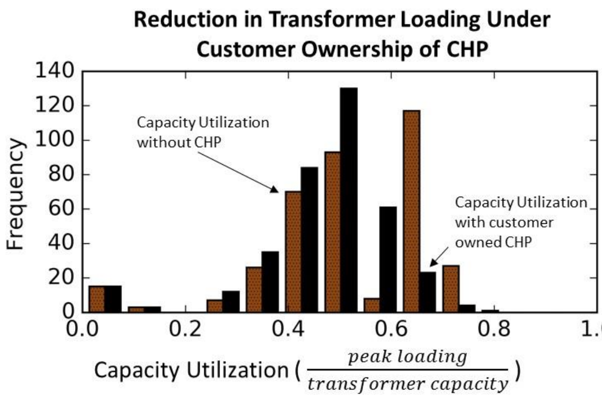
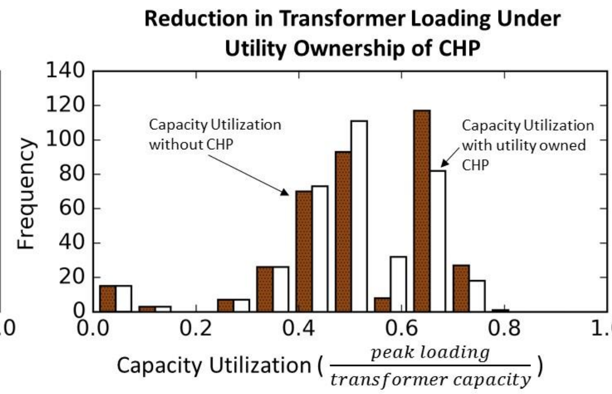


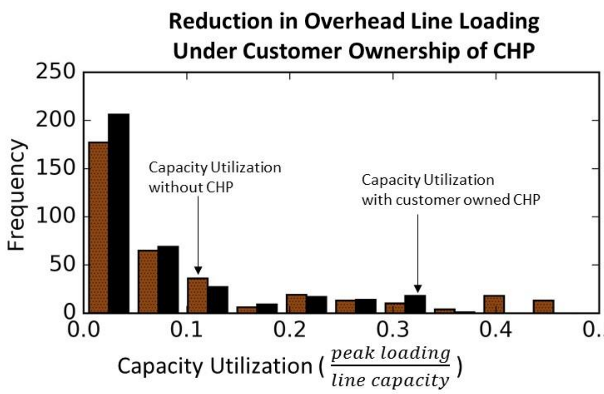
Figure 2-22: Feasible power purchase agreement range for each commercial load. Utilities could offer individual PPAs ranging from $0.0/kWh to $0.02/kWh to compensate for the opportunity cost foregone by not renting the space the CHP occupies. $0.0/kWh PPAs are possible when the CHP reduces customer demand charges enough to compensate for the opportunity cost.

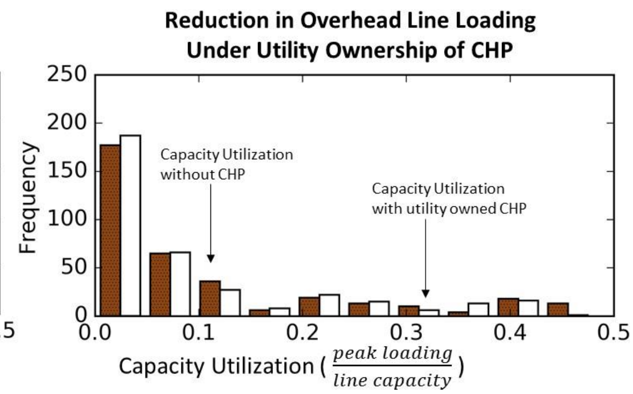
Network

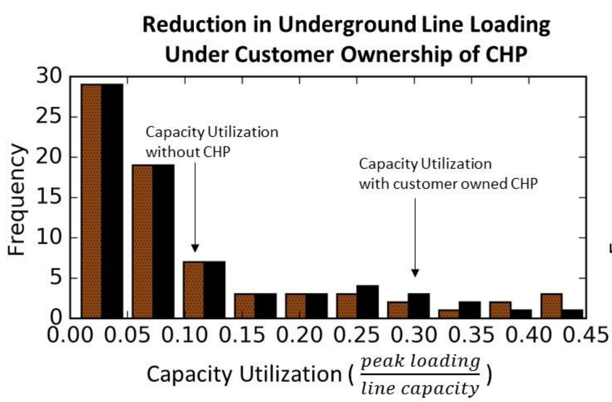
The capacity utilization histograms are shown in Figure 2-23. The distribution transformers, underground lines, and overhead lines all show reduced congestion when CHP are placed on the network. The commercial CHP installations do not reduce congestion on the triplex lines, which only feed residential customers.

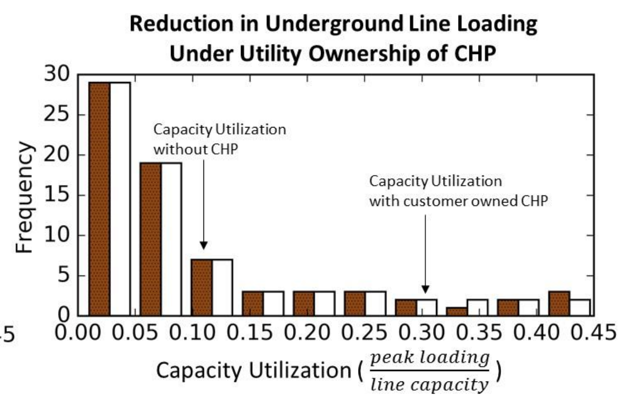

Reduction in Transformer Loading Under Customer Ownership of CHP
Capacity Utilization without CHP
Capacity Utilization with customer owned CHP
Frequency
Capacity Utilization ($\frac{peak\ loading}{transformer\ capacity}$)


Reduction in Transformer Loading Under Utility Ownership of CHP
Capacity Utilization without CHP
Capacity Utilization with utility owned CHP
Frequency
Capacity Utilization ($\frac{peak\ loading}{transformer\ capacity}$)


Reduction in Overhead Line Loading Under Customer Ownership of CHP
Capacity Utilization without CHP
Capacity Utilization with customer owned CHP
Frequency
Capacity Utilization ($\frac{peak\ loading}{line\ capacity}$)


Reduction in Overhead Line Loading Under Utility Ownership of CHP
Capacity Utilization without CHP
Capacity Utilization with utility owned CHP
Frequency
Capacity Utilization ($\frac{peak\ loading}{line\ capacity}$)


Reduction in Underground Line Loading Under Customer Ownership of CHP
Capacity Utilization without CHP
Capacity Utilization with customer owned CHP
Frequency
Capacity Utilization ($\frac{peak\ loading}{line\ capacity}$)


Reduction in Underground Line Loading Under Utility Ownership of CHP
Capacity Utilization without CHP
Capacity Utilization with customer owned CHP
Frequency
Capacity Utilization ($\frac{peak\ loading}{line\ capacity}$)

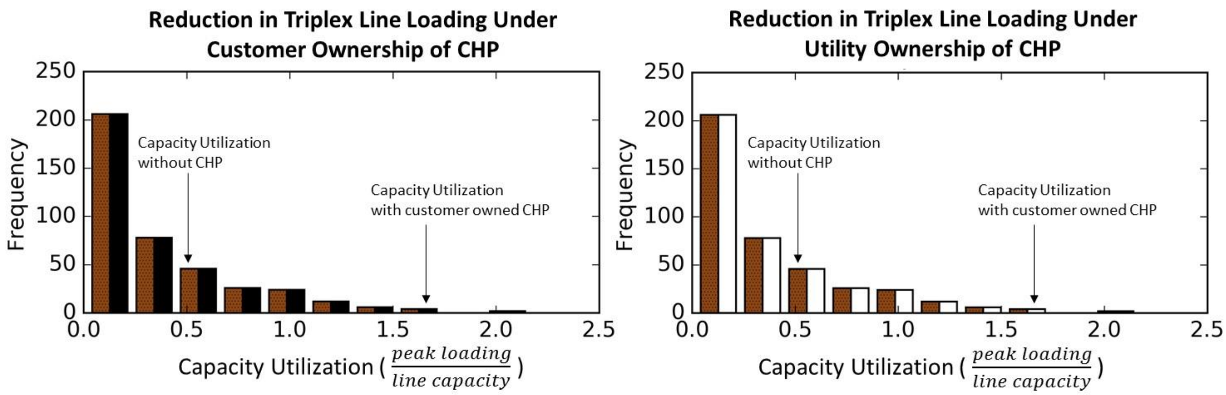
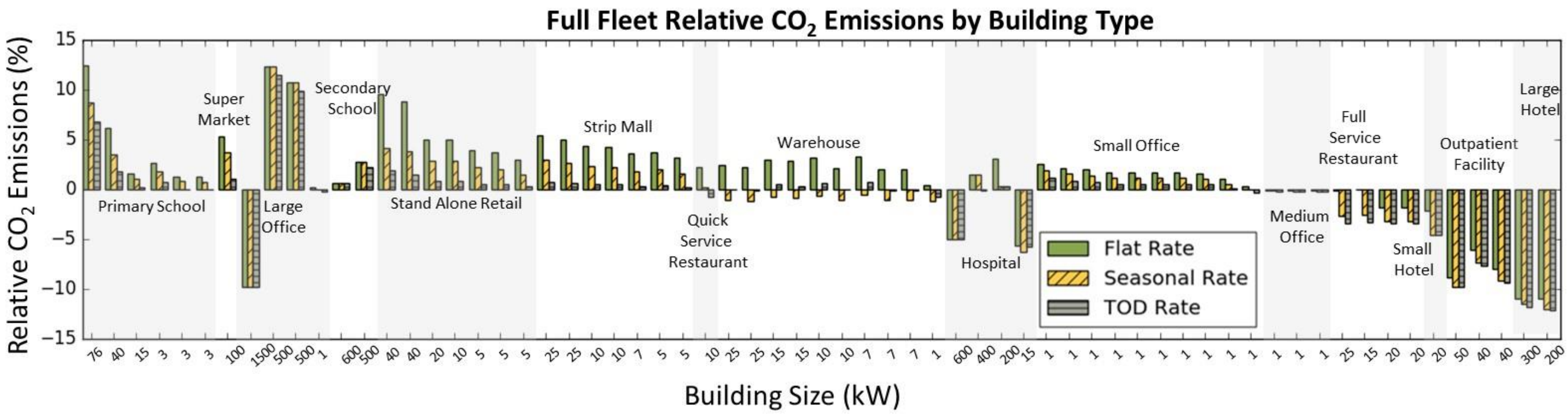


Figure 2-23: Network equipment capacity utilization histograms. The capacity utilization (the ratio of a components maximum observed load to its rating) of overhead lines, and underground lines are similar for both CHP ownership scenarios. The larger number of customer owned CHP shifts the transformer capacity utilization histogram further to the left, suggesting that the higher quantity of customer owned CHP is more effective at deferring network capacity investments.

Emissions

Figure 2-24 shows the annual relative CO_2, SO_2 and NO_x for the fleet of CHP. Each building displays different relative emissions, and Figure 2-6 shows that higher emitting buildings will be installed more as penetrations increase. The higher penetration of higher emitting buildings and time-varying rates leads to large differences in emission between customer and utility owned CHP fleets, as shown in Figure 2 (main text) and Figure 2-25. Figure 2-25 also shows this relationship is consistent for different years with different LMPs and natural gas prices.


Full Fleet Relative CO_2 Emissions by Building Type
Relative CO_2 Emissions (%)
Building Size (kW)
Primary School
Super Market
Large Office
Secondary School
Stand Alone Retail
Strip Mall
Quick Service Restaurant
Warehouse
Hospital
Small Office
Medium Office
Full Service Restaurant
Small Hotel
Outpatient Facility
Large Hotel
Flat Rate
Seasonal Rate
TOD Rate

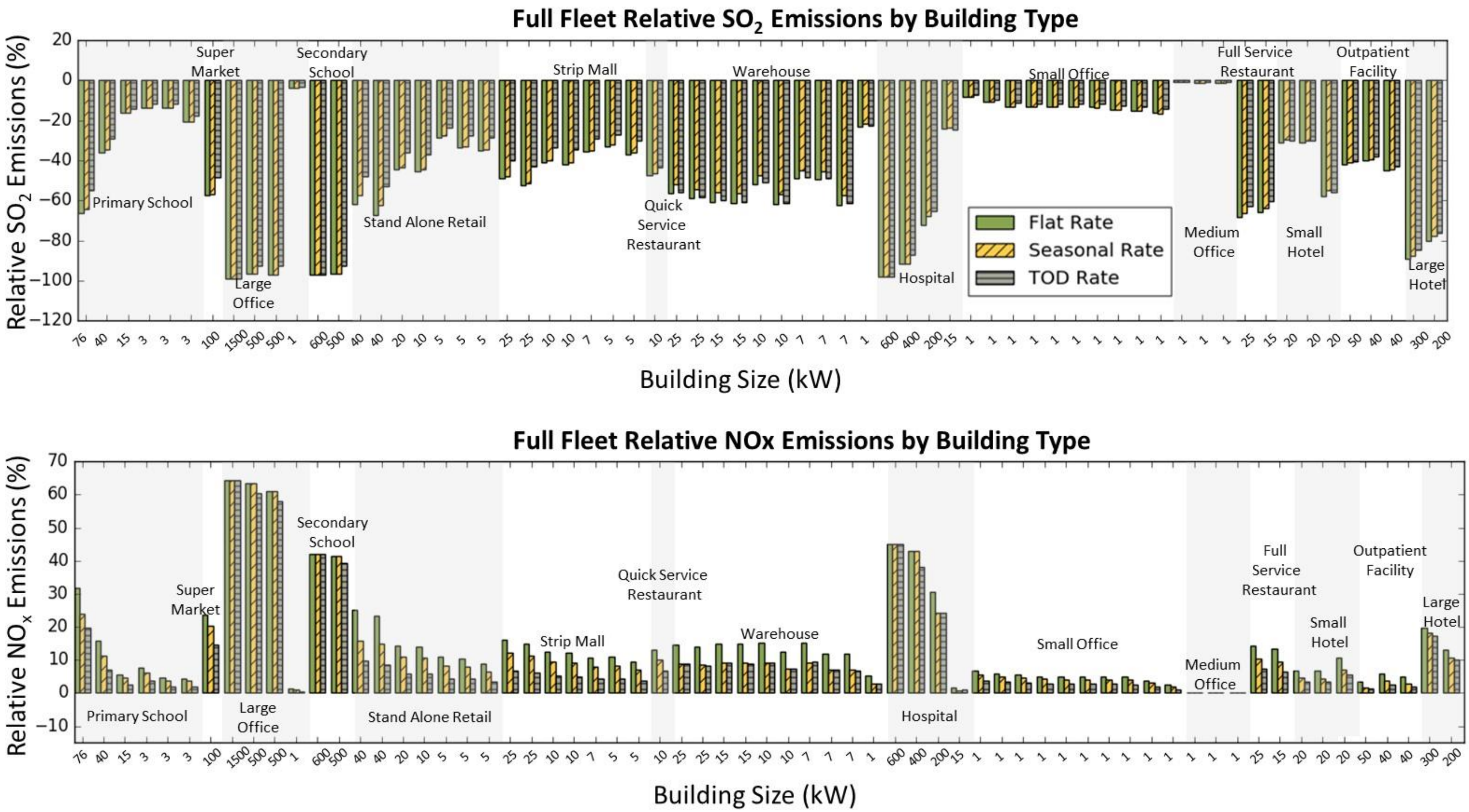


Figure 2-24: Relative CO_2, SO_2, and NO_x building level emissions. Each building type has identical heat and electrical load shapes, but the magnitudes of the loads vary. This causes the optimal CHP size and relative emissions to vary. For buildings with small CHP, seasonal and time-of-day rates are effective at reducing CO_2 and NO_x emissions.

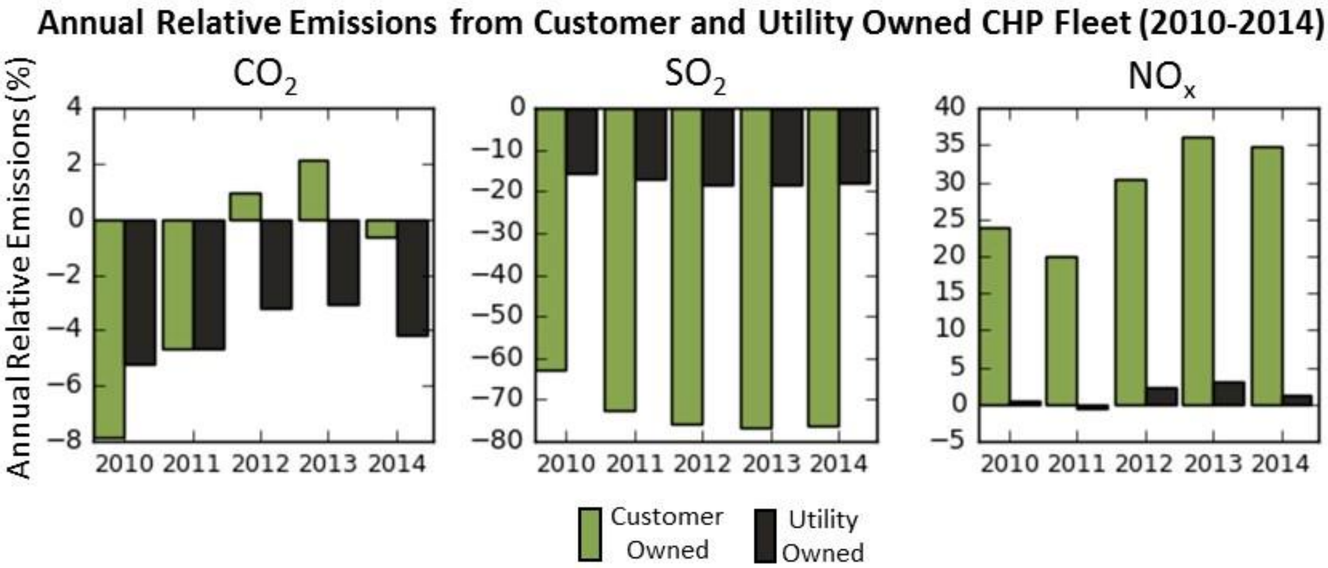


Figure 2-25: Relative CO_2, SO_2, and NO_x CHP Fleet emissions 2010-2014. The relative emissions are generally consistent with 2014. The year 2010 is an exception. High natural gas prices reduced customer owned CHP emissions but also led to unprofitable operating conditions.

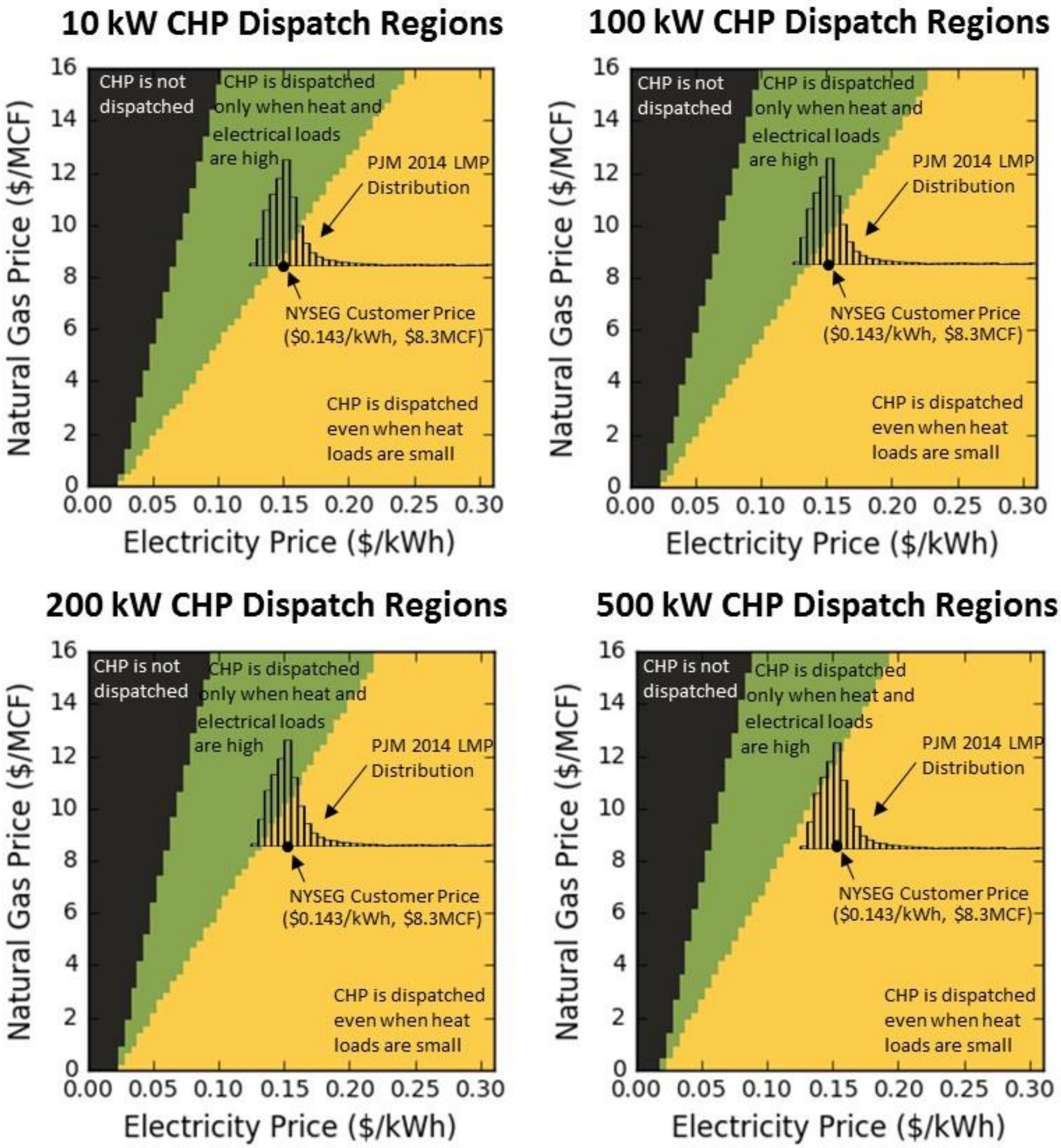


Figure 2-26: Sensitivity of dispatch of a 10kW, 100kw, 200kW and 500kW CHP to natural gas and electricity prices. CHP are not turned on in the black region. In the green region, CHP are only turned on if a heat and electric load is present. In the yellow region, CHP are dispatched at times even when only electric load is present. Dispatch in the green zone is likely to reduce emissions. Dispatch in the yellow zone may not reduce emissions if CHP heat production does not offset building heat load. For small CHP the customer owner's dispatch behavior, presented earlier, with electricity and natural gas at $0.143/kWh and $8.3/MCF falls in the yellow region. And, the utility is subject to a time varying LMP and so, it often falls within the green region**,** leading to lower utility emissions. Larger CHP becomes less sensitive to these effects, so time-varying rates will not be effective at reducing large CHP emissions.

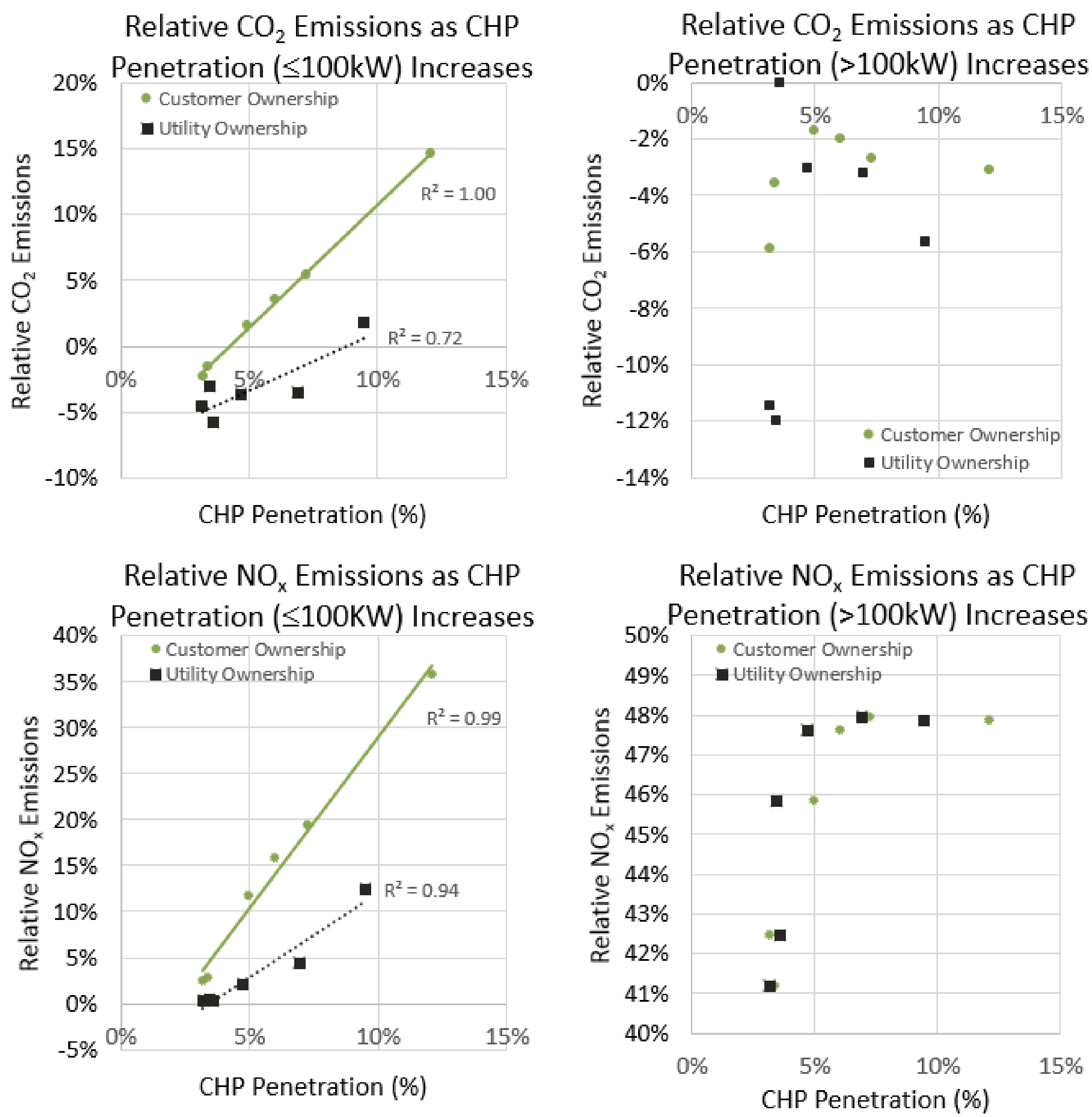


Figure 2-27: Emissions as the penetration of small CHP (<100 kW) and large CHP (>100kW) increases. Emissions increase as the penetration of small CHP increase but time-varying rates are effective at reducing these emissions. Emissions do not increase for large CHP and time-varying rates are ineffective at reducing emissions. The CHP fleet penetration correspond to the following scenarios moving from left to right: 30% Increase in CHP Capital Costs, 30% Increase in Discount Rate, Base Case, 30% Decrease in Discount Rate, 30% Decrease in CHP Capital Costs, 50% Decrease in Capital Costs and Discount Rate.

Economics

Total system savings are positive for both ownership scenarios indicating that the capital costs and energy costs of delivering power with CHP are lower than the alternative grid and wholesale energy costs (Figure 2-28). System savings are higher under the customer ownership scenario because customers installed more CHP capacity. Customer savings are low under the utility ownership scenario because the customer benefits only from PPA revenue and a reduced demand charge. Utility losses are also consistently high under customer ownership because the utility loses revenue from reduced demand charges and reduced energy sales that embody the sunk costs of the distribution system infrastructure. These utility losses would be reduced by about 30% if the utility sold natural gas.

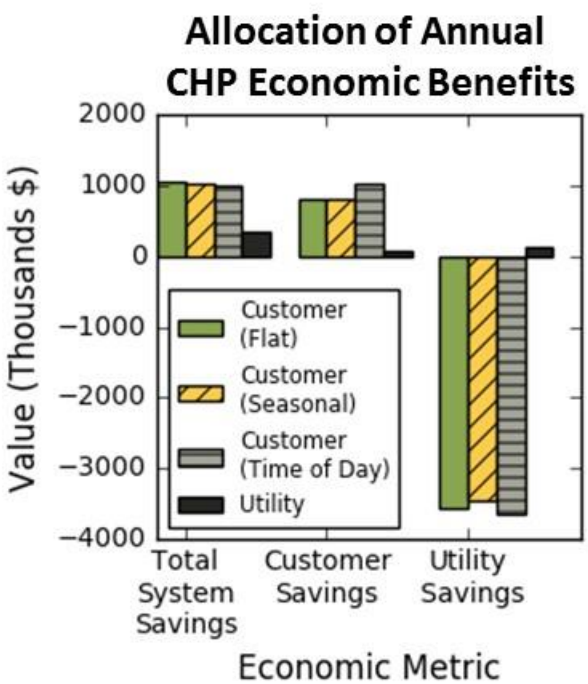


Figure 2-28: Allocation of CHP Savings for the base case and time-varying rates. Total system savings are positive for both owners indicating that the capital costs and energy costs of delivering power with CHP are cheaper than the grid. The high utility losses reflect lost energy sales and sunk distribution infrastructure costs. Time-varying rates do not have a large effect on customer or utility savings suggesting that time-varying rates can achieve emission reductions without negatively affecting the CHP payback period.

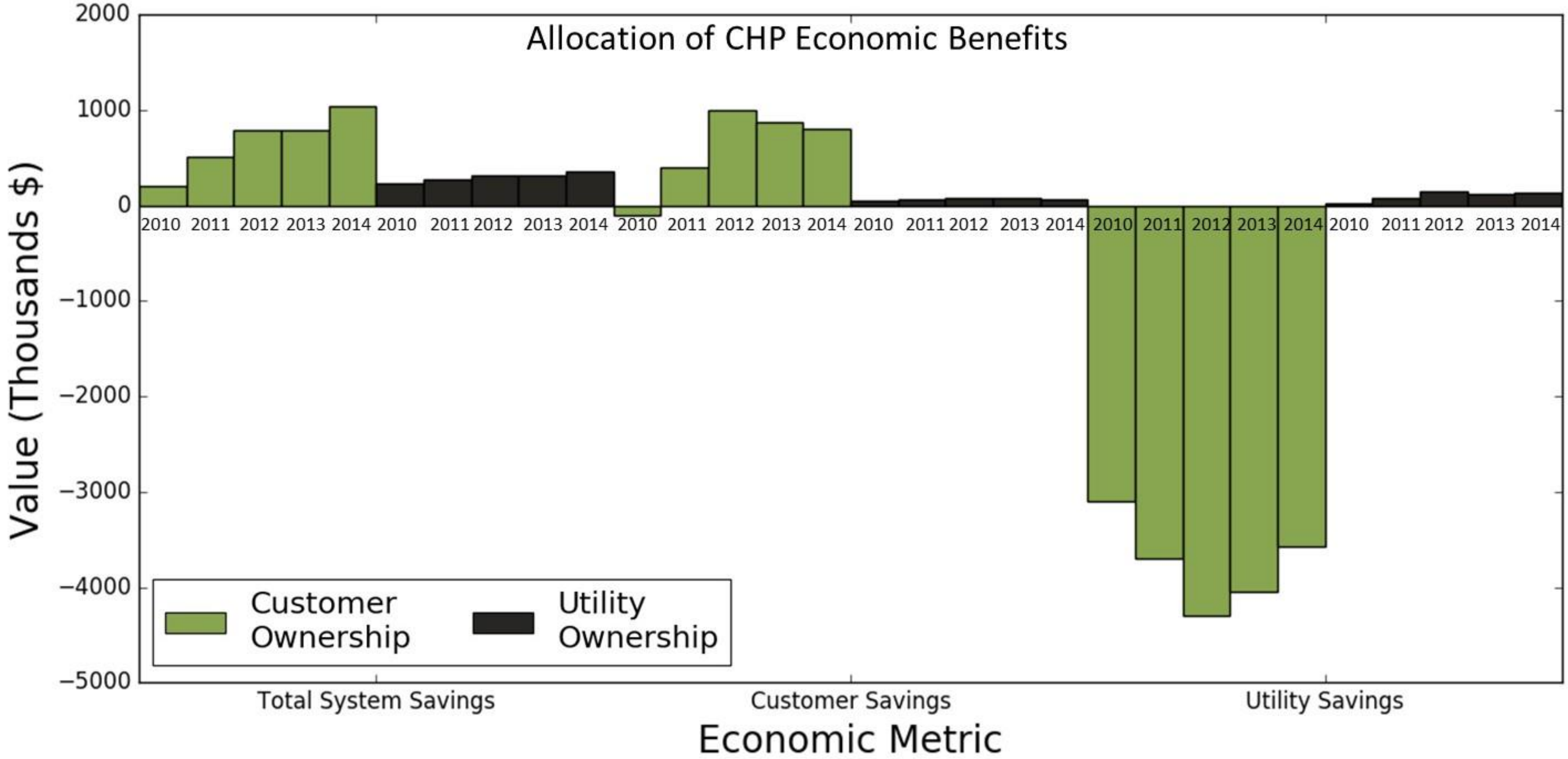


Figure 2-29: CHP Economic Benefits 2010-2014. System savings, customer savings, and utility savings were calculated for the years 2010-2014. Some variation is caused by high natural gas prices in 2010 and 2011.

Options for Reducing Wasted Heat

Although commercial CHP installations have the potential to have high fuel utilization efficiencies, inconstant heat loads and wasted heat can limit these efficiencies and result in higher emissions than the bulk electric grid. In our section on Emissions, we suggested using time-varying rates to limit heat production during times of low heat loads, but other options exist.

Microgrids

Microgrids are an electrical power system that connect multiple loads and can operate independently of the local distribution network. By connecting multiple heat loads, they may create more uniform heating and reduce wasted heat. Additionally, larger CHP sizes have higher electrical efficiencies and lower heat-to-power ratios, which will also reduce wasted heat.

Despite the apparent advantages of microgrids, we did not observe consistent emission reductions from microgrids, as shown in Figure 2-20. Microgrids composed of a warehouse and secondary school tend to produce lower emissions than if CHP were placed at those loads separately. The opposite is true for microgrids composed of a quick-service restaurant and strip mall.

There are two factors reducing the ability of microgrids to reduce emissions. First, the microgrid CHP sizes in our analysis were found by maximizing net present value (NPV), and do not account for emissions. Second, the heat loads of many commercial buildings are highly correlated. This correlation is apparent in Figure 2-9 and it is calculated in Figure 2-31. Most commercial buildings are service oriented, and their heat loads are highest during regular business hours. Thus, any combination of commercial buildings will still have low heat loads at night and the CHP will waste heat.

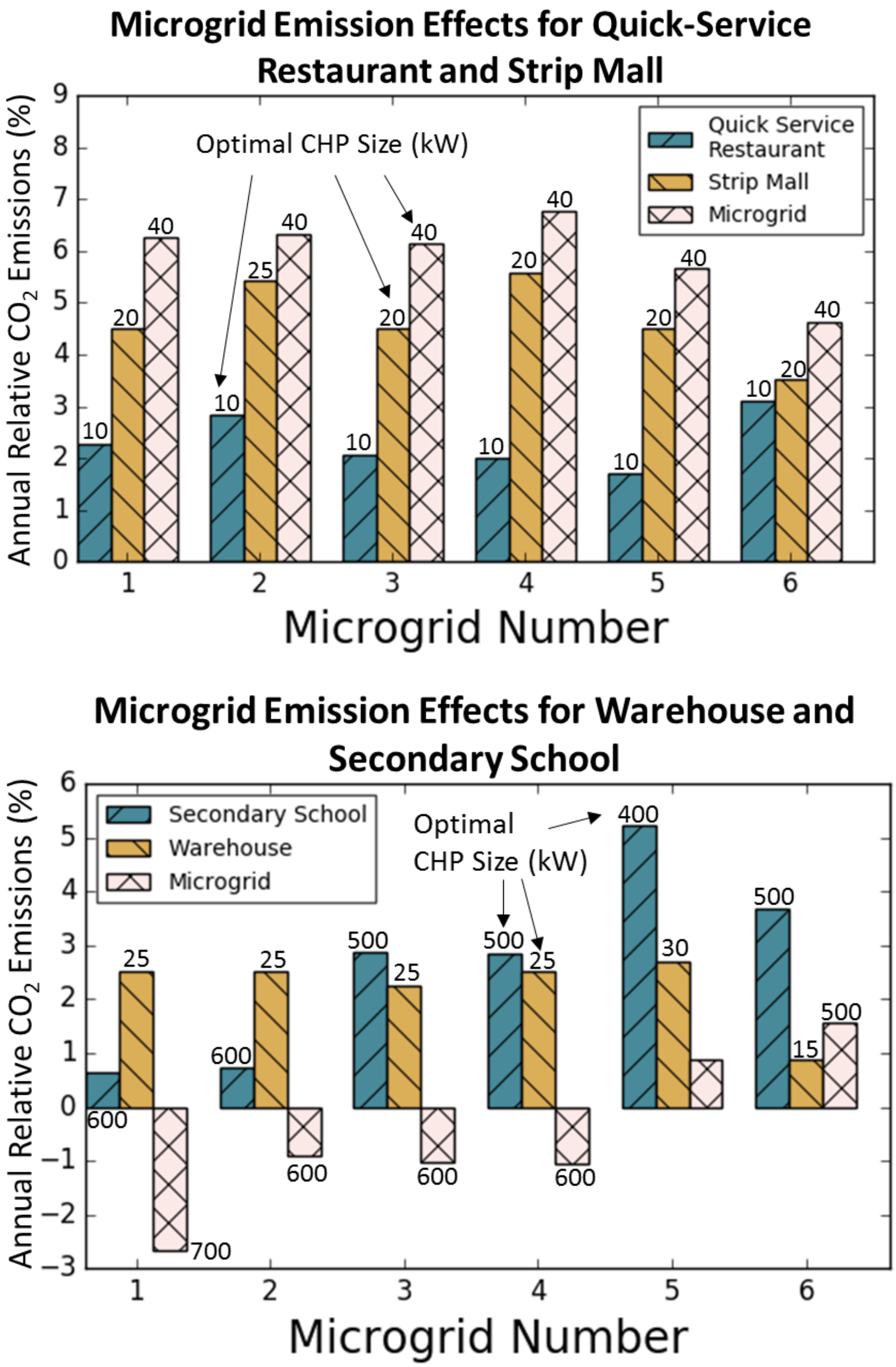


Figure 2-30: Microgrid emission effects for different sets of commercial buildings. Microgrids created from primary and secondary schools reduce overall emissions. Microgrids created quick-service restaurants and strip malls tend to increase emissions. Microgrids may reduce emissions because larger CHP have higher electrical efficiencies and lower heat-to-power ratios. Combining loads may also even out the heat load and reduce wasted heat. However, optimally sizing CHP by maximizing net present value (NPV) may eliminate these effects.

Correlation Matrix for Commercial Building Heat Loads

	Large Office	Primary School	Sec. School	Large Hotel	Hosp.	Small Office	Medium Office	retail Retail	Strip Mall	Super Market	Quick Service Rest.	Full Service Rest.	Small Hotel	Out Patient	Ware-house	Mid Apt
Large Office	***1.00***	0.79	0.78	0.63	0.42	0.94	0.97	0.72	0.71	0.74	0.65	0.64	0.59	0.40	0.61	0.67
Primary School	0.79	***1.00***	0.99	0.56	0.34	0.77	0.82	0.74	0.73	0.72	0.60	0.61	0.55	0.46	0.51	0.61
Secondary School	0.78	0.99	***1.00***	0.58	0.32	0.75	0.82	0.73	0.73	0.73	0.60	0.61	0.55	0.46	0.48	0.60
Large Hotel	0.63	0.56	0.58	***1.00***	0.40	0.64	0.67	0.66	0.66	0.77	0.74	0.78	0.68	0.41	0.56	0.69
Hospital	0.42	0.34	0.32	0.40	***1.00***	0.39	0.43	0.36	0.36	0.40	0.60	0.56	0.68	0.58	0.77	0.68
Small Office	0.94	0.77	0.75	0.64	0.39	***1.00***	0.97	0.71	0.70	0.73	0.65	0.64	0.58	0.35	0.60	0.65
Medium Office	0.97	0.82	0.82	0.67	0.43	0.97	***1.00***	0.75	0.74	0.78	0.68	0.68	0.63	0.41	0.62	0.70
Stand-alone Retail	0.72	0.74	0.73	0.66	0.36	0.71	0.75	***1.00***	1.00	0.82	0.62	0.65	0.60	0.54	0.54	0.65
Strip Mall	0.71	0.73	0.73	0.66	0.36	0.70	0.74	1.00	***1.00***	0.82	0.61	0.64	0.59	0.55	0.52	0.63
SuperMarket	0.74	0.72	0.73	0.77	0.40	0.73	0.78	0.82	0.82	***1.00***	0.71	0.76	0.67	0.51	0.57	0.71
Quick Service Restaurant	0.65	0.60	0.60	0.74	0.60	0.65	0.68	0.62	0.61	0.71	***1.00***	0.98	0.77	0.49	0.76	0.81
Full Service Restaurant	0.64	0.61	0.61	0.78	0.56	0.64	0.68	0.65	0.64	0.76	0.98	***1.00***	0.76	0.49	0.71	0.78
Small Hotel	0.59	0.55	0.55	0.68	0.68	0.58	0.63	0.60	0.59	0.67	0.77	0.76	***1.00***	0.56	0.87	0.92
OutPatient	0.40	0.46	0.46	0.41	0.58	0.35	0.41	0.54	0.55	0.51	0.49	0.49	0.56	***1.00***	0.50	0.55
Warehouse	0.61	0.51	0.48	0.56	0.77	0.60	0.62	0.54	0.52	0.57	0.76	0.71	0.87	0.50	***1.00***	0.92
Midrise Apartment	0.67	0.61	0.60	0.69	0.68	0.65	0.70	0.65	0.63	0.71	0.81	0.78	0.92	0.55	0.92	***1.00***
Mean	**0.70**	**0.67**	**0.67**	**0.65**	**0.52**	**0.69**	**0.73**	**0.69**	**0.69**	**0.71**	**0.70**	**0.71**	**0.69**	**0.52**	**0.66**	**0.72**

Figure 2-31: Commercial building heat load correlation matrix. Commercial building heating loads are highly correlated.

Heat Storage

Heat storage can act to smooth daily fluctuations in a buildings heat load. This option is best described by Barbieri et al. (2012). Higher capacity hot water tanks are a relatively low-cost storage option and were shown to reduce emissions (Smith, Mago and Fumo 2013). Their main limitation occurs during times of consistently low heat loads, such as during the summer months. During these times, heat storage may be most effective when used with seasonal rates or absorption chillers.

Absorption Chiller

Hot water absorption chillers use heat energy to cool buildings. During summer months, they could use heat from CHP generation to cool commercial buildings and reduce emissions. We believe more research is needed on absorption chillers but were skeptical that they are ready for widespread adoption now. Although, large absorptions chillers are commonly found in industry, academic interest in commercial building sized chillers (e.g. about 10kW) are relatively recent. (Yin 2006) Also, hot water absorption chillers are on the market, but options and sizes are limited. Our own economic assessment is preliminary, but several challenges exist:

- The only quote we were able to receive was on the internet site Alibaba. An 11.5kW-th hot water absorption chiller was quoted at $1,300/kW-th. Thus, the capital cost is only slightly less than a CHP generator but is more limited in its ability to avoid energy costs.
- Hot water absorption chillers, like CHP, will be most economical in buildings with consistent cooling loads. Unfortunately, these buildings are also likely to have consistent heat loads and are less likely to have excess heat to use in an absorption chiller.
- Absorption chillers have relatively low coefficients of performance, around 0.6, (Prasartkaew 2014) whereas electric chillers have coefficients of performance of 3 or higher. Both factors limit the ability of hot water absorption chillers to reduce energy costs.

CHP Generation that Produce Less Heat

In our analysis we focus on reciprocating engine CHP because it has the low capital costs and load following capabilities. However, we have also considered the possibility that different CHP generation type may have higher electrical efficiencies and produce less heat. Unfortunately, microturbines are more expensive and would similar heat output than reciprocating engines. Fuel cells would reduce heat production but are currently uneconomical in most commercial settings.

Table 2-10: Comparison of CHP Generation Types and Operating Characteristics **(U.S. EPA 2015)**.

CHP Type	**Size** (kW)	**Capital Cost** ($/kW)	**Electrical Efficiency** (HHV)	**Heat to Power Ratio**
Reciprocating Engine	100	$2,900	27.0%	1.96
Microturbine	65	$3,220	23.8%	1.96
	200	$3,150	26.7%	1.36
Fuel Cell	300	$10,000*	47%	1.0
*The Fuel Cell capital cost includes only the package cost and not additional installation and engineering fees.				

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2.10 Commentary on Chapter 2 and Future Research

An important finding in chapter 2 is that small CHP on some types of commercial buildings can increase CO_2 emissions relative to the bulk electric grid. Further, we demonstrate that time varying rates can encourage more efficient operation of these CHP and reduce emissions. Since the publication of chapter 2 in Environmental Research Letters in 2016, we have received valuable feedback. This feedback has revealed nuances about our assumptions and results that may offer opportunities for further research. These include how CHP is sized, how CHP is operated to avoid short term costs, and how CHP penetrations may grow based on expected electricity and natural gas prices.

Studies often assume that CHP is sized to heat loads. However, as we explain in Chapter 2, heats loads are not constant on some commercial buildings and changing policies and economic conditions may make it more profitable to size larger CHP even if heat is wasted. This behavior has been observed in New York city, which has high electricity prices, and in the peer reviewed literature (Barbieri, Melino and Morini 2012) (Smith, Mago and Fumo 2013) (Mago, Chamra and Hueffed 2009).

A low tolerance for long pay back periods in the industry can lead to smaller CHP sizes than we modeled. In our paper, we chose a size that maximized the rate of return and required payback periods to be within the equipment lifetime. This resulted in larger CHP sizes, and it would be useful to study how shorter payback periods would affect CHP size and the quantity of wasted heat. Regardless of industry practice today, different payback periods should be included in the sensitivity analysis for CHP sizing. Long payback periods are typical for residential rooftop solar installations. In Pennsylvania, Governor Wolf recently signed a bill allowing property assessed clean energy (PACE) financing that makes it easier to pay for clean energy projects (including CHP) over long periods of time (Vaughn 2018). Thus, it seems possible that a future with high penetrations of commercial CHP could include larger CHP with longer payback periods, more wasted heat, and less efficient operation.

Studies often assume that CHP is operated constantly. While this assumption is reasonable for CHP with constant heat loads, it may not be true for CHP on commercial buildings with time varying heat loads. In our paper, we assumed that CHP could turn off if the CHP operation did not reduce energy costs. However, this assumption would increase O&M costs. We did not include these costs because we are unaware of any estimates that describe the increased costs of O&M associated with turning CHP off or costs associated with variable operation. Research on these costs would be beneficial.

In our paper, we examined how utility owned CHP might differ from customer owned CHP. We found that customer owned CHP led to more CHP, primarily due to increased revenue from avoiding demand charges. Several factors could change this finding. First, customer owned CHP could lose revenue through a combination of standby charges and CHP forced outages that prevent CHP from reducing monthly demand charges. Both factors would lead to fewer customer-owned CHP. Future analysis of customer owned CHP would also benefit from incorporating a more granular representation of the different supply charges and delivery charges to commercial customers of different sizes.

Second, in our analysis we implicitly assumed high short term avoided costs associated with utility-owned CHP operation. Our avoided costs combined New York's locational marginal prices with all additional costs in NYSEG's cost of service. For a typical deregulated investor owned utility, short term avoided costs would be better represented by locational marginal prices, generation capacity demand charges, ancillary services and possibly transmission access charges. For traditionally regulated utilities, short term avoided costs may only include avoided fuel costs and it is unlikely that an investor owned utility would consider avoided generation, transmission and distribution capacity as a form of avoided costs unless the CHP clearly deferred capital investments to later years. These factors would lead to fewer utility-owned CHP. We also assumed in our analysis that utilities could not include CHP in their rate base. Including CHP in the rate base would likely lead to more utility owned CHP. It would be useful to study how the combination of these factors could affect the relative emissions of utility owned CHP.

Finally, the high CHP penetrations in our analysis were based on CHP scenarios with varying capital costs and energy costs. We did not explicitly link these costs to future cost projections. Future research that incorporates actual cost projections with different sizing assumptions, and operating practices, as discussed above would be valuable. This research should also include policies that affect CHP adoption, such as PACE financing, natural gas discounts, standby tariffs, and tax credits.

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Chapter 3: Can solar PV reliably reduce loading on distribution networks?

Abstract

Utility managers and solar photovoltaic (PV) advocates often disagree about whether rooftop solar can reliably reduce loading on distribution network feeders. We examined 23 prototypical feeders for 6 locations in the United States and two real feeders in eastern Pennsylvania. Using 19 years of weather data, we simulated 30 minute resolution substation loading and solar output for hypothetical solar peak penetrations[9]. A positive correlation between peak loading and solar generation improves the effective capacity of solar (i.e. the net load reduction relative to solar system AC capacity). In our quantitative analysis, the effective PV capacity under worst-case loading conditions was above 40% at low penetrations for 19 of the 23 feeders examined. For all feeders, the effective capacity of solar decreases with penetration. Utility engineers often use statistical weather normalization and transformer aging criteria to plan for capacity, both of which allow a small amount of overloading risk. When these planning criteria are used with solar and transformer aging is fixed at pre-solar levels, we find that the effective capacity of solar is consistently higher than found under worst-case load conditions. Alternatively, relatively small amounts of energy storage used with solar can achieve high effective capacities without any overloading events. We found that pairing solar PV with a one hour duration battery rated at 5% of the feeder peak loads could achieve an effective capacity of 50% or more for all feeders when the peak load penetration of solar is at or below 20%.

[9] In Chapter 3, we use solar peak penetration to describe how much rooftop solar is on a feeder. It is defined as the nominal AC rooftop solar capacity divided by the feeder peak load.

3.1 Introduction

Rooftop solar capacity has been growing rapidly in the United States, leading policymakers to reevaluate net energy metering (NEM) and other regulatory policies. Many states have studied Value of Solar (VOS) tariffs as an alternative to NEM (Rocky Mountain Institute 2013). VOS studies are avoided cost studies for rooftop solar. Typical avoided cost categories are energy, transmission capacity, generation capacity, and environmental damages. Despite solar often being located on distribution networks, the value of solar on distribution networks has been treated with less rigor than transmission and generation value of solar components or omitted altogether. The Rocky Mountain Institute (RMI) describes the distribution value of solar as a “significant methodological gap” due to the inherent complexity and heterogeneity of distribution networks (2013). In a review of VOS methods for the National Renewable Energy Lab (NREL), Denholm et al. write “Further research is required to develop and validate such ELCC [Transmission Effective Load Carrying Capability]-like approaches to distribution capacity value. Until such calculation approaches are validated, utilities may be reluctant to reduce feeder capacity with solar PV because of concerns about high loads during period of low solar output” (2014).

In this chapter, we focus on characterizing a fundamental metric for estimating the capacity value of solar on distribution networks. To be consistent with power systems standards, we call this metric the Distribution Effective Load Carrying Capability (D-ELCC), which we define generally as the net load reduction relative to solar PV AC capacity. The D-ELCC values in this chapter can be used by policy makers to understand how solar might reduce large capital investments on distribution networks and produce value for all ratepayers. ELCC estimates for the bulk electric grid may differ from the D-ELCC because:

1. **Distribution feeders may be more vulnerable to variability in loading and solar generation.** The small geographic footprint of distribution feeders means that solar will not benefit much from geographic smoothing of the effects of intermittent cloud cover.
2. **The risk of overloading is managed differently on distribution feeders than on the bulk power grid.** While both sectors of the electric grid are risk averse, the bulk power grid manages risk through a combination of planning (e.g. a 1-in-10 year loss of load expectation) and operational (e.g. demand response, spinning reserve, under frequency load shedding) standards. On distribution feeders, engineers may be highly risk-averse and plan for capacity based on worst-case scenarios. Or, depending on the feeder and utility, engineers may allow some risk of overloads. Transformers, for example, are designed to operate above their nameplate capacity for short durations.

We next review analogous Effective Load Carrying Capability (ELCC) studies for the bulk power grid and D-ELCC estimates in consultant reports since there appears to be no peer-reviewed literature.

3.2 Comparison with Previous Research

Perez et al. estimated the Effective Load Carrying Capability (ELCC) of solar for 39 utilities and all states excluding Alaska using 2 years of hourly weather and loading data. They found ELCCs on the transmission network from 11%-60% at low solar PV energy penetrations and 4-40% at a 20% solar energy penetration for fixed axis solar installations with a 30° tilt (Perez, et al. 2006). Furthermore, they found that ELCCs could be increased to 100% with small amounts of storage. They did not account for the contingency analysis typically included in ELCC studies, which ensure that the loss of load expectation (i.e. the risk of shedding load) remains constant under different grid constraints and generator failures (e.g. (Denholm, et al. 2014) and (Madaeni, Sioshansi and Denholm 2013)). We also exclude any form of contingency analysis from our estimates. We assume that the highly distributed nature of solar will make individual solar system failures and distribution line outages unimportant, or that solar will be placed directly at substations.

The Peak Capacity Allocation Factor (PCAF) is another method used to estimate the effective capacity of solar on distribution networks. In the PCAF method, hours with load within one standard deviation of the maximums peak are estimated, and distributed energy resources are compensated if they generate energy during those hours. The PCAF method is described in many value of solar studies by the consulting firm E3 (Energy and Environmental Economics), such as for New York (E3 2016). The PCAF method is similar to the D-ELCC metric we describe in this chapter, and it could probably be adapted to include the utility planning practices that we use in our Method section to define the D-ELCC. Current implementations could equally benefit from more years of weather, solar, and loading data, which are a key part of our analysis. Overall, the PCAF method is useful for estimating the hourly capacity value of solar. The D-ELCC is better for visualizing the effect of varying solar penetrations on solar PV's capacity value.

Distribution network utilities have also published estimates of the effective capacity of solar. In their 2016 Preferred Resources Pilot Portfolio Design Report, Southern California Edison (2017) define a "dependable" output curve for solar that is approximately 20% of nominal solar AC capacity at noon and rapidly declining for their commercial, residential, and system peak. Southern California Edison's method appears to base this "dependable" output only on the performance of solar during a cloudy day. They do not appear to account for any possible relationship between peak load conditions and better solar performance.

EPRI (2017) performed a study on several distribution feeders in Spain and despite using a fairly high "probable" D-ELCC for solar (around 60% in the early afternoon) they found that late peaking feeders in the region made solar's effective capacity negligible. A low D-ELCC for evening peaking feeders is an undeniable short-coming of solar. While most of our analysis is on prototypical feeders that tend to peak in the afternoon, we also estimate the D-ELCC for two real feeders from an eastern Pennsylvania utility that peak in the evening.

In the remainder of the chapter, we describe our method, results, and policy conclusions. We first describe our load, feeder, and solar modeling; these primarily use GridLab-D (PNNL 2018) and the NREL Physical Solar Model (PSM) dataset (NREL 2018). Next, we define two D-ELCC metrics based on typical utility planning practices. Our first estimate, D-ELCC$_{worst}$ is based on the worst-case loading associated with several solar penetrations and aims to prevent any overloading associated with solar. Our second estimate, D-ELCC$_{age}$, does allow overloading associated with solar but the aggregate deterioration of the transformer insulation condition (commonly referred to as transformer aging) cannot exceed the deterioration caused by weather normalization. Each method is based on 19 years of weather and loading data to reflect the long investment horizons faced by utility engineers. Overall, we find that a positive correlation between peak loading days and solar generation appears to improve solar's D-ELCC$_{worst}$. It is typically above 40% at low penetrations but decreases with penetration. When small amounts of overloading are allowed, D-ELCC$_{age}$ is consistently above 50%. Alternatively, small amounts of energy storage can be used to achieve a 50% D-ELCC if solar peak penetrations are at or below 20%.

3.3 Method

3.3.1 Feeder and Load Modeling

We use the U.S. Department of Energy's Pacific Northwest National Laboratory (PNNL) feeder taxonomy (K. P. Schneider, et al. 2008) to capture some of the heterogeneity in US distribution networks. The PNNL feeder taxonomy is a set of 23 distribution network feeders selected through clustering for use as representative feeders for the United States. They are based on 575 real feeders from 17 separate investor owned, rural electric, and municipal utilities but with changes made by PNNL to remove proprietary information. A description of the feeder taxonomy is in Table 3-1.

To create time-varying loads, the feeder taxonomy was populated with temperature and humidity dependent building models and made available to the public by Fuller, et al. (2012). Residential buildings parameters were based on the Energy Information Administration's (EIA) Residential Energy Consumption Survey (EIA 2018). Non-weather-dependent load profiles were based on the Bonneville Power Administration's End-Use Load and Consumer Assessment Program (Prat, et al. 1989), and show the characteristic morning and evening peak typical for most residential customers. Commercial buildings were modeled using building codes and end-use metering studies (Fuller, Kumar and Bonebrake 2012). All commercial buildings were modeled as office buildings, big box stores, and strip malls.

We also used two PECO feeders. PECO is the electric and gas utility for the Philadelphia area, and uses CYMDIST, a popular distribution powerflow solver, with static spot loads that do not vary with time. We converted the CYMDIST feeders to the GridLab-D format using the National Rural Electric Cooperative Association (NRECA)'s Open Modeling Framework (OMF) (NRECA 2018) and populated the spot loads with secondary systems and weather-dependent customer loads. Our objective was to ensure that both substation loading and simulated peak load hours were close to the values observed in SCADA readings.

We used a genetic algorithm to adjust residential and commercial building parameters so that the simulated feeder load time-series matched hourly SCADA readings. Our objective function minimized the difference between the simulated and SCADA load profiles from May-September 2016. The decision variables were the air conditioning coefficient of performance, insulation R values, cooling set points, floor areas, scaling factors for predefined temperature independent load profiles with constant power loads, the proportion of commercial buildings modeled as strip malls, office buildings, and big box stores, the percentage of residential homes with air conditioners, and the percentage of residential homes with hot water heaters. Further details of our genetic algorithm implementation can be found in the Supplementary Materials (Section 3.7.1).

Figure 3-1 compares our simulated load with SCADA loading in the year 2016 for both PECO feeders. Simulated loads and SCADA readings are close on Feeder #1. On Feeder #2, the simulated load underestimates the peak load, but the peak hour, which is important for estimating solar's effective capacity, is still close to the observed hour. Feeder #2 is an industrial feeder and the error is likely caused by exogenous effects, such as shifting factory production schedules. These exogenous effects are difficult to include in GridLab-D's weather-dependent models.

Table 3-1: Taxonomy Feeder Descriptions. Customer class types are abbreviated as R(Residential), C(Commercial), A(Agricultural), and I(Industrial). Agricultural and industrial time-series loads are modeled with residential and commercial load models. The PECO feeders are not shown. PECO Feeder #1 and Feeder #2 have peak loads of 6MW and 17 MW, and peak hours at 5pm and 6pm, respectively.

Climate Region	Feeder ID	Peak	Development	Customer Class Type	Peak Hour
Temperate California	R1-12-1	7 MW	suburban/rural	96% R, 2% C, 2% A	1 pm
	R1-12-2	3 MW	suburban/rural	95% R, 5% C	4 pm
	R1-12-3	1 MW	urban	5% R, 95% C	3 pm
	R1-12-4	5 MW	suburban	95% R, 5% C	4 pm
	R1-25-1	2 MW	rural	22% R, 18% C, 56% A, 4% I	3 pm
Cold New York	R2-12-1	6 MW	urban	50% R, 49% C, 1% A	2 pm
	R2-12-2	6 MW	suburban	95% R, 5% C	12 pm
	R2-12-3	1 MW	suburban	91% R, 1% C, 8% A	12 pm
	R2-25-1	17 MW	suburban	72% R, 18% C, 10% A	2 pm
	R2-35-1	9 MW	rural	18% R, 1%C, 79% A	12 pm
Hot/Arid Arizona	R3-12-1	8 MW	urban	87% R, 13% C	4 pm
	R3-12-2	4 MW	urban	92% C, 8% I	4 pm
	R3-12-3	7 MW	suburban	93% R, 7% A	12 pm
Hot/Cold North Carolina	R4-12-1	6 MW	urban/rural	89% R, 11% C	12 pm
	R4-12-2	2 MW	suburban/urban	88% R, 12% C	12 pm
	R4-25-3	1 MW	rural	99% R, 1% C	12 pm
Hot/Humid Texas	R5-12-1	9 MW	suburban/urban	85% R, 15% C	2 pm
	R5-12-2	4 MW	suburban/urban	66% R, 34% C	2 pm
	R5-12-3	9 MW	rural	94% R, 6% C	2 pm
	R5-12-4	7 MW	suburban/urban	85% R, 15% C	2 pm
	R5-12-5	9 MW	suburban/urban	93% R, 7% C	2 pm
	R5-25-1	12 MW	suburban/urban	95% R, 5% C	2 pm
	R5-35-1	12 MW	suburban/urban	88% R, 12% C	2 pm

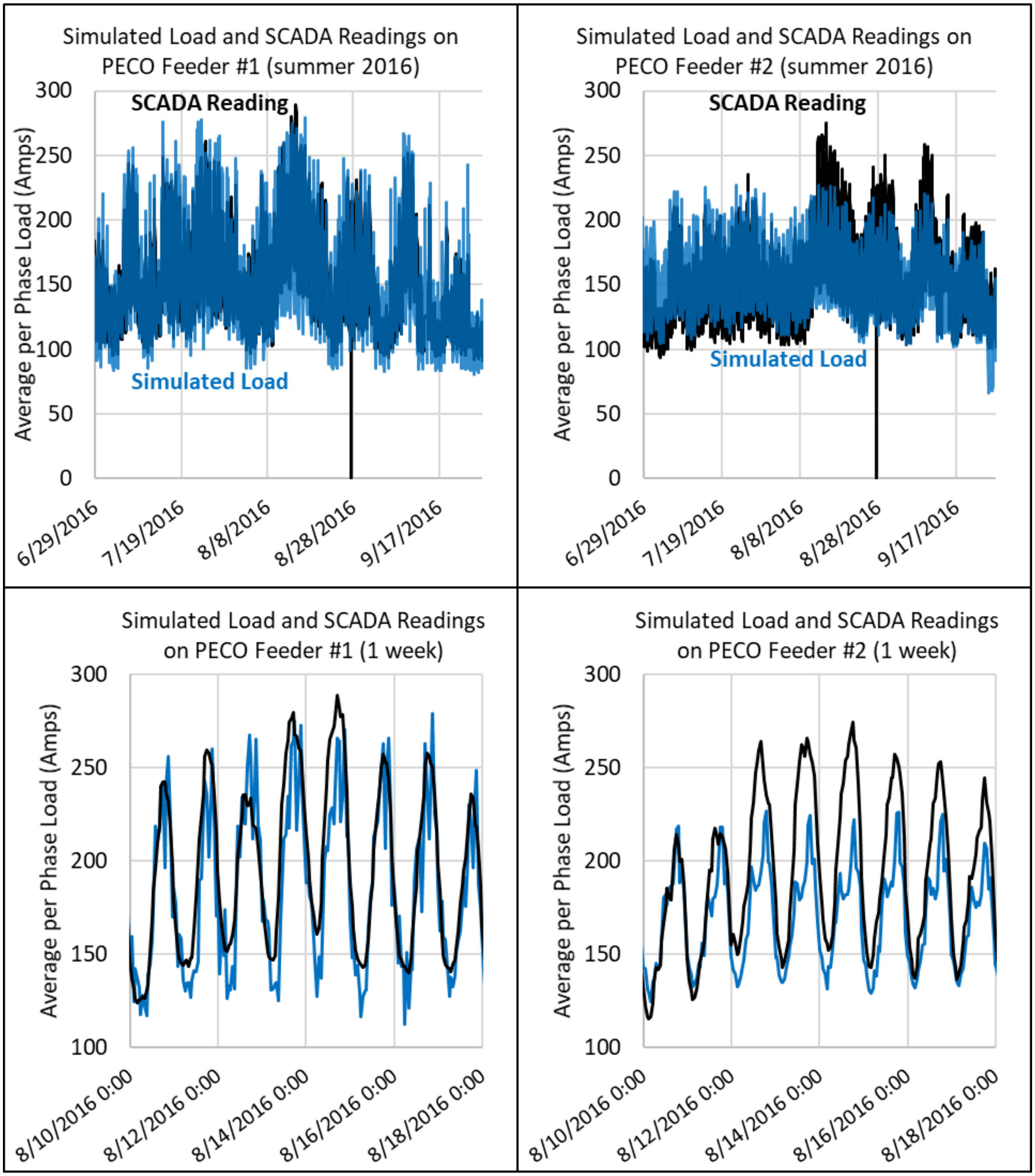

Figure 3-1: Comparison of SCADA substation loading from eastern utility and modeled loading using GridLab-D. GridLab-D building models were tuned to capture the weather dependence of the feeder load. The simulated peak hours closely matched SCADA readings. On Feeder #2, non-weather exogenous effects cause the simulated peak to underestimate several peaks.

3.3.2 Solar Modeling

We used solar radiation and weather data from NREL's National Solar Radiation Database, Physical Solar Model-Version 3 (PSM-V3) (NREL 2018). PSM-V3 estimates solar irradiance from satellite data from 1998-2016 with a geographic resolution of 4-km by 4-km and a 30-minute time resolution (Habte, Sengupta and Lopez 2017). Compared to ground measurements, mean bias errors are approximately ±5% for GHI and ±10 % for DNI. RMS errors are as high as 20% for GHI and 40% for DNI. Our results also include 1 year of data from Vibrant Clean Energy, which provides 5-minute resolution solar irradiance data (Vibrant Clean Energy 2018). Vibrant reports correlations with ground measurements of 93% for GHI and 82% for DNI. The Vibrant and PSM-V3 irradiance correlations range from 94-98% for each location studied.

Developing good solar radiation datasets is an area of active research, and comparisons between these satellite models and ground-based measurements are imperfect. For example, several authors have found typical uncertainties of 3-5% even in well-maintained ground-based radiometers (Reda 2011) (Myers, et al. 2001) (Habte, et al. 2014).

Solar generation was modeled using GridLab-D's solar panel and inverter objects (PNNL 2018). GridLab-D uses the same solar modeling as NREL's System Advisory Model (SAM) (Tuffner, Hammerstrom and Singh 2012), a widely used engineering-economic tool (NREL 2018). For all solar panels and locations, we assumed a solar panel tilt of 30 degrees, a solar multiplier of 1.20, an inverter efficiency of 96%, a panel efficiency of 17% and a constant power factor of 1.0. A south facing panel orientation was used for all feeders. West facing panels were also used for the two evening peaking Pennsylvania feeders. Solar AC capacity factors were 18-20%.

3.3.3 Distribution-Effective Load Carrying Capability Definition

We define the Distribution-Effective Load Carrying Capability generally as the change in substation peak demand relative to the total solar system AC capacity. We report the average D-ELCC in the main body of the chapter; the marginal D-ELCC (the additional D-ELCC when an additional increment of PV is added) is provided in the Supplementary Materials (Section 3.7.6).

3.3.3.1 Worst Case D-ELCC

We use two metrics to estimate the D-ELCC with 19 years of available data. We define the worst-case D-ELCC at solar penetration *p* as

$$D-ELCC(p)_{worst} = \frac{Max\ Peak(at\ p=0)\ over\ all\ years - Max\ Peak(at\ p)\ over\ all\ years}{Rooftop\ Solar\ Capacity\ at\ p} \tag{3-1}$$

The penetration, p, is defined as the AC solar capacity relative to the peak feeder load.

This metric describes how much solar can reduce the largest net peak load over all 19 years for each penetration. A low D-ELCC occurs if solar performs very poorly (e.g. due to cloudy conditions) on the largest peak over all years for each penetration. In contrast, this metric ignores the D-ELCC in any year when solar is performing poorly if the peak load in that year is relatively low. Thus, D-ELCC$_{worst}$ should reflect any positive correlation between solar performance and larger peaks due to hot weather. In our results, we also show the D-ELCC for individual years.

3.3.3.2 Transformer Aging D-ELCC

Often, transformers are the main capacity constraint in capacity expansion projects. We calculate the transformer aging D-ELCC (D-ELCC$_{age}$) using PJM weather normalization and both IEEE and IEC transforming aging estimating procedures. D-ELCC$_{age}$ allows overloading associated with solar, but the aggregate deterioration of the transformer insulation condition (commonly referred to as transformer aging) cannot exceed the deterioration caused by weather normalization without solar**.**

The PJM weather normalization procedure, described in PJM Manual 19 (2017), performs ordinary least squares regression with summertime peak daily loads as the dependent variable and weighted temperature humidity indices (WTHI) as the independent variable. It then solves the regression equation at a weather standard associated with extreme weather. The WTHI is based on the dry bulb temperature and humidity with a 20% weight based on previous days to account for the thermal inertia of buildings. PJM defines the weather standard as the 50th percentile of past yearly peak WTHI's. Details of PJM's weather normalization procedure are in the Supplementary Materials (Section 3.7.2).

A problem with weather normalization is that it does not guarantee similar levels of overloading at different solar penetrations. So, we modify PJM's weather normalization procedure in our estimate of the D-ELCC$_{age}$. Our modification is summarized by Equation 3-2 and Figure 3-2. First, we define overloading as transformer aging. While overloading could be expressed in terms of the maximum overload (kW) or the total overload (kWh), we use transformer aging because it can estimate how both high loading from a loss of solar output on a cloudy day and low loading from solar on typical days affect transformer insulation condition. To correct for increased or decreased transformer aging, we use quantile regression and iteratively search for the quantile (q*) resulting in the same aging as the 50th percentile quantile regression without solar. We use the IEC Standard 60076-7 (2005) "exponential model" to estimate the increased aging of transformers caused by overloading. Our estimates are based on a medium power transformer (2.5-100MVA) with ONAF cooling (Oil Natural Air Forced, i.e. the oil circulates naturally but air is forced over the cooling fins) and non-thermally upgraded paper insulation. Additionally, we follow the IEEE Standard C57.91™ (2012) normal life expectancy loading which limits the transformer hotspot temperature to a 130°C. Details of our transformer aging procedure can be found in the Supplementary Materials (Section 3.7.3). Figure 3-7 in the Supplementary Materials shows how a 50% penetration of solar affects transformer loading and hotspot temperatures over time.

$$D - ELCC(p)_{age} = \frac{W/N\ Peak(at\ p = 0,\ q = 50\%) - W/N\ Peak(at\ p, q = q^{*})}{Rooftop\ Solar\ Capacity\ at\ penetration\ p} \qquad (3\text{-}2)$$

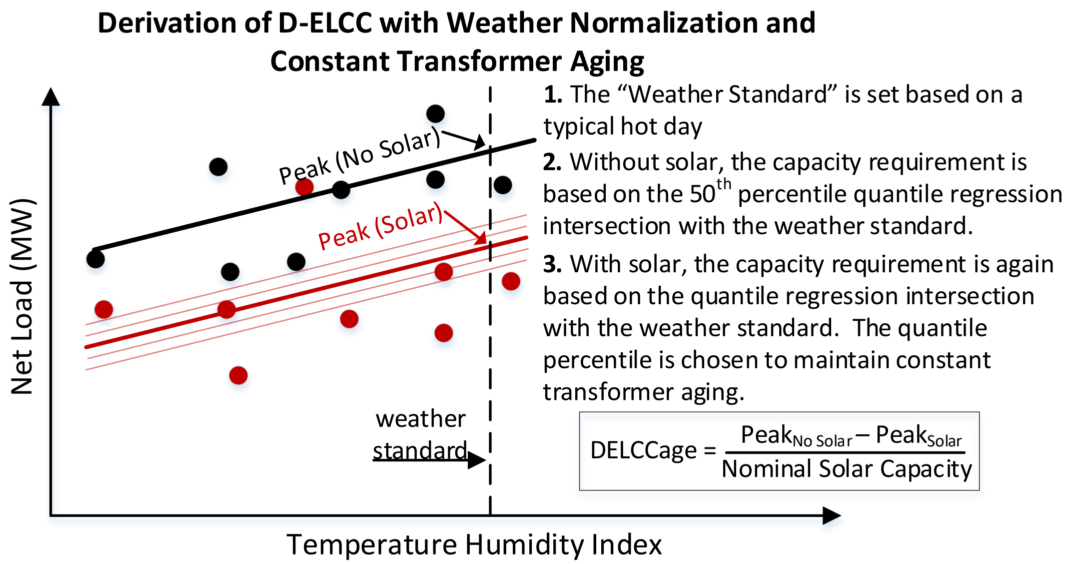

Figure 3-2: Method for estimating the D-ELCC with Weather Normalization (D-ELCC$_{age}$) and maintaining transformer condition. D-ELCC$_{age}$ allows allow overloading associated with solar but the aggregate deterioration of the transformer insulation condition (commonly referred to as transformer aging) cannot exceed the deterioration caused by weather normalization without solar. Peak loads with solar are shown in red. Peak loads without solar are shown in black.

3.4 Results

Figure 3-3 demonstrates how solar performs on peak loading days at very low PV penetrations for the PG&E and PECO service territories. Real loading data are used for all scatterplots and real solar generation data from SoCore Energy (2016) is used for the California scatterplots. Each point shows a daily peak event as a fraction of the maximum peak and the solar output at the hour of the daily load peak as a fraction of maximum solar output.

There are two important features of the plots in Figure 3-3. First, we never observed a complete loss of solar generation during a peak loading event. Second, there is a trend towards greater solar output as loads increase. This trend is caused by the high correlation between temperature and load and between temperature and solar insolation. Solar output is worst on peak events on the two Pennsylvania feeders that peak in the evening. When west facing panels are used, solar output during the peak load events is higher, as discussed below. An exhaustive set of solar performance scatterplots is shown in the Supplementary Materials (Section 3.7.7) for all taxonomy feeders and the two PECO feeders using every year of simulated loading.

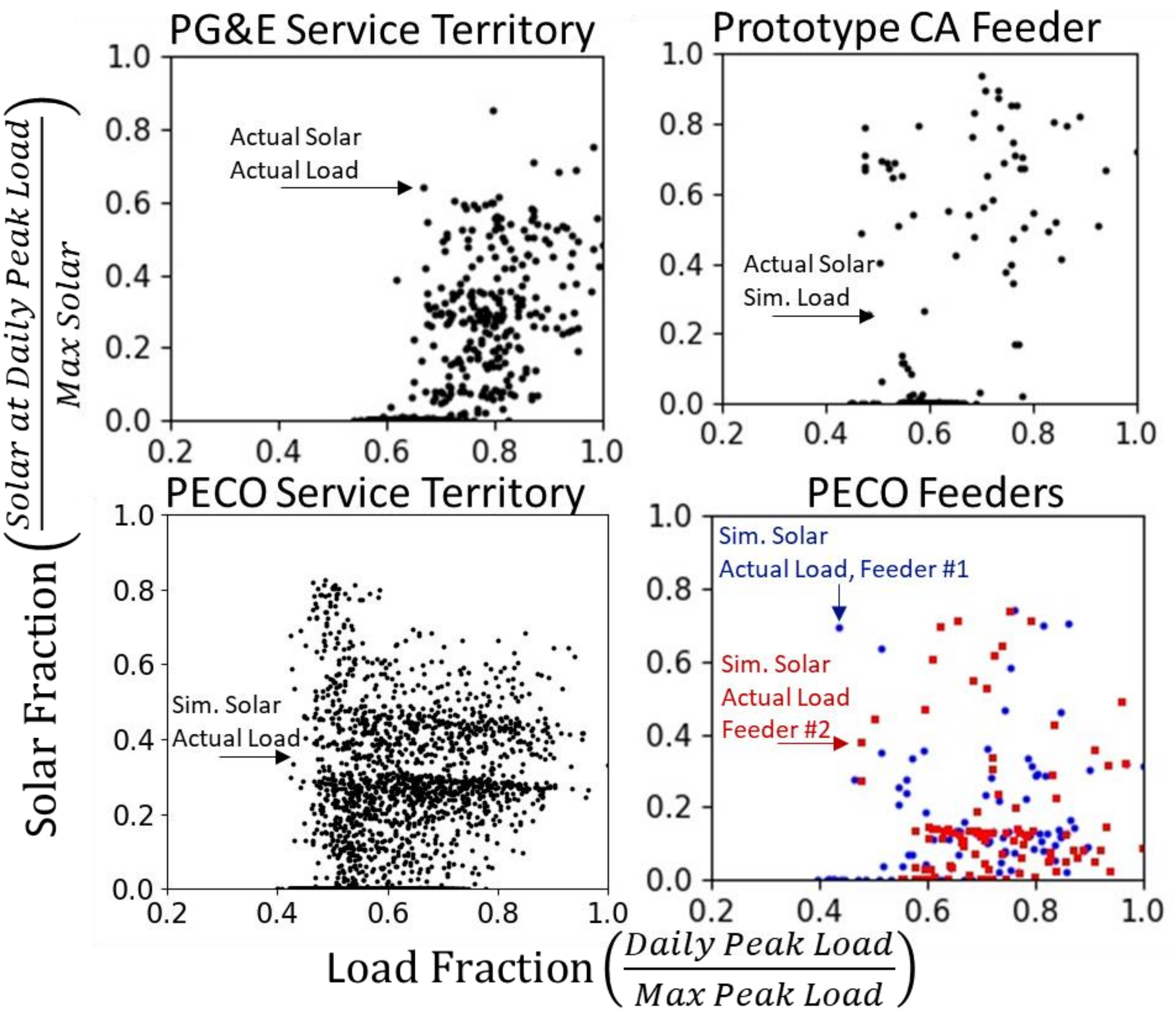

Figure 3-3: Solar performance is higher during peak loading times in California and eastern Pennsylvania. Solar performance for PECO and PG&E service territories are shown on the left. Solar performance for feeders is shown on the right. PG&E service territory (top left): the solar profile is based on a solar installation near Sacramento and the load is taken from CAISO market data. Prototype California feeder (top right): the solar profile is based on the Sacramento installation and the load is simulated using feeder R1-12.47-1. PECO Service Territory (bottom left): the solar profile is simulated using GridLab-D and NREL's Physical Solar Model, and the load is taken from PJM data. PECO Feeders (bottom right): solar profiles are simulated for summer months using GridLab-D and NREL's Physical Solar model with south facing panels, and the summer load profiles are from 2016 SCADA readings.

Figure 3-4 shows the average D-ELCC for both feeders in eastern Pennsylvania for south facing and west facing orientations. Figure 3-5 shows the average D-ELCC for five locations and sixteen of the PNNL taxonomy feeders. Each figure includes the yearly D-ELCC, D-ELCC$_{worst}$, D-ELCC$_{age}$, and the D-ELCC using a 5-minute time resolution with the 2014

Vibrant Clean Energy weather data. A worst-case D-ELCC based on SCADA measurements and simulated solar is also shown for the year 2016 for the PECO feeders. The marginal D-ELCC values are shown in the Supplementary Materials (Figure 3-9, Figure 3-11, Figure 3-12). Features of these results are discussed below.

D-ELCC estimates are strongly affected by the peak hour. In Table 3-3 of the Supplementary Materials (Section 3.7.5), the peak hour for each feeder is shown. Both PECO feeders peak in the evening and exhibit a lower effective capacity than most of the taxonomy feeders which peak in the afternoon. The evening peaking feeders benefit from the west facing solar panel orientation.

D-ELCC$_{worst}$, shown in black, is strongly affected by regional climate. In California, Arizona, and Texas, the D-ELCC$_{worst}$ is always over 40% at low penetrations. Even in climates with a weaker solar resource, effective capacity estimates were typically above 40% at low penetrations. Every Minnesota feeder (see Figure 4 of the Supplementary Materials) had a D-ELCC$_{worst}$ greater than 40% at low penetrations. However, several exceptions exist where solar performs poorly. On feeder R4-25.00-1 in North Carolina, an abnormally high morning peak in the late winter causes the effective capacity of solar to be very low. Additionally, two feeders in New York (R2-12.47-3 and R2-25.00-1) are dominated by cloud events and have a low D-ELCC$_{worst}$. The Texas feeders, with D-ELCC$_{worst}$ values around 40%, are lower than expected for a region with a high solar resource and remain very flat at higher penetrations. Details can be found in Figure 3-14 of the Supplementary Materials, which shows the loading and solar profile on the peak load days that are used in the estimate for D-ELCC$_{worst}$.

The transformer aging D-ELCC with an allowance for “planned loading beyond nameplate capacity”, as described by IEEE C57.91™ (2012) is shown with black dashed lines. The D-ELCC$_{age}$ maintains a constant level of transformer aging but by allowing occasional overload events, solar on each feeder achieves a capacity value of 60% at low penetrations. The decline in D-ELCC$_{age}$ is relatively small as the solar penetration increases.

On all feeders, small amounts of energy storage used with solar can achieve high effective capacities without any overloading events. To find the energy storage requirement, we assume a target D-ELCC, and size the energy storage to the maximum overload event. Figure 3-6 shows the full set of energy storage capacity requirements and duration for each feeder. Energy capacity requirements are provided relative to peak feeder load in %-hour units for conversion to kWh. For all feeders, a one hour energy storage duration rated at 5% of the feeder peak loads could achieve an effective capacity of 50% when the peak load penetration of solar is below 20%. The storage duration with solar is shorter than deferral projects using only storage. For example, Lazard (2017) assumes a 6 hour duration and Hledik et al. (2018) use a 4 hour duration for their energy storage capacity deferral scenarios.

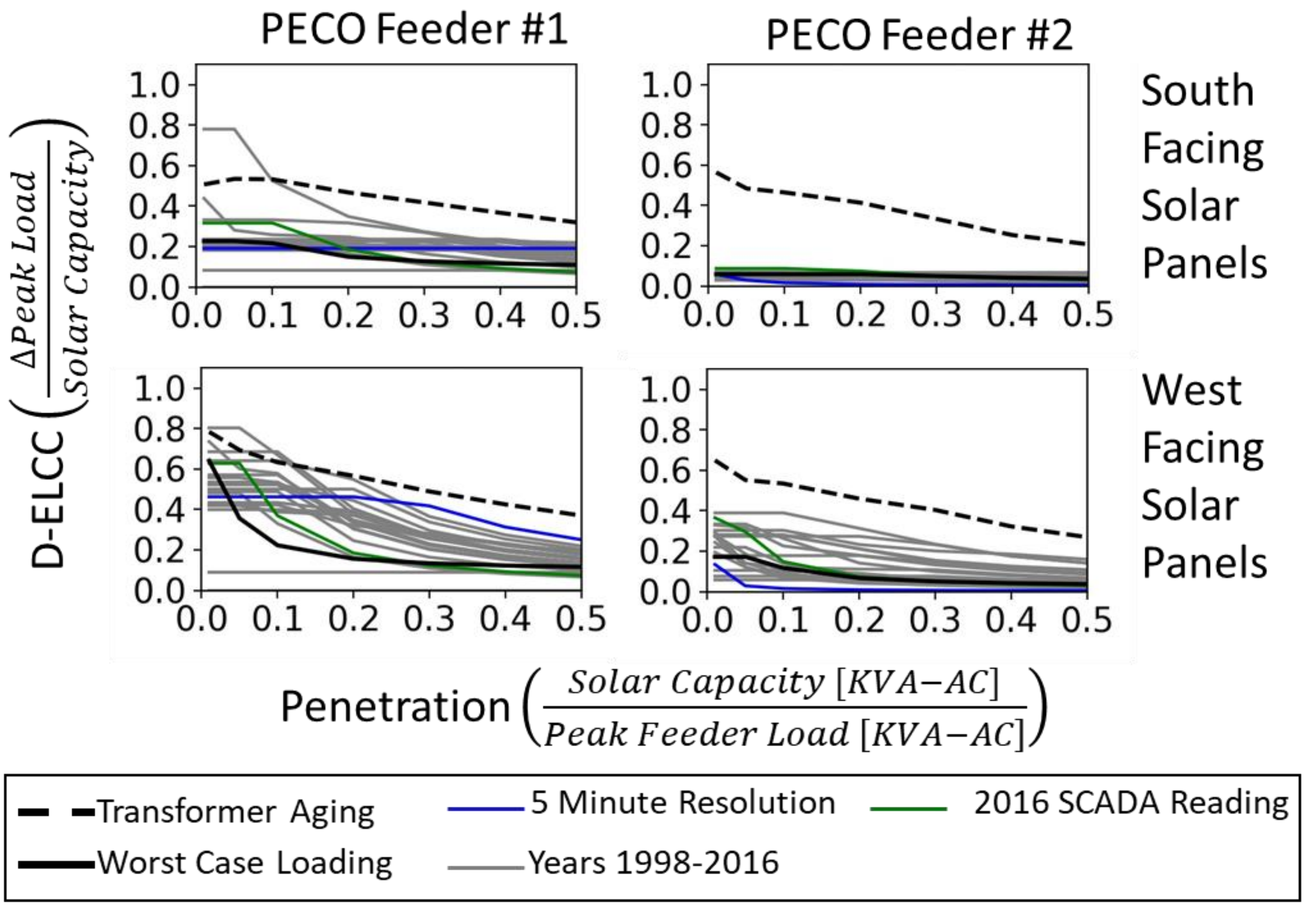

Figure 3-4: Distribution Effective Load Carrying Capability (D-ELCC) for two evening peaking feeders in the PECO service territory.

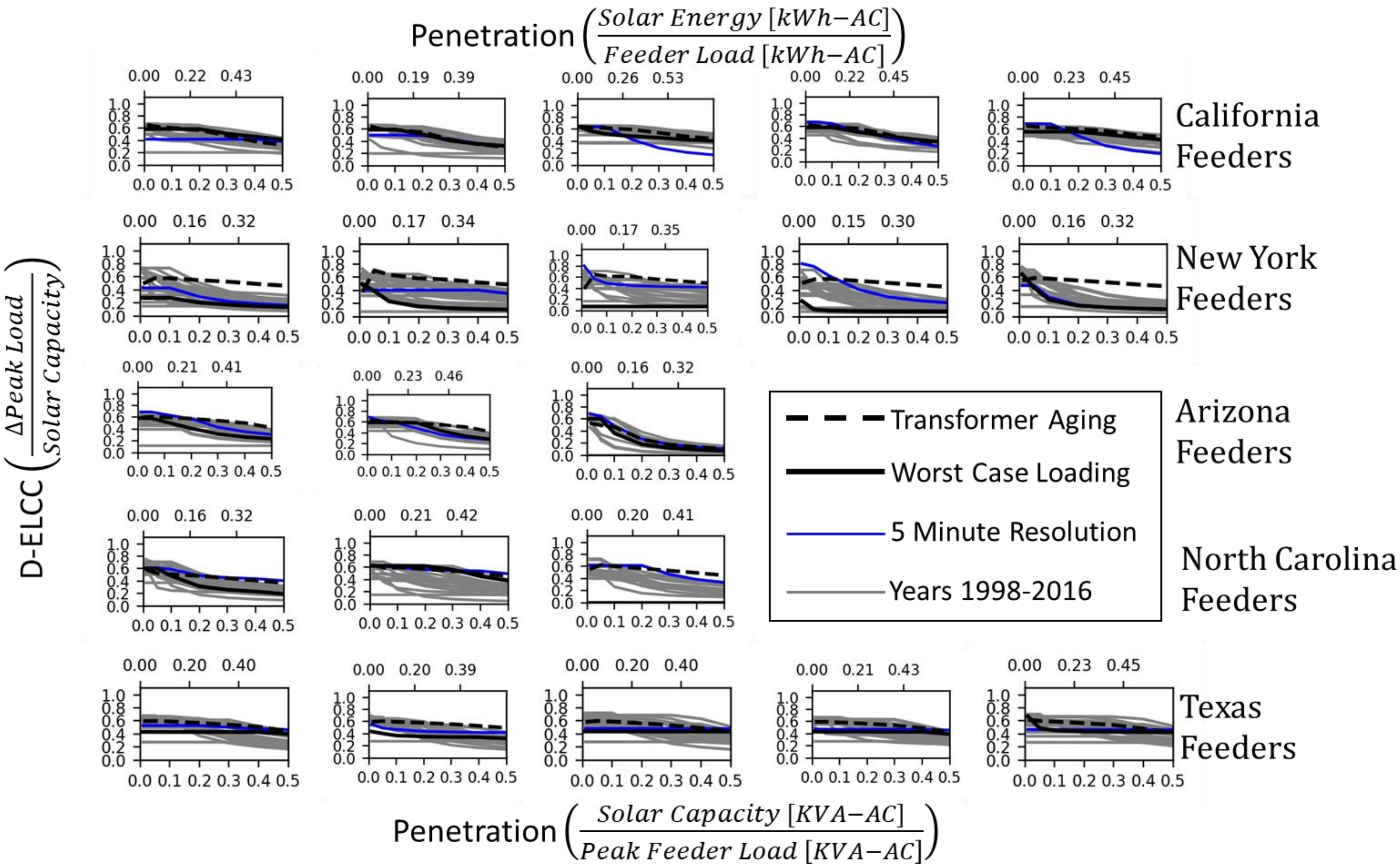

Figure 3-5: Distribution-Effective Load Carrying Capability (D-ELCC) for representative feeders in major US climate regions. Columns show the taxonomy feeders in order from left to right. California Feeders: R1-12.47-1, R1-12.47-2, R1-12.47-3, R1-12.47-4, R1-25.00-1. New York Feeders: R2-12.47-1, R2-12.47-2, R2-12.47-3, R2-25.00-1, R2-35.00-1. Arizona: R3-12.47-1, R3-12.47-2, R3-12.47-3. North Carolina Feeders: R4-12.47-1, R4-12.47-2, R4-25.00-1. Texas feeders: R5-12.47-1, R5-12.47-2, R5-12.47-3, R5-12.47-4, R5-12.47-5.

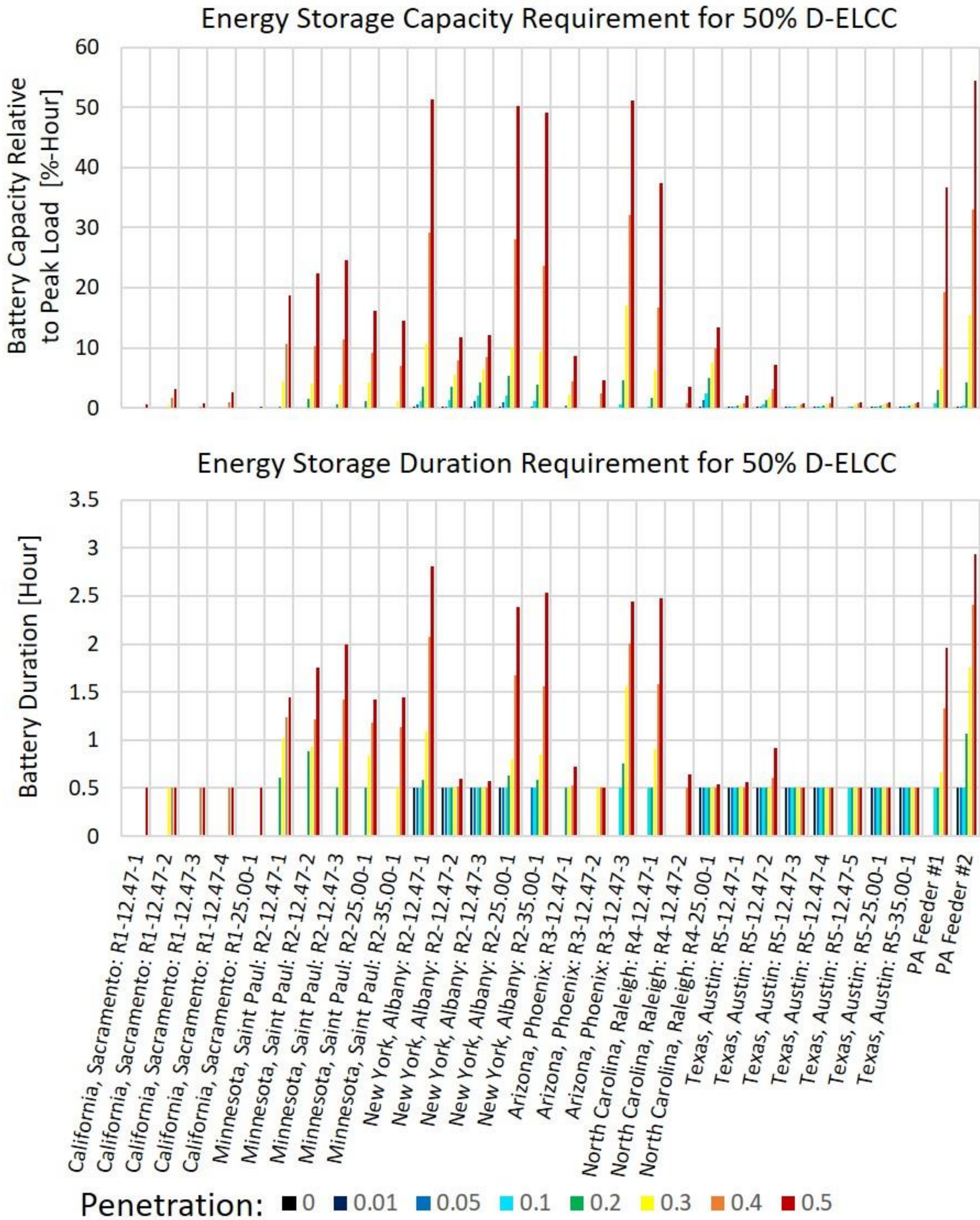

Figure 3-6: Energy storage capacity and duration requirements for a 50% D-ELCC when used with solar. Storage capacity units are in %-hour of feeder peak (kW) allowing for the conversion to storage capacity units of kWh. For all feeders, a one hour energy storage duration rated at 5% of the feeder peak loads could achieve an effective capacity of 50% when the peak load penetration of solar is below 20%.

3.5 Conclusion

We have performed feeder-level analysis based on 19 years of loading and solar profiles. Correlations between solar output and peak loads, flexibility in transformer overloading, and the relatively small amounts of energy storage needed to achieve high D-ELCCs all suggest that solar could act as a valuable capacity resource. As a point of comparison, we found that New York Feeder R2-12.47-3 at a 20% solar peak penetration of its 1 MW peak, had a worst-case D-ELCC of only 10%, due to cloudy conditions in the region, but had a transformer aging D-ELCC of 56% because some overloading was allowed, and could achieve a 50% D-ELCC without any overloading with 50 kWh of energy storage.

Utility managers and public utility commissions (PUCs) should consider strategies to take advantage of the effective capacity of solar. In afternoon peaking feeders in regions with a strong solar resource, solar is sufficient by itself to reduce loading on substations and defer investments. In regions with a weaker solar resource, large gains in the effective capacity of solar with small amounts of energy storage may make solar and energy storage an economic option for capacity deferral projects. The capacity value of solar may be lost if energy storage systems are oversized and overcompensate for the risks associated with solar. Figure 3-6 offers guidance on appropriate energy storage capacity when used with different penetrations of solar. In Chapters 4 and 5 we examine the economic tradeoff between the increased deferral value created by solar with storage and typical installed battery costs.

The greatest opportunity for value creation with solar is in capacity expansion projects where transformers are the primary capacity constraint. In our D-ELCC$_{age}$ method we allow occasional “planned loading beyond nameplate capacity” as described by IEEE C57.91™. Relying on this inherent flexibility of transformers, rather than costly energy storage, will increase the value of solar. In Chapters 4 and 5, we examine the additional value created from deferral opportunities in the PECO service territory when solar is credited with the transformer aging D-ELCC.

3.6 References

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3.7 Supporting Materials

3.7.1 Genetic Algorithm for Substation Load Matching

We used a genetic algorithm to find a global set of building parameters that created a reasonable match between simulated loading and actual SCADA measurements. The decision variables were the air conditioning coefficient of performance, insulation R values, cooling set points, floor areas, scaling factors for predefined temperature independent ZIP load profiles, the proportion of commercial buildings modeled as strip malls, office buildings, and big box stores, the percentage of residential homes with air conditioners, and the percentage of residential homes with hot water heaters.

We used a population of 400 and a parent size of 100. The computation time for a single time-series powerflow run are typically over one hour, so it was important to parallelize all simulation trials and to use good initial conditions with a narrow search space. To determine these parameters, we started with estimates for the northern United States (region 2 of the GridLab-D feeder taxonomy) (K. P. Schneider, et al. 2008). It was necessary to first perform several trials of the genetic algorithm with a wide search space. Altogether, this was a time-consuming process that could benefit from further research.

Unlike typical genetic algorithm implementations, we used real (not integer) decision variables. During each iteration, a new population of 400 was created based on the top 100 best solutions. The top 100 solutions were carried over without change (i.e. Elitism). The remaining 300 were a crossover of the top 100, with mutations. We used an adaptive mutation. A 5% variation was added to a trait if the mutation occurred, but the probability of mutation decreased as the objective function improved. The traits for each crossover child were selected from all the solutions (i.e. k-point crossover).

3.7.2 Weather Normalization Procedure

We used PJM's weather normalization described in PJM Manual 19 (2017). Weather normalization requires several steps. First, each daily peak in the summer is associated with a weighted temperature humidity index (WTHI). The temperature humidity index is defined as:

$$If\ DB \geq 58,$$

$$THEN\ THI = DB - 0.55 * (1 - HUM) * (DB - 58)$$

$$ELSE\ THI = DB$$

Where, THI = Temperature Humidity Index, DB = Dry Bulb Temperature (°F), HUM = Relative Humidity

An 80/20% weight is applied using the current and previous day. Months including March through September are used, but the WTHI must be at least 74 to be included in the regression. The weather normalization regression is fit to all WTHIs and Peak Days (MWs) and solved at the weather standard to find the weather normalized peak. PJM defines the weather standards as the average of the peak WTHIs over the last 20 years. We used the 90th percentile of the peak WTHI's to ensure that we were not overestimating the risk associated with using weather normalization.

3.7.3 Transformer Aging

We use the IEC Standard 60076-7 (2005) "exponential model" to estimate the increased aging of transformers caused by overloading. Transformers that are frequently loaded above nameplate capacity experience high internal temperatures, and their paper insulation deteriorates more quickly. These internal temperatures are modeled as a heat transfer problem based on the "hotspot" (i.e. the hottest temperature in the transformer windings), "top oil" (i.e. the temperature at the top of the oil tank), and ambient temperature. The deterioration of the paper insulation and transformer age is modeled empirically using the Arrhenius equation and the hotspot temperature. Additionally, various transformer cooling parameters and the cooling system are important. Our estimates are based on ONAF cooling (Oil Natural Air Forced, i.e. the oil circulates naturally but air is forced over the cooling fins), non-thermally upgraded insulation paper and parameters for a typical “medium power” transformers, shown in Table 3-2. Medium power transformers are defined by the IEC as ranging from 2.5-100MVA.

The IEEE Standard C57.91™ (2012) describes several typical “load cycles” for sizing transformers: normal life expectancy loading, planned loading beyond nameplate rating, long-time emergency loading and short-time emergency loading. We use the ratings defined by “planned loading beyond nameplate capacity”, which is limited to a 130°C hotspot but can withstand frequent overload occurrences. In contrast, short-time emergency overloading condition can occur infrequently, but the hotspot temperature can be as high as 180°C. Figure shows the transformer load factor for California feeder R1-12.47-1. A quantile was chosen that allows frequent overloads but limits the hotspot temperature to 130°C and results in the same transformer aging with and without solar.

Table 3-2: IEC Standard 60076-7 transformer aging model parameters.

Transformer Aging Parameters	Value
Cooling System	ONAF
Paper Insulation	Not thermally upgraded
Load Cycle	“Planned loading beyond nameplate rating”
Maximum Top Oil Temperature	110°C
Maximum Hot Spot Temperature	130°C
Oil exponent	0.8
Winding exponent	1.3
Loss ratio	6
Hot-spot factor	1.3
Oil time constant	150
Winding time constant	7
Hot-spot to top-oil gradient	26
K11	0.5
K21	2.0
K22	2.0

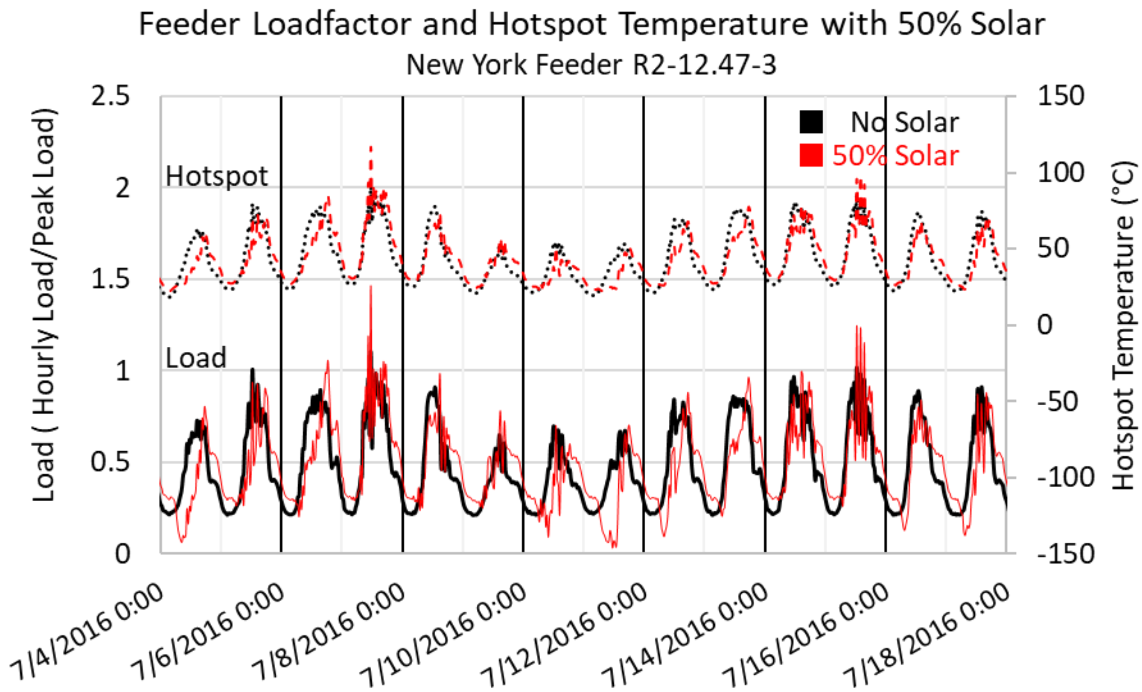
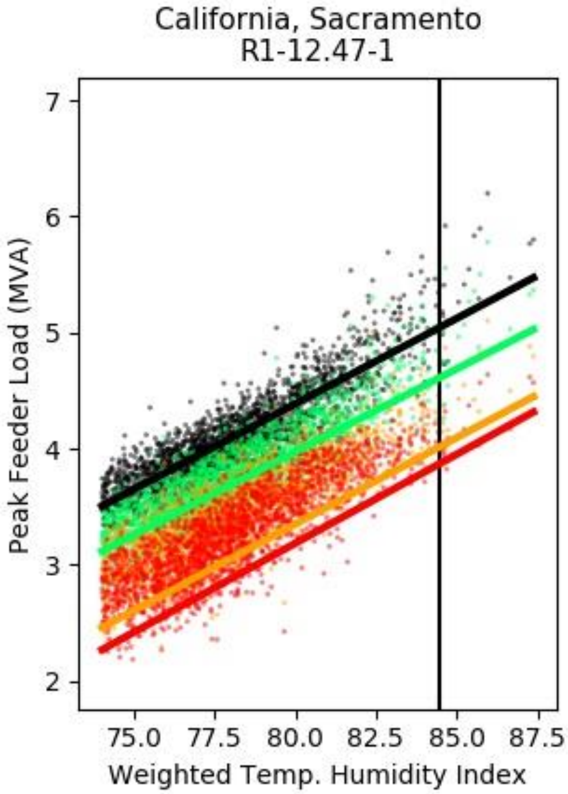
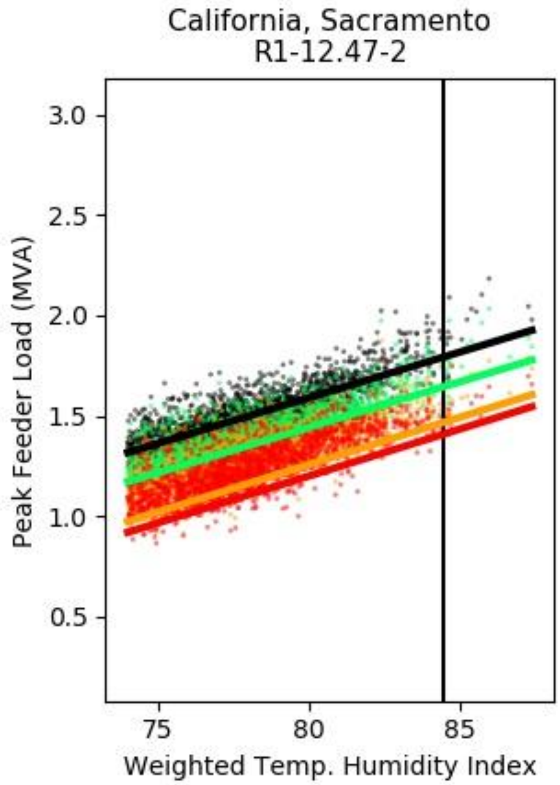
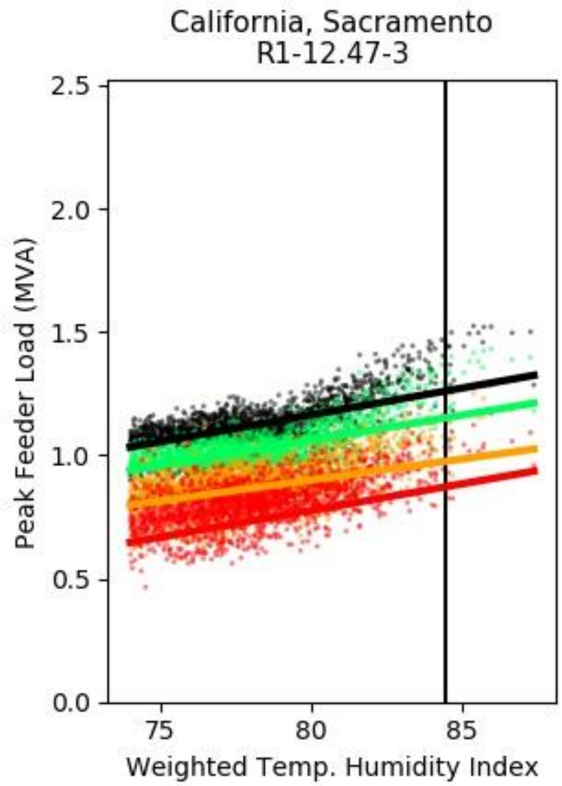


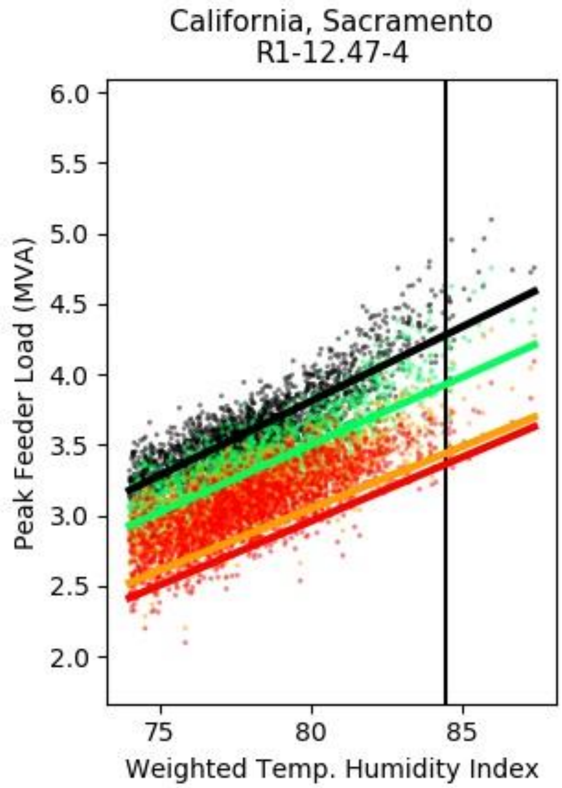
Figure 3-7: Transformer load factor and hotspot on New York Feeder R2-12.47-3. High penetrations of solar result in frequent overloads but overall, transformer aging caused by high hotspot temperatures is the same with and without solar.

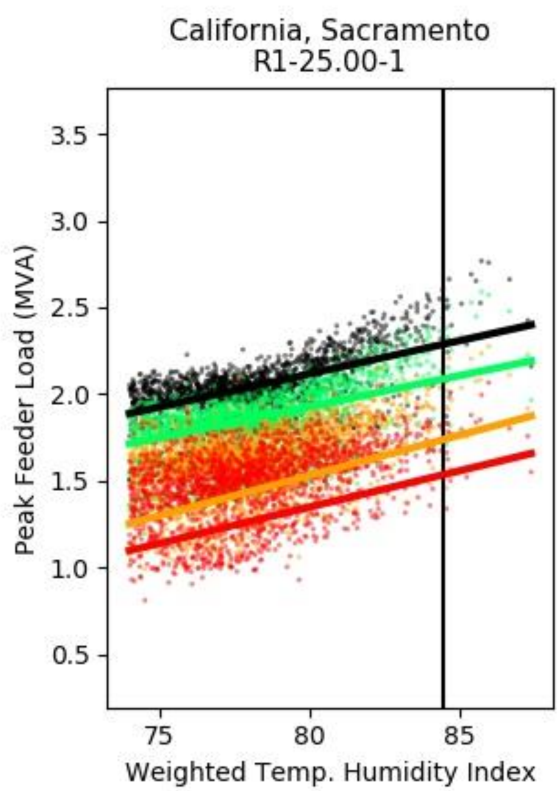
3.7.4 Weather Normalization Results

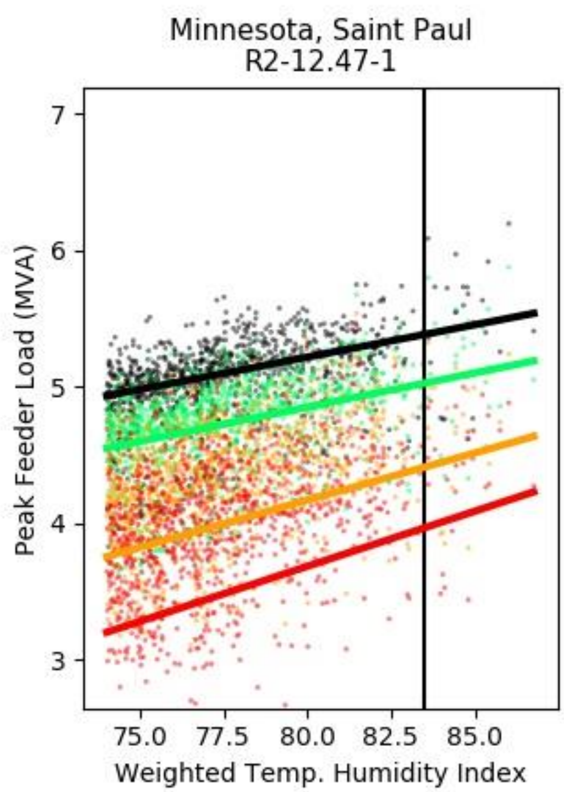


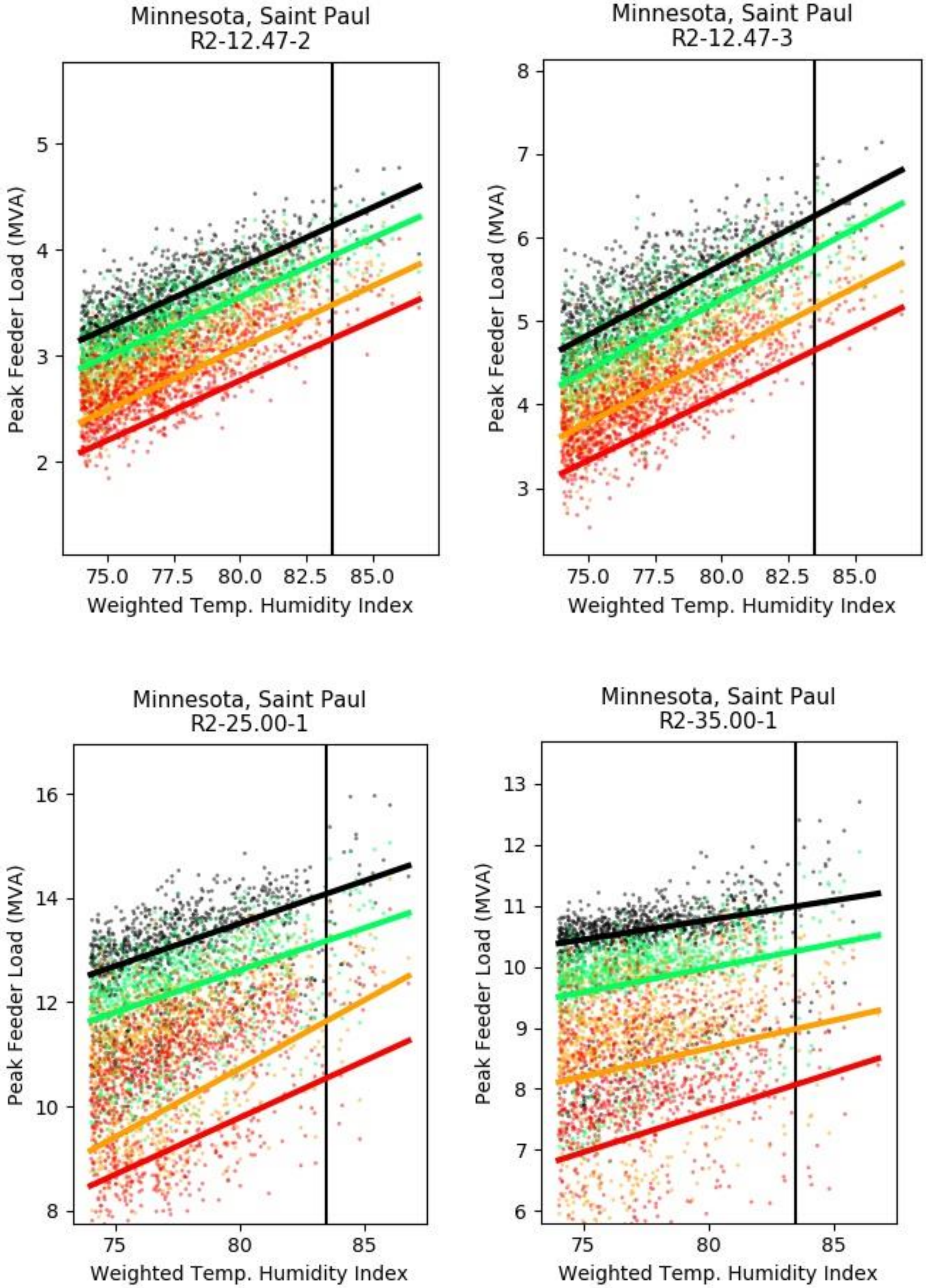


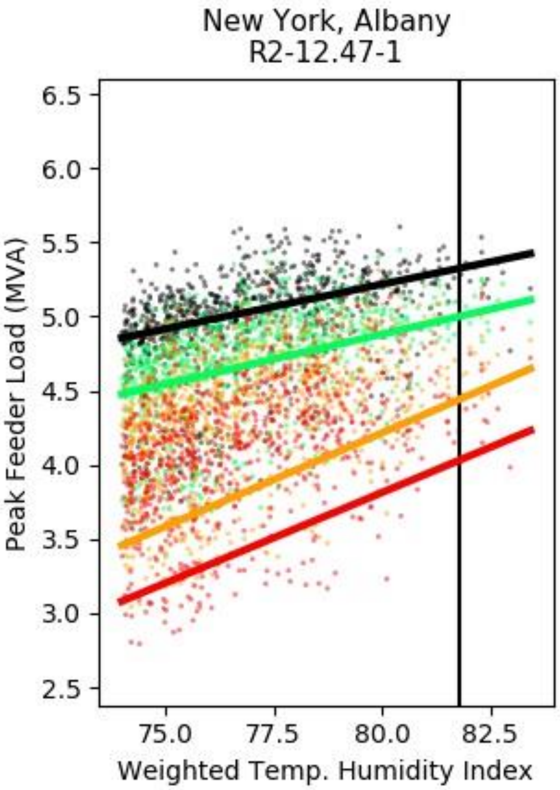

California, Sacramento
R1-12.47-3
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
0.0
0.5
1.0
1.5
2.0
2.5
75
80
85

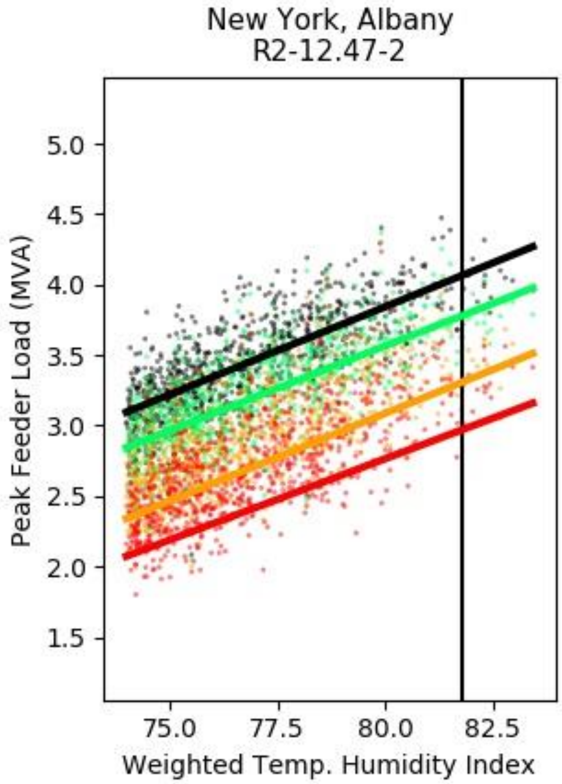

California, Sacramento
R1-12.47-4
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5
6.0
75
80
85


California, Sacramento
R1-25.00-1
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
0.5
1.0
1.5
2.0
2.5
3.0
3.5
75
80
85


Minnesota, Saint Paul
R2-12.47-1
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
3
4
5
6
7
75.0
77.5
80.0
82.5
85.0


Minnesota, Saint Paul
R2-12.47-2
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
Minnesota, Saint Paul
R2-12.47-3
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
Minnesota, Saint Paul
R2-25.00-1
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
Minnesota, Saint Paul
R2-35.00-1
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index


New York, Albany
R2-12.47-1
Peak Feeder Load (MVA)
6.5
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2.5
75.0
77.5
80.0
82.5
Weighted Temp. Humidity Index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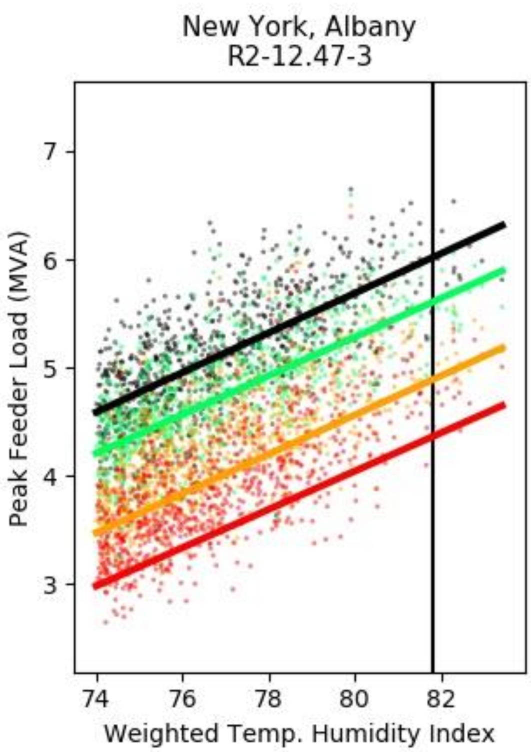
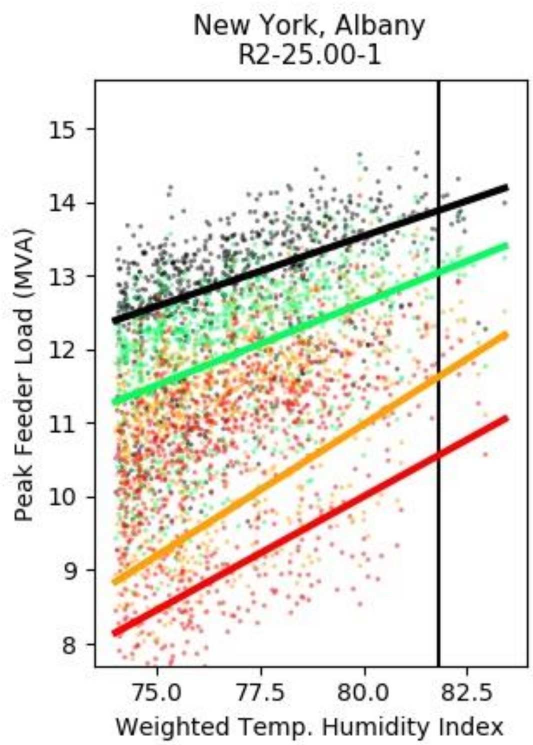
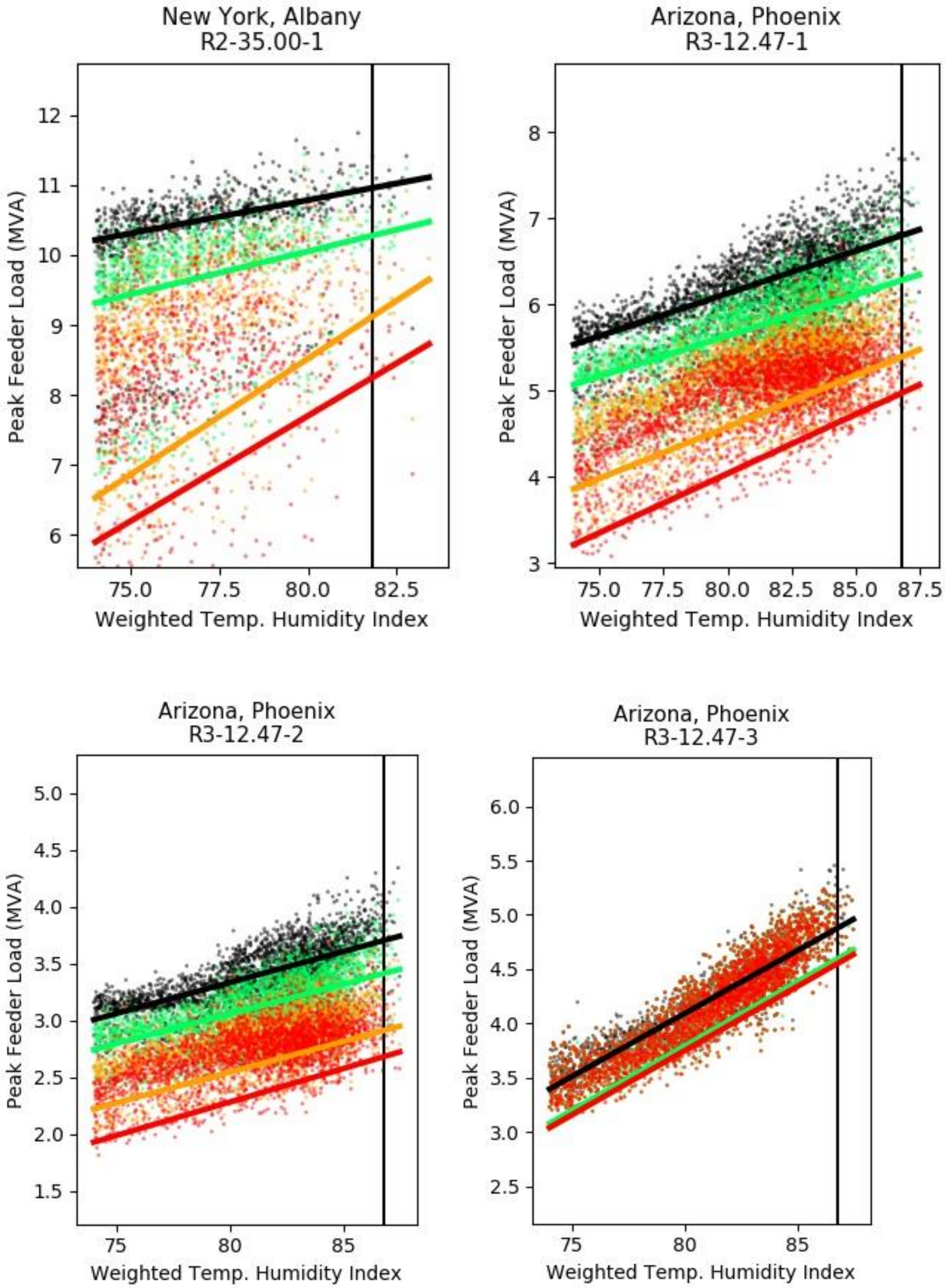
R2-12.47-2
Peak Feeder Load (MVA)
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
75.0
77.5
80.0
82.5
Weighted Temp. Humidity Index


New York, Albany
R2-12.47-3
Peak Feeder Load (MVA)
7
6
5
4
3
74
76
78
80
82
Weighted Temp. Humidity Index


New York, Albany
R2-25.00-1
Peak Feeder Load (MVA)
15
14
13
12
11
10
9
8
75.0
77.5
80.0
82.5
Weighted Temp. Humidity Index


New York, Albany
R2-35.00-1
Arizona, Phoenix
R3-12.47-1
Arizona, Phoenix
R3-12.47-2
Arizona, Phoenix
R3-12.47-3
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
12
11
10
9
8
7
6
75.0
77.5
80.0
82.5
85.0
87.5
5.0
4.5
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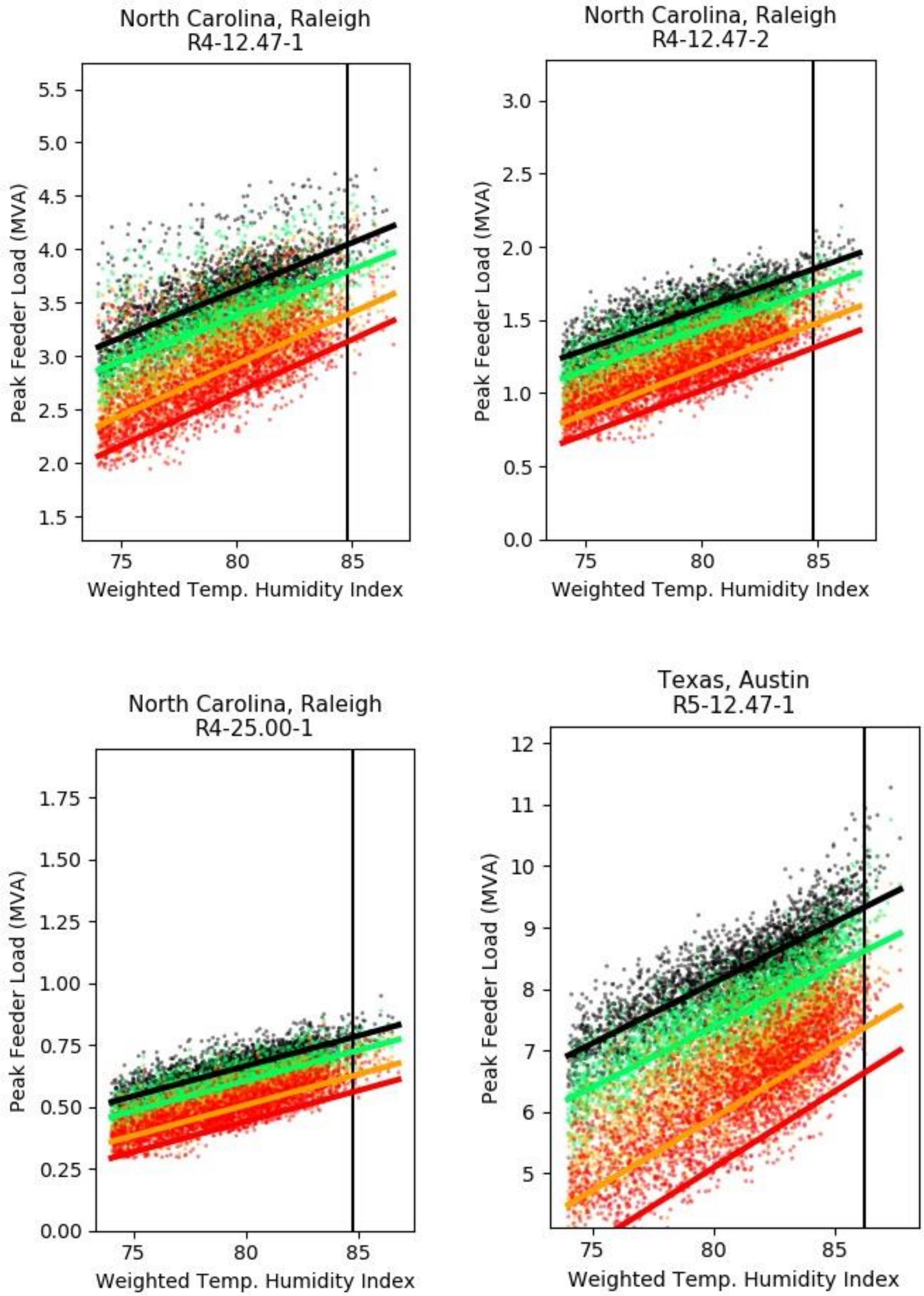
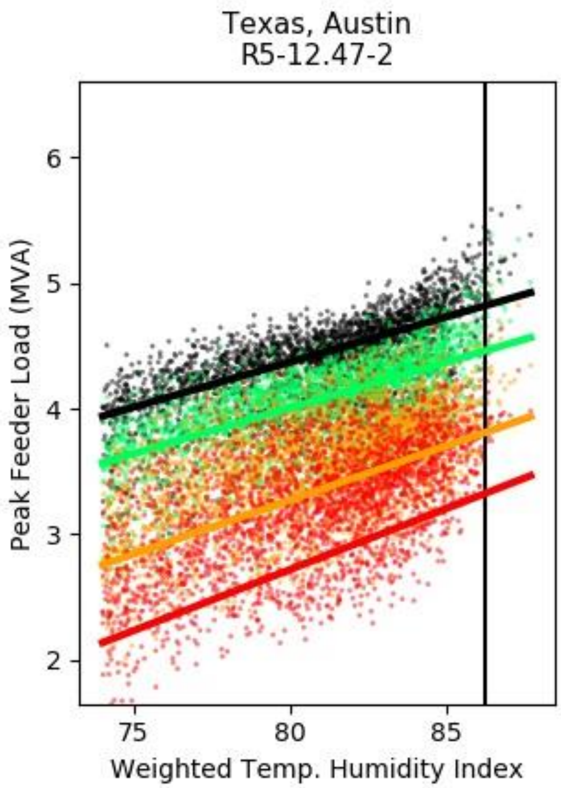
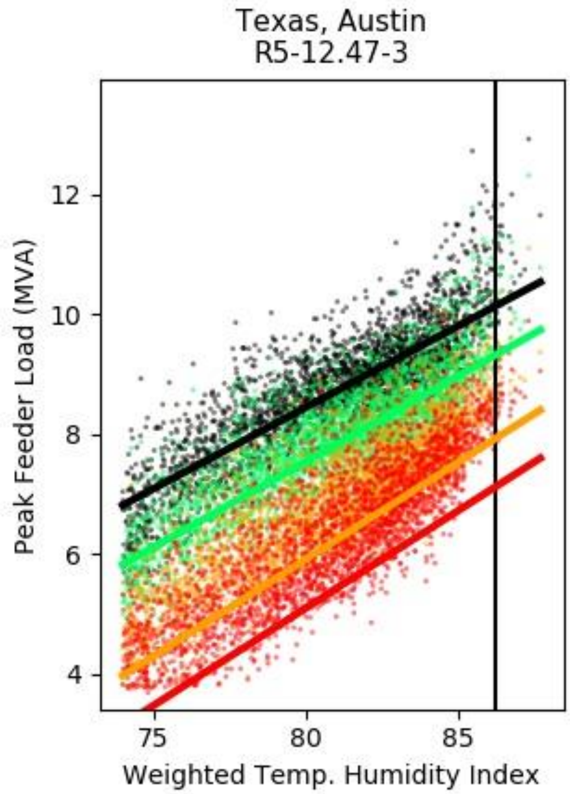
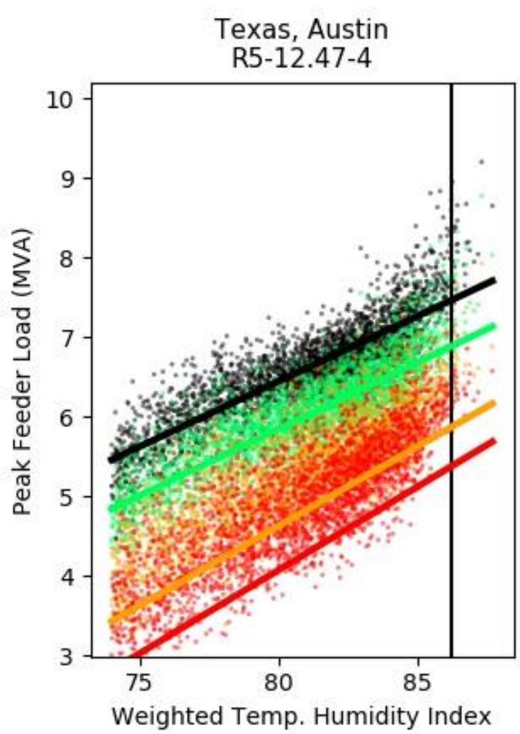
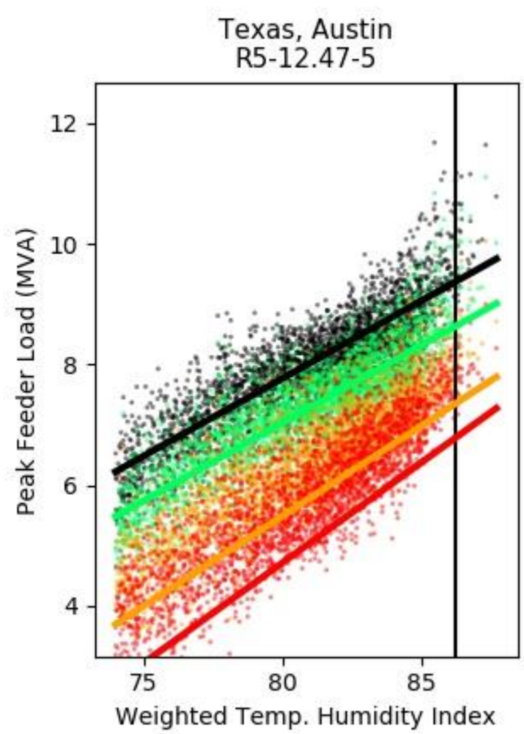
1.5
6.0
5.5
75
80
85

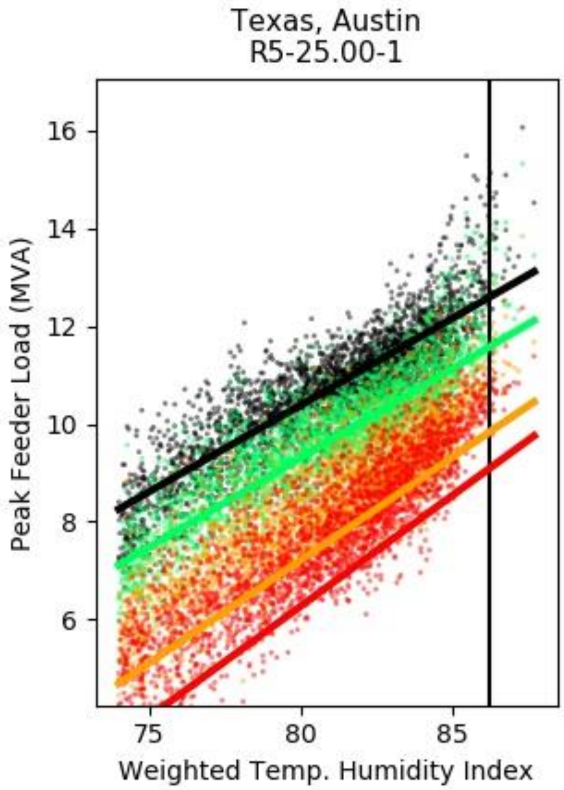

North Carolina, Raleigh
R4-12.47-1
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
North Carolina, Raleigh
R4-12.47-2
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
North Carolina, Raleigh
R4-25.00-1
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index
Texas, Austin
R5-12.47-1
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index

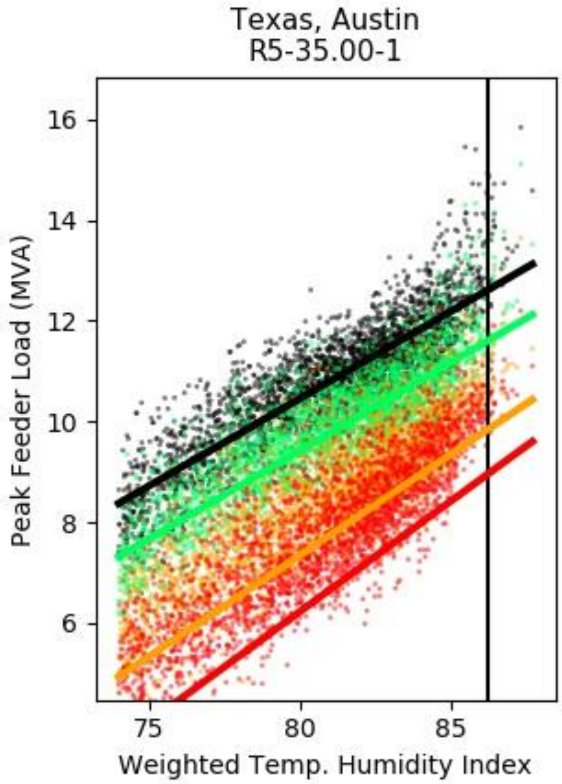

Texas, Austin
R5-12.47-2
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index


Texas, Austin
R5-12.47-3
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index

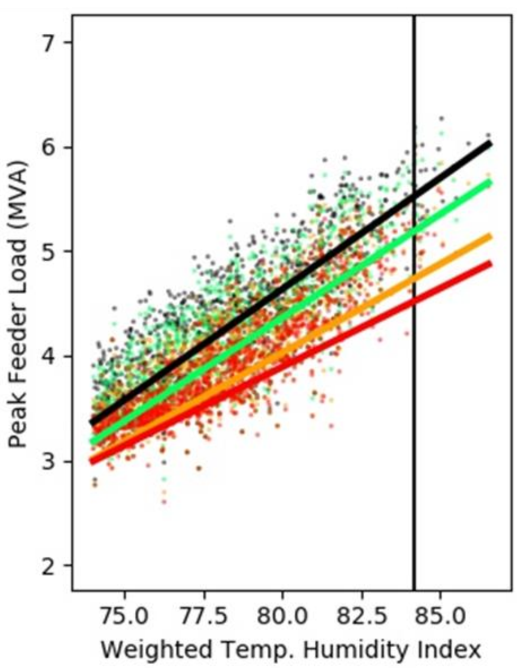

Texas, Austin
R5-12.47-4
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index


Texas, Austin
R5-12.47-5
Peak Feeder Load (MVA)
Weighted Temp. Humidity Index

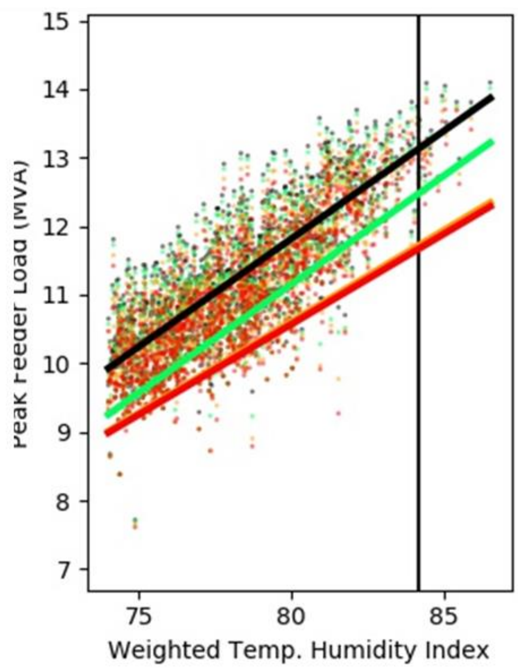




PA Feeder #1



PA Feeder #2



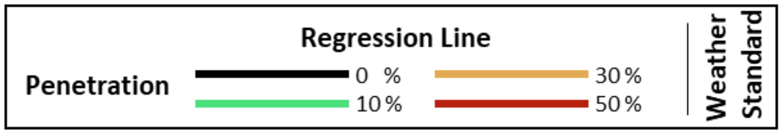


Figure 3-8: Weather Normalization of feeder taxonomy loads. Weather normalization regresses peak load events on weather indices and solves the resulting equation at an extreme weather event to estimate capacity requirements. The amount of overloading risk is quantified by the points that fall above the intersection of the regression line and the weather standard.

3.7.5 Peak Hour by Location, Feeder, and penetration

Table 3-3: Peak Hour for each location, feeder and penetration. The peak hour is not strongly related to the penetration.

Location	**Penetration**							
	0	**0.01**	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
California, Sacramento: R1-12.47-1	13	13	13	13	13	16	16	11
California, Sacramento: R1-12.47-2	13	13	13	13	11	11	11	11
California, Sacramento: R1-12.47-3	13	13	15	15	15	16	16	16
California, Sacramento: R1-12.47-4	13	13	13	13	16	16	17	17
California, Sacramento: R1-25.00-1	14	14	14	14	14	16	16	16
Minnesota, Saint Paul: R2-12.47-1	15	15	15	15	14	15	15	15
Minnesota, Saint Paul: R2-12.47-2	13	13	13	16	16	14	14	14
Minnesota, Saint Paul: R2-12.47-3	14	14	14	14	17	17	14	14
Minnesota, Saint Paul: R2-25.00-1	14	14	14	17	17	17	17	18
Minnesota, Saint Paul: R2-35.00-1	13	13	13	13	14	14	14	14
New York, Albany: R2-12.47-1	12	12	12	12	15	11	11	11
New York, Albany: R2-12.47-2	14	14	11	11	11	11	11	11
New York, Albany: R2-12.47-3	11	11	11	11	11	11	11	11
New York, Albany: R2-25.00-1	14	11	11	11	11	11	11	11
New York, Albany: R2-35.00-1	11	13	11	11	11	11	11	11
Arizona, Phoenix: R3-12.47-1	14	14	16	16	16	16	16	16
Arizona, Phoenix: R3-12.47-2	14	14	14	14	14	15	15	15
Arizona, Phoenix: R3-12.47-3	14	14	14	20	20	20	20	20
North Carolina, Raleigh: R4-12.47-1	12	12	12	14	14	14	14	18
North Carolina, Raleigh: R4-12.47-2	12	12	12	12	12	14	14	15
North Carolina, Raleigh: R4-25.00-1	6	6	6	6	6	6	6	6
Texas, Austin: R5-12.47-1	14	14	14	14	14	14	14	16
Texas, Austin: R5-12.47-2	14	14	14	14	14	14	14	16
Texas, Austin: R5-12.47-3	14	14	14	14	14	14	14	14
Texas, Austin: R5-12.47-4	14	14	14	14	14	14	14	14
Texas, Austin: R5-12.47-5	13	13	14	14	14	14	14	14
Texas, Austin: R5-25.00-1	14	14	14	14	14	14	14	14
Texas, Austin: R5-35.00-1	14	14	14	14	14	14	14	14
Pennsylvania Feeder #1	17	17	17	17	17	17	17	17
Pennsylvania Feeder #1	18	18	18	18	18	19	19	19

3.7.6 Supplementary D-ELCC Results

3.7.6.1 Marginal Distribution-Effective Load Carrying Capability

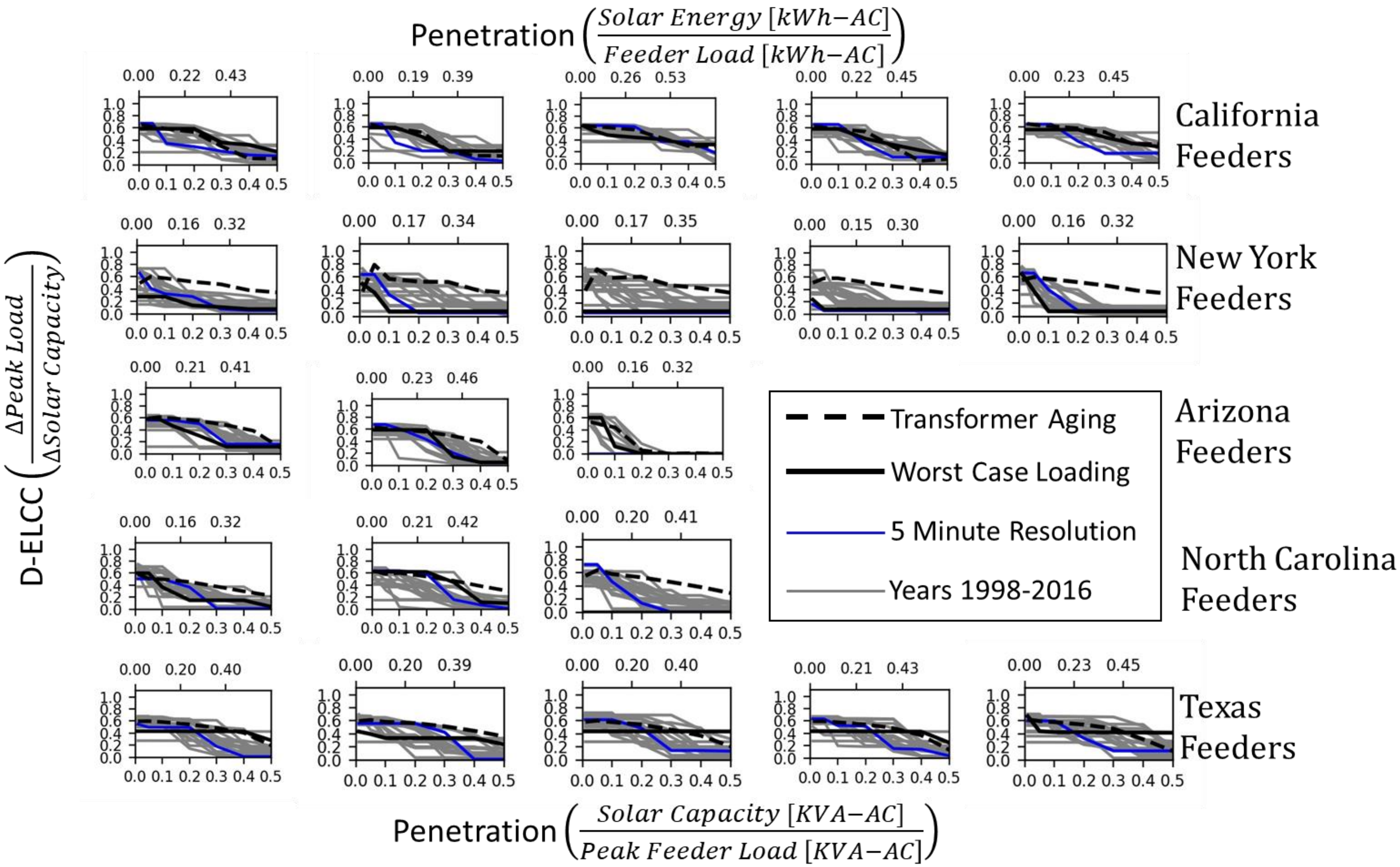


Figure 3-9: Marginal Distribution-Effective Load Carrying Capability for the PNNL Feeder Taxonomy. Columns show the taxonomy feeders in order from left to right. California Feeders: R1-12.47-1, R1-12.47-2, R1-12.47-3, R1-12.47-4, R1-25.00-1. New York Feeders: R2-12.47-1, R2-12.47-2, R2-12.47-3, R2-25.00-1, R2-35.00-1. Arizona: R3-12.47-1, R3-12.47-2, R3-12.47-3. North Carolina Feeders: R4-12.47-1, R4-12.47-2, R4-25.00-1. Texas feeders: R5-12.47-1, R5-12.47-2, R5-12.47-3, R5-12.47-4, R5-12.47-5.

3.7.6.2 Average and Marginal D-ELCC for Texas and Minnesota

The following D-ELCC plots were not in the main body of the chapter due to space constraints.

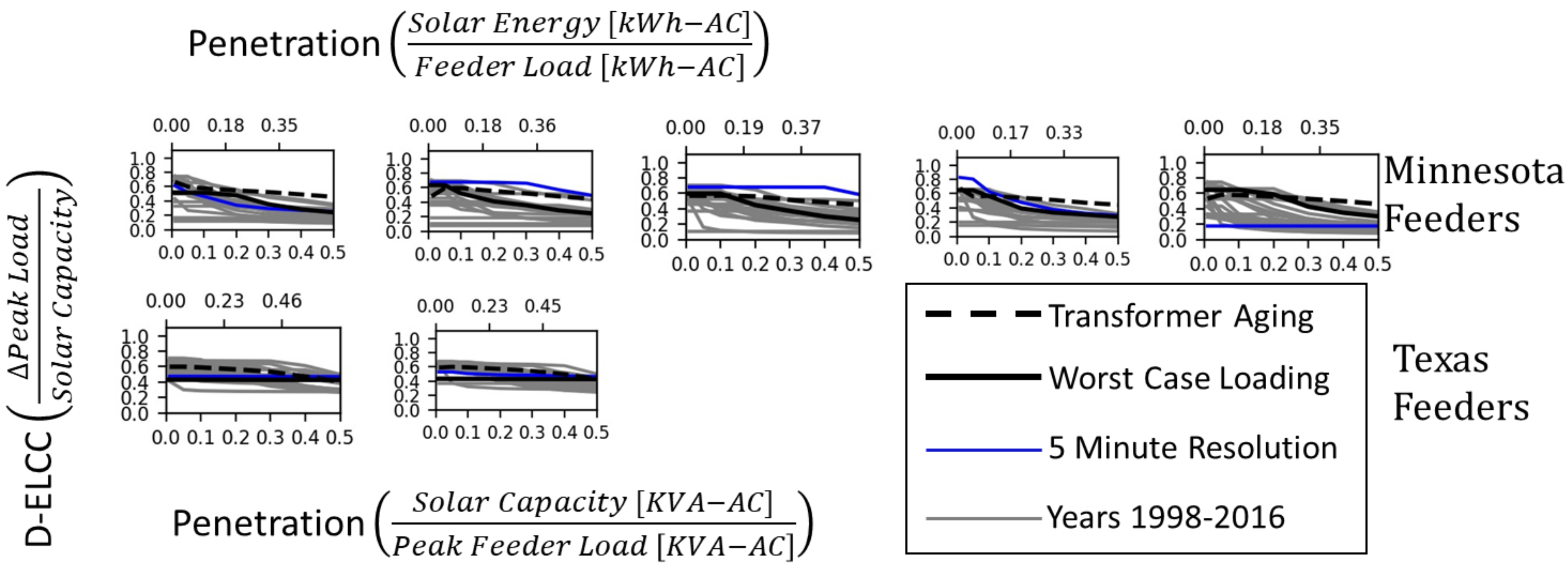


Figure 3-10: Average Distribution Effective Loading Capability (additional feeders). Columns show the taxonomy feeders in order from left to right. Minnesota Feeders: R2-12.47-1, R2-12.47-2, R2-12.47-3, R2-25.00-1, R2-35.00-1. Texas Feeders: R5-25.00-1, R5-35.00-1

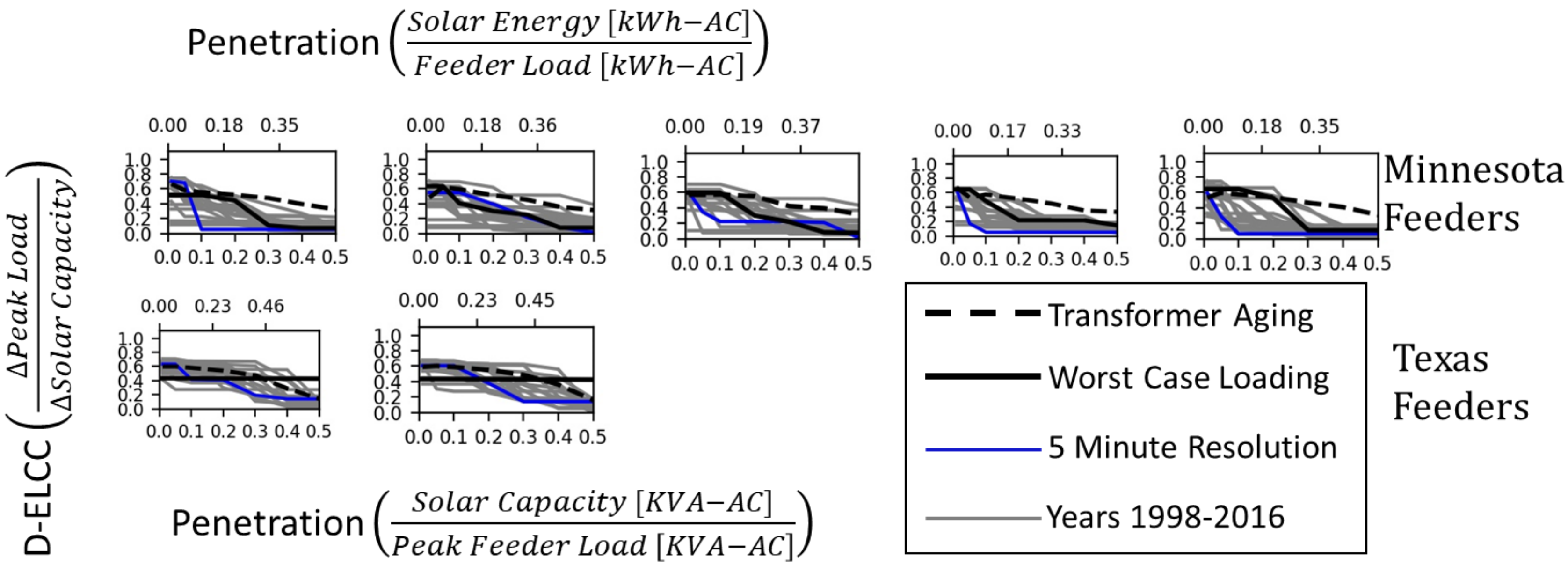


Figure 3-11: Marginal Distribution Effective Loading Capability (additional feeders). Columns show the taxonomy feeders in order from left to right. Minnesota Feeders: R2-12.47-1, R2-12.47-2, R2-12.47-3, R2-25.00-1, R2-35.00-1. Texas Feeders: R5-25.00-1, R5-35.00-1

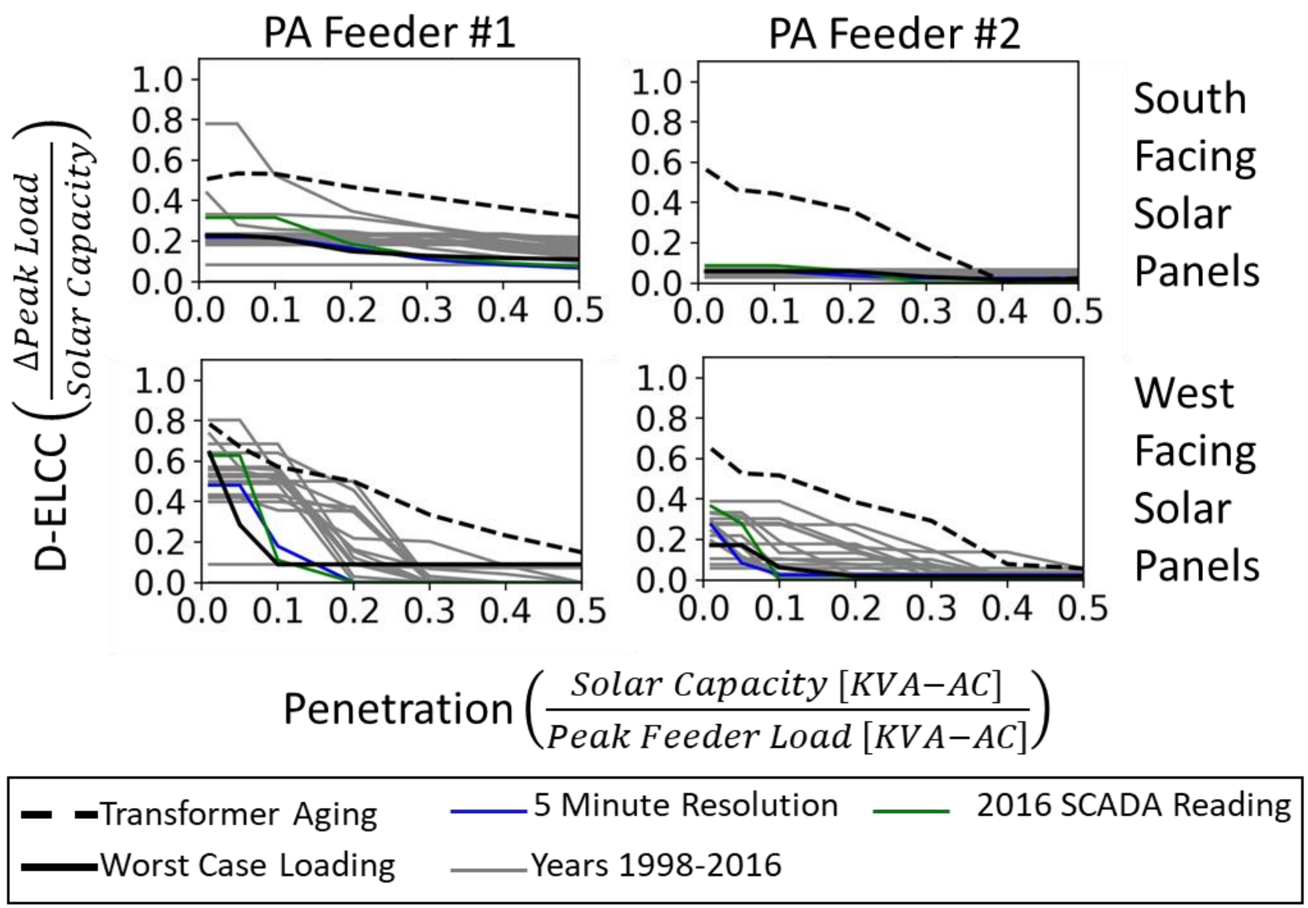
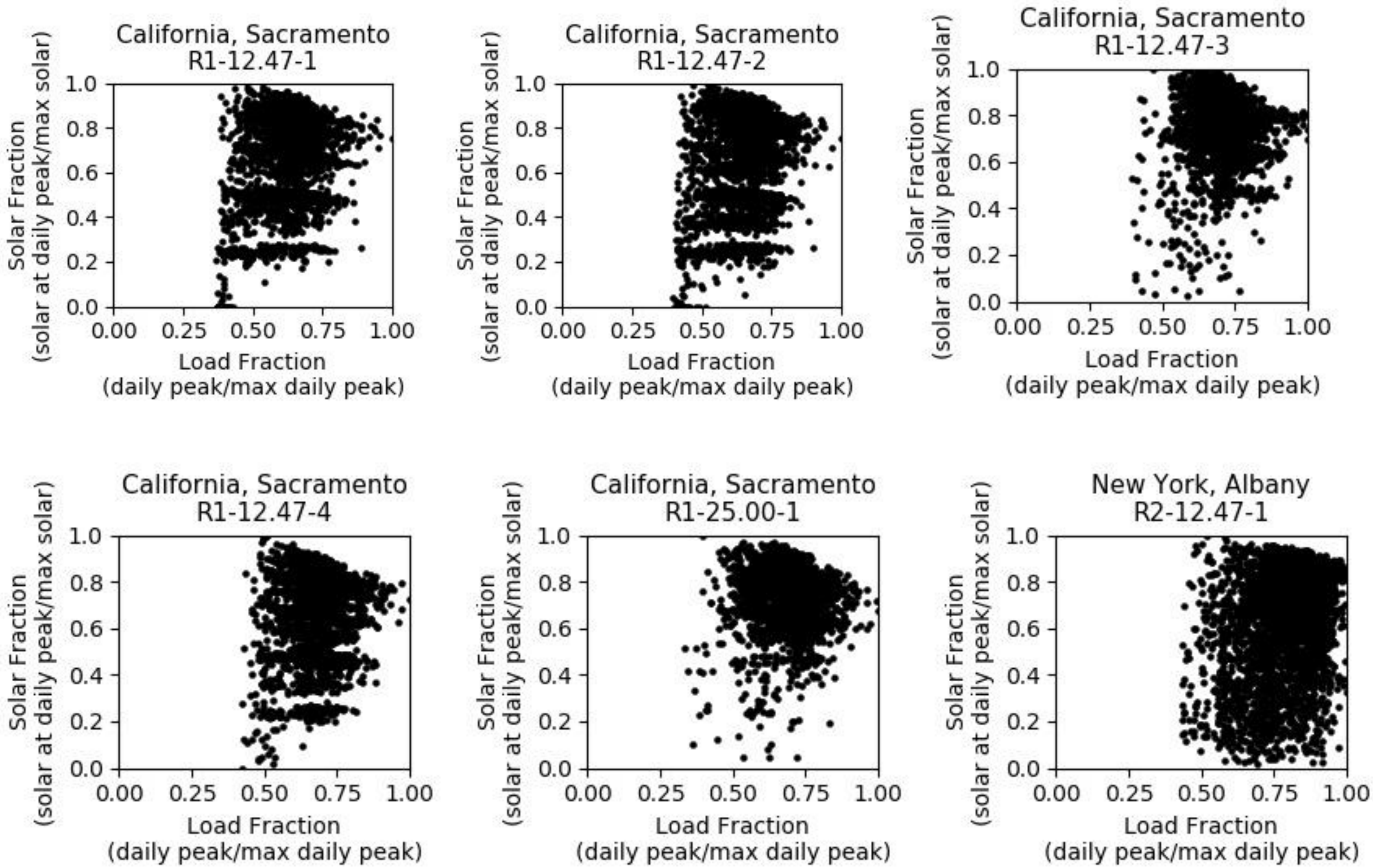
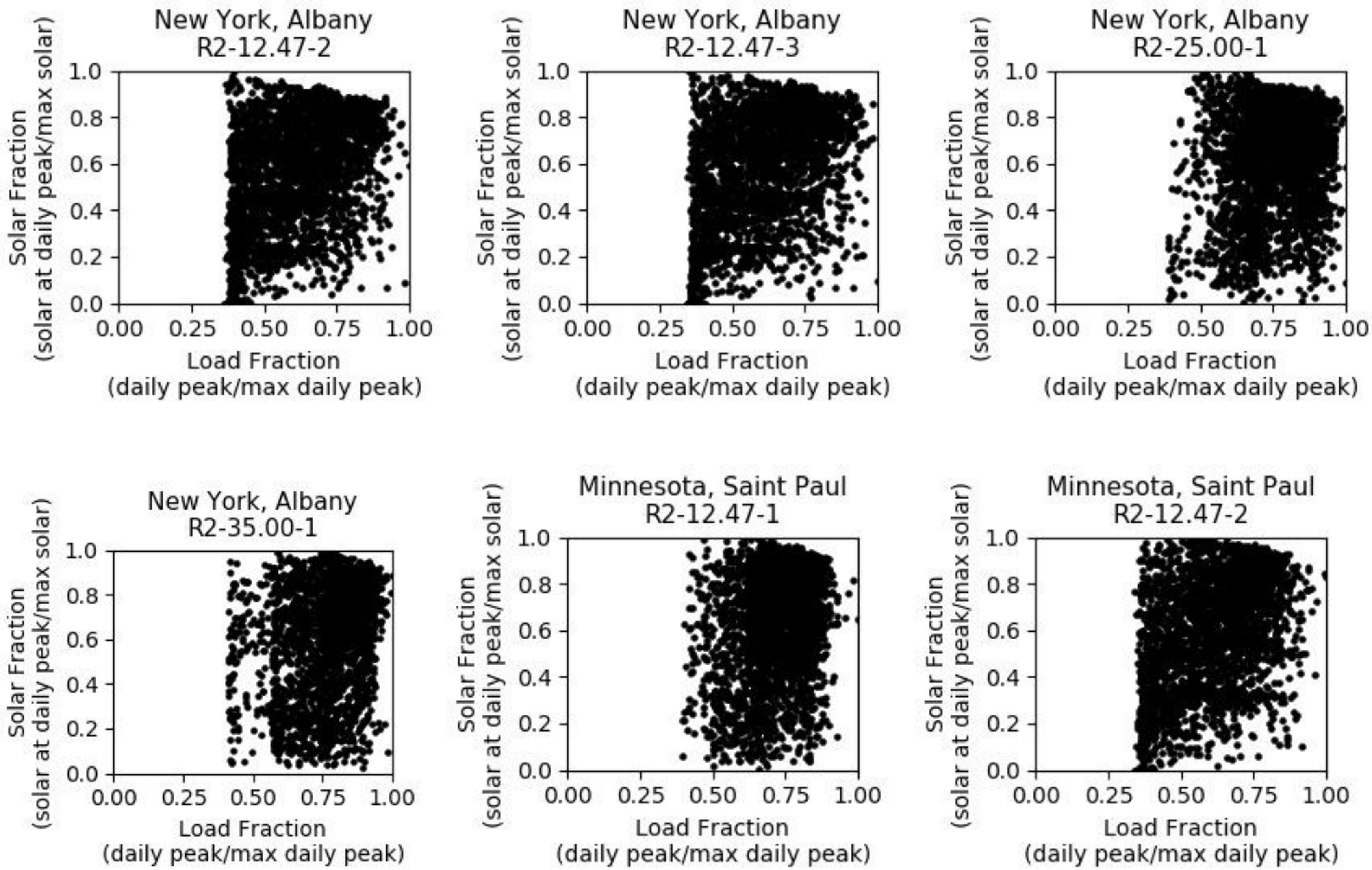
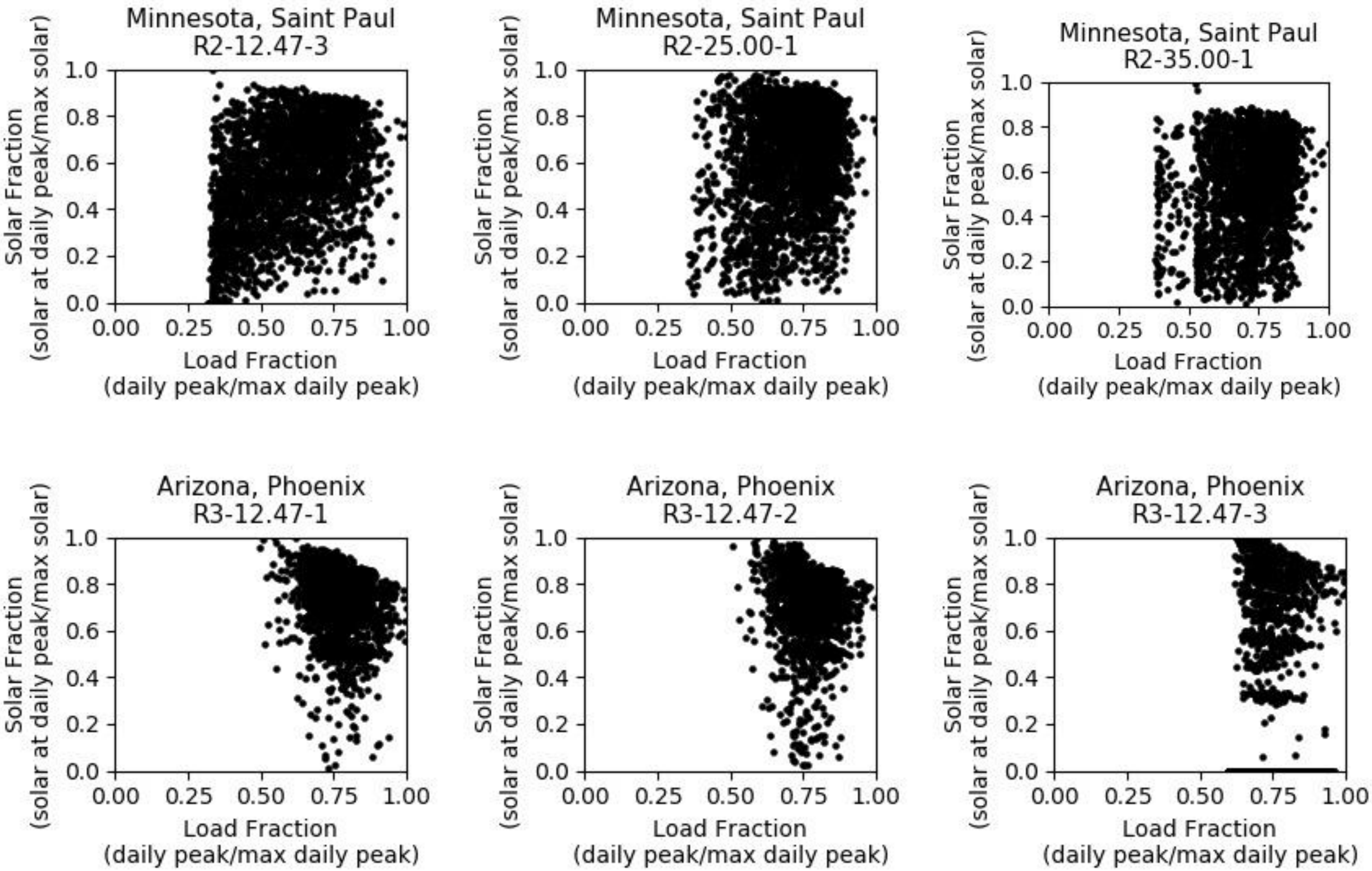


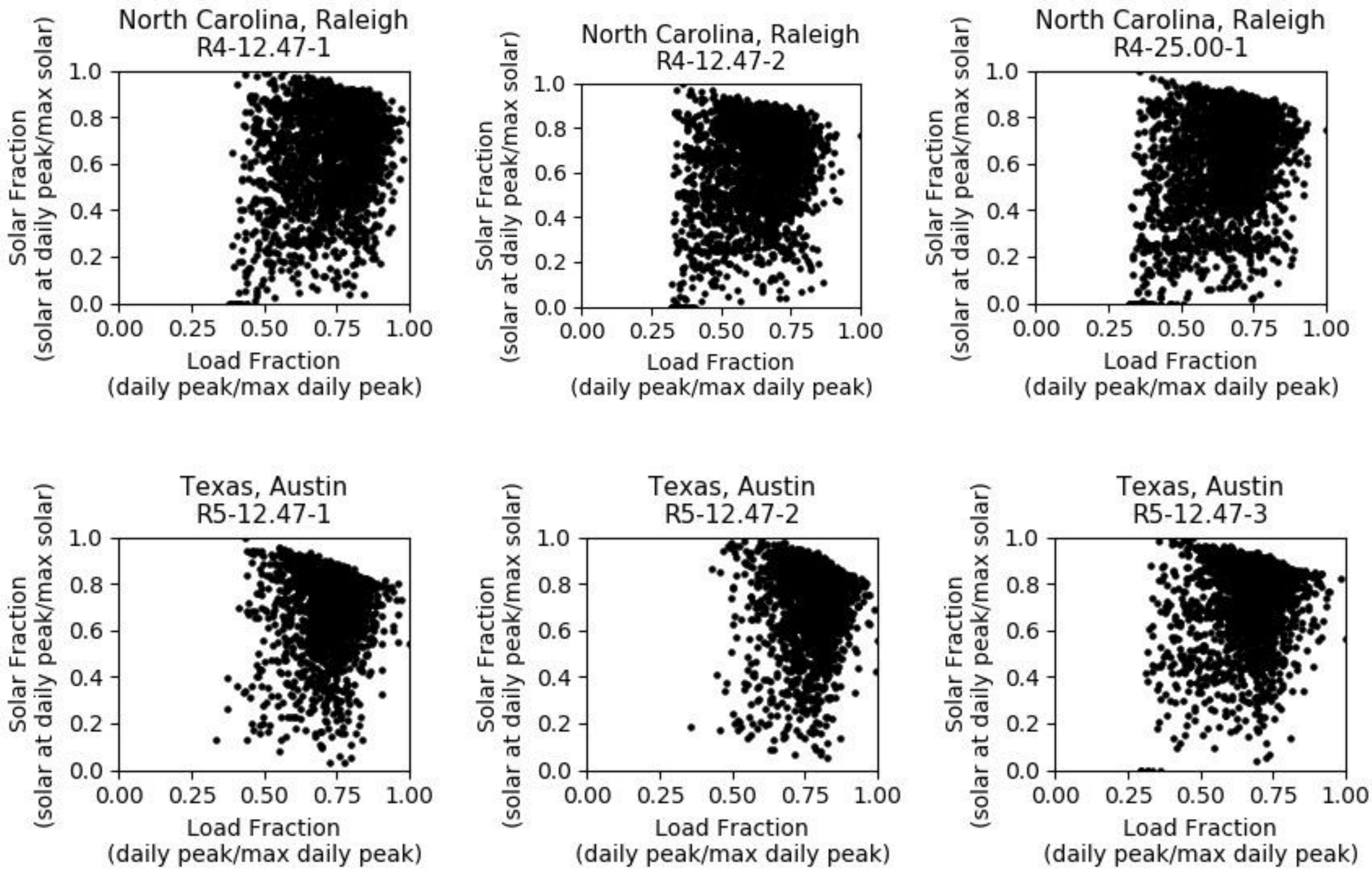
Figure 3-12: Marginal Distribution Effective Load Carrying Capability for Pennsylvania Feeders.

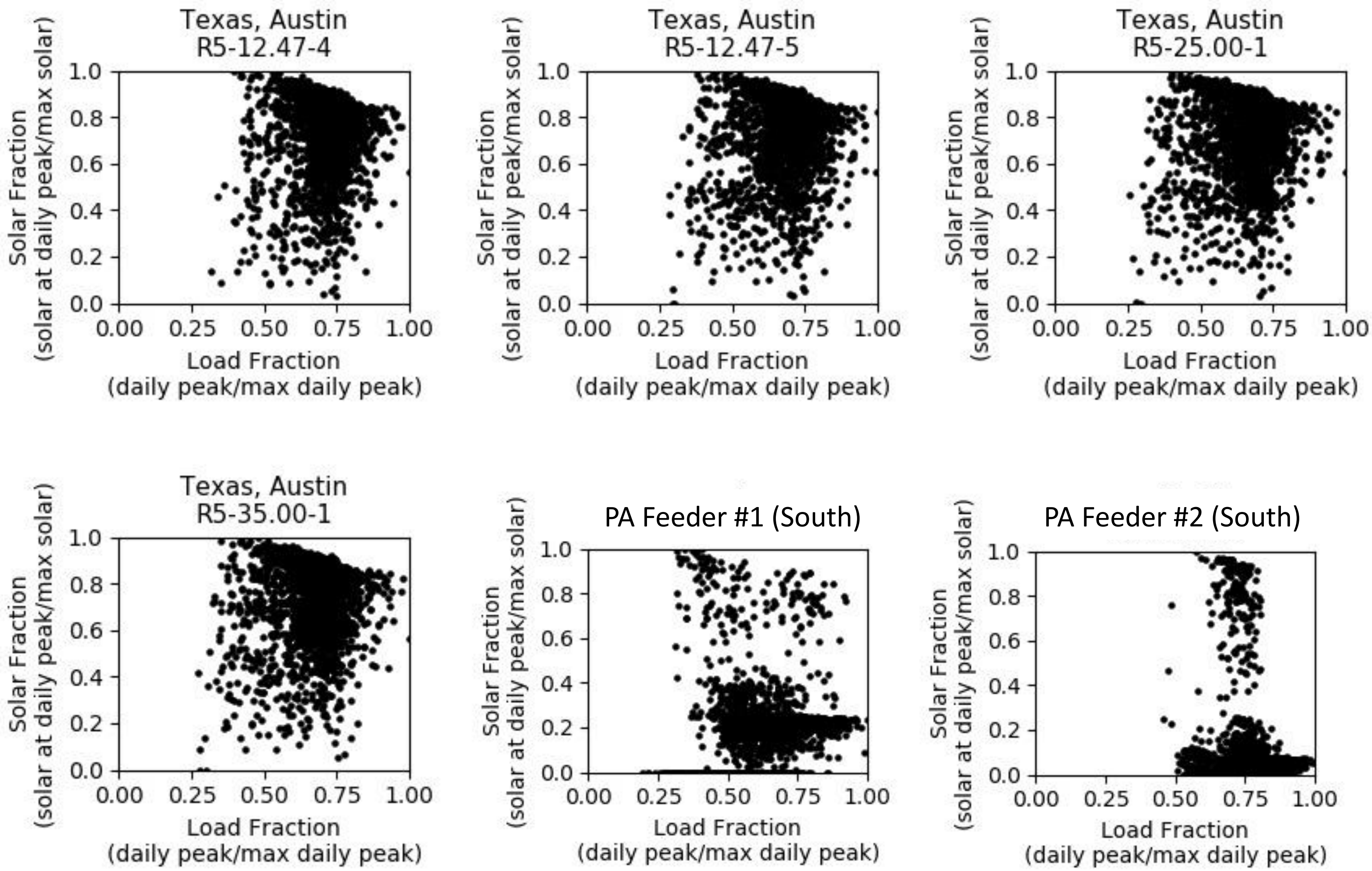
3.7.7 Solar Performance Scatterplot




New York, Albany
R2-12.47-2
New York, Albany
R2-12.47-3
New York, Albany
R2-25.00-1
New York, Albany
R2-35.00-1
Minnesota, Saint Paul
R2-12.47-1
Minnesota, Saint Paul
R2-12.47-2
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00


Minnesota, Saint Paul
R2-12.47-3
Minnesota, Saint Paul
R2-25.00-1
Minnesota, Saint Paul
R2-35.00-1
Arizona, Phoenix
R3-12.47-1
Arizona, Phoenix
R3-12.47-2
Arizona, Phoenix
R3-12.47-3
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00


North Carolina, Raleigh
R4-12.47-1
North Carolina, Raleigh
R4-12.47-2
North Carolina, Raleigh
R4-25.00-1
Texas, Austin
R5-12.47-1
Texas, Austin
R5-12.47-2
Texas, Austin
R5-12.47-3
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00


Texas, Austin
R5-12.47-4
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
Texas, Austin
R5-12.47-5
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
Texas, Austin
R5-25.00-1
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
Texas, Austin
R5-35.00-1
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
PA Feeder #1 (South)
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
PA Feeder #2 (South)
Solar Fraction
(solar at daily peak/max solar)
Load Fraction
(daily peak/max daily peak)
0.00
0.25
0.50
0.75
1.00
0.0
0.2
0.4
0.6
0.8
1.0

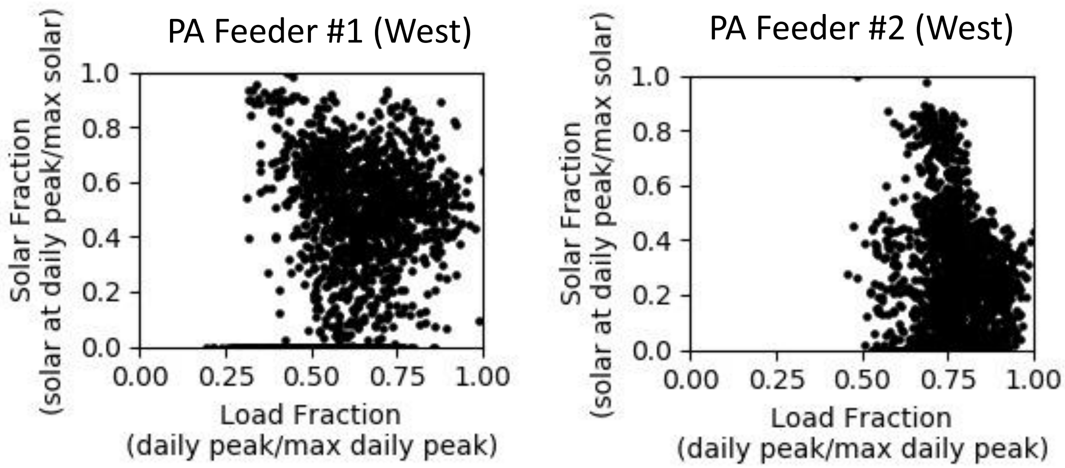
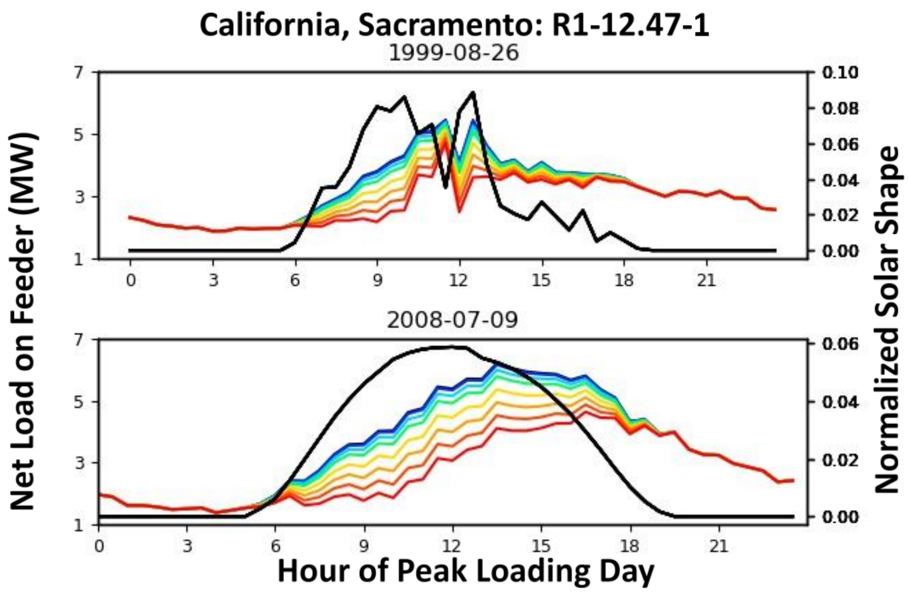
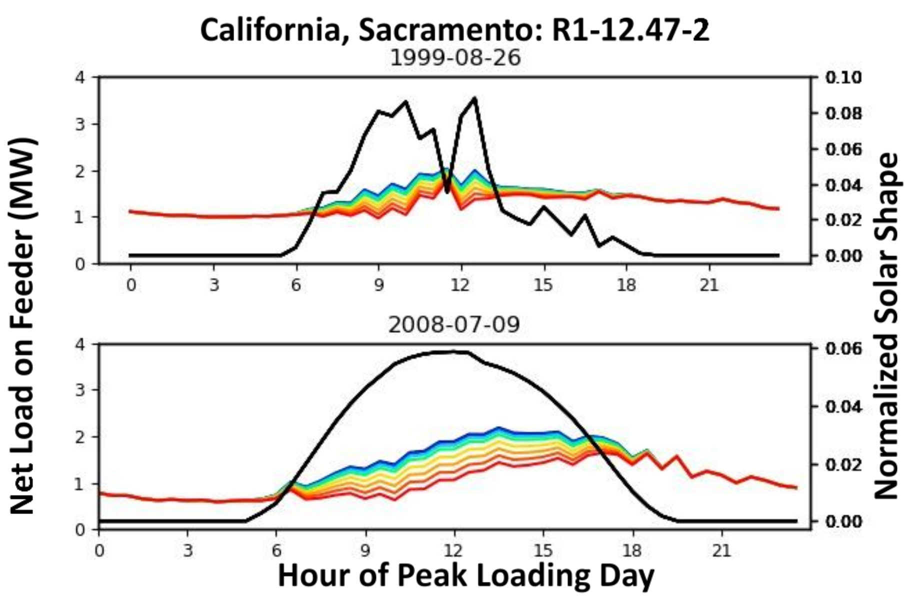
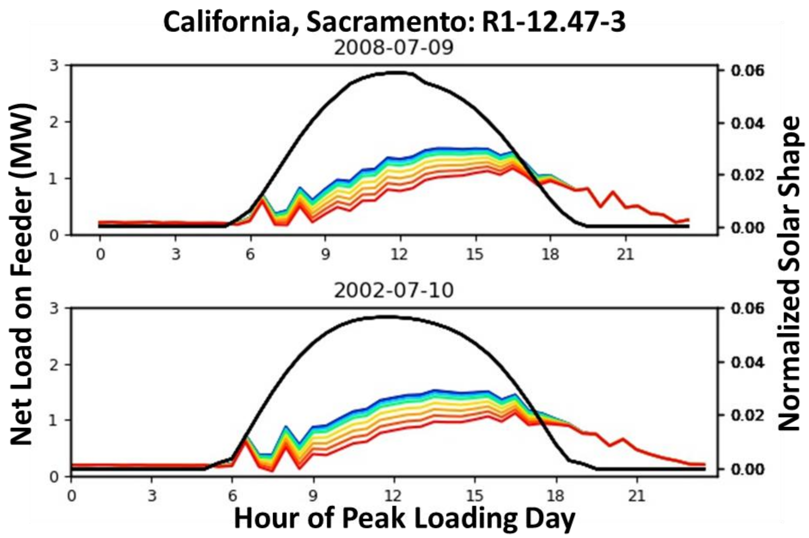


Figure 3-13: Solar Performance Scatterplot. The solar performance scatterplots show a trend towards greater solar output during peak load events.

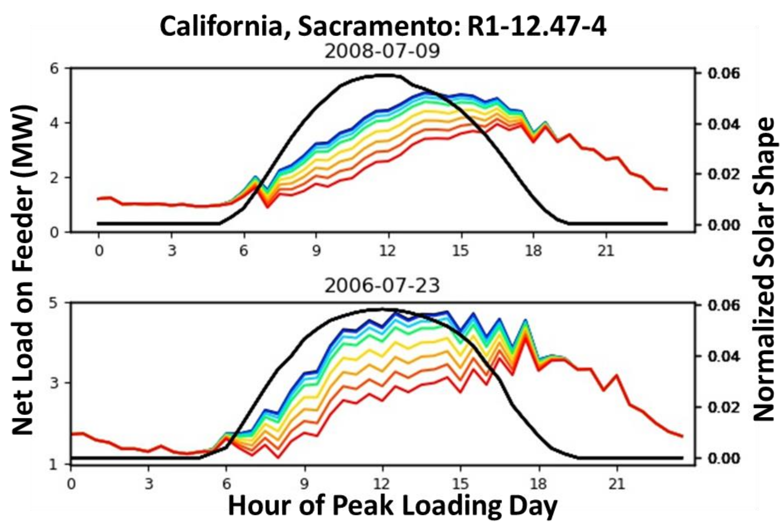
3.7.8 Net Load on Peak Days



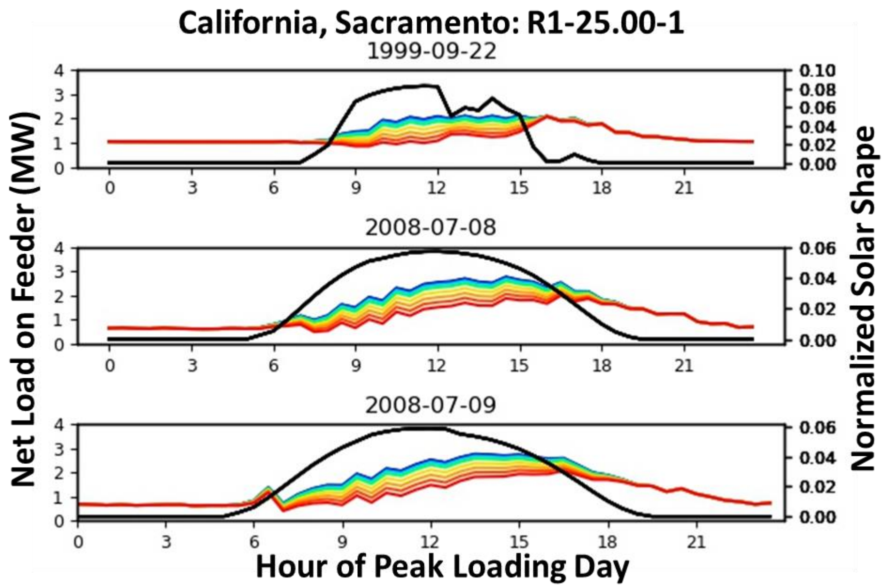


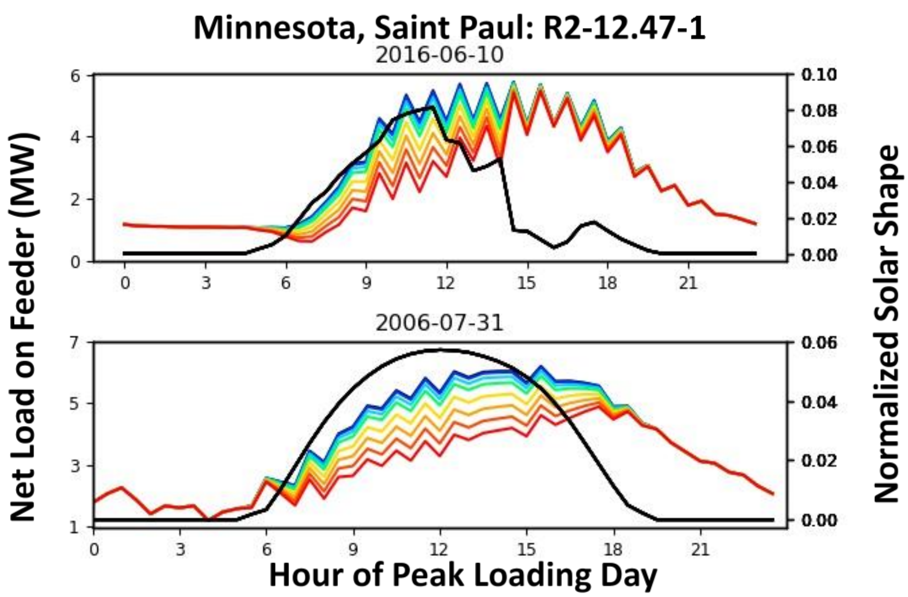


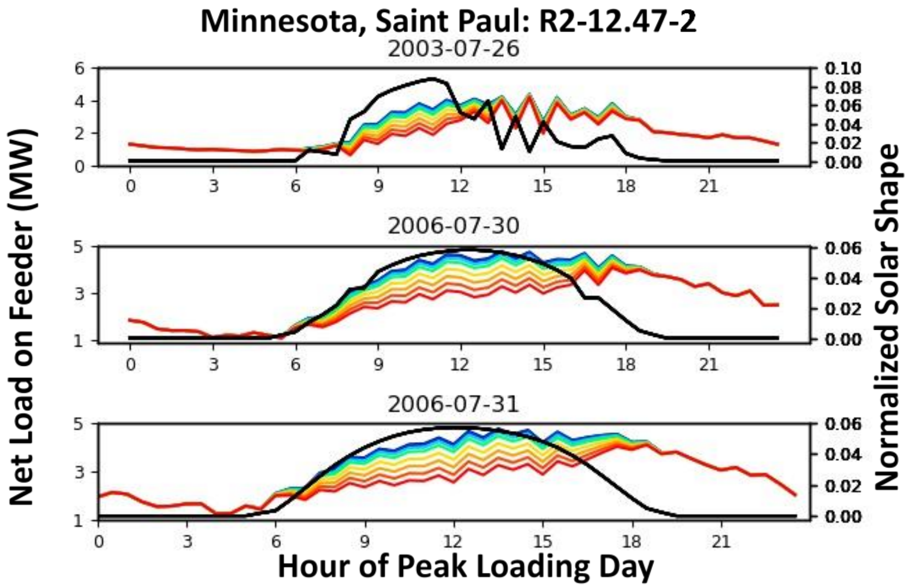
California, Sacramento: R1-12.47-3
2008-07-09
2002-07-10
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day



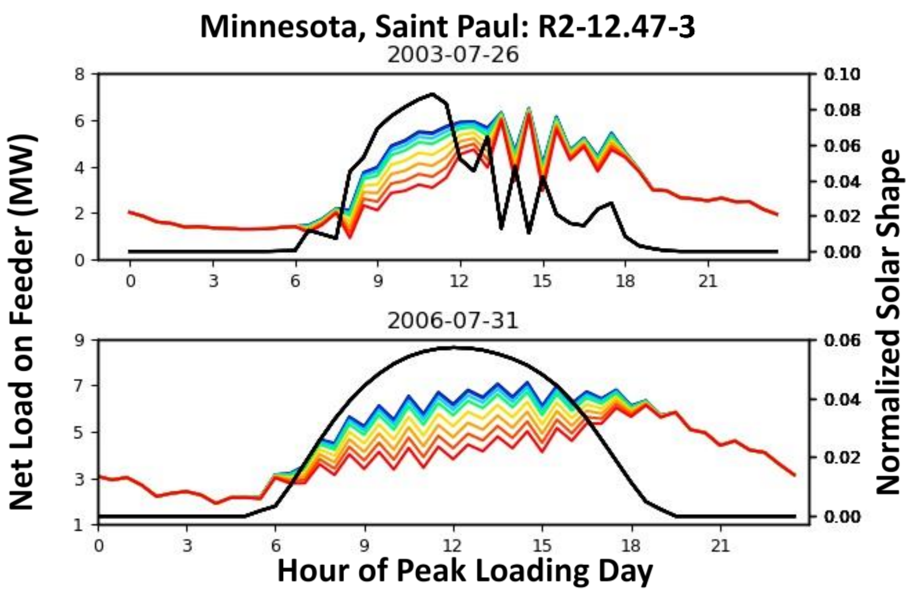
California, Sacramento: R1-12.47-4
2008-07-09
2006-07-23
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day


California, Sacramento: R1-25.00-1
1999-09-22
2008-07-08
2008-07-09
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

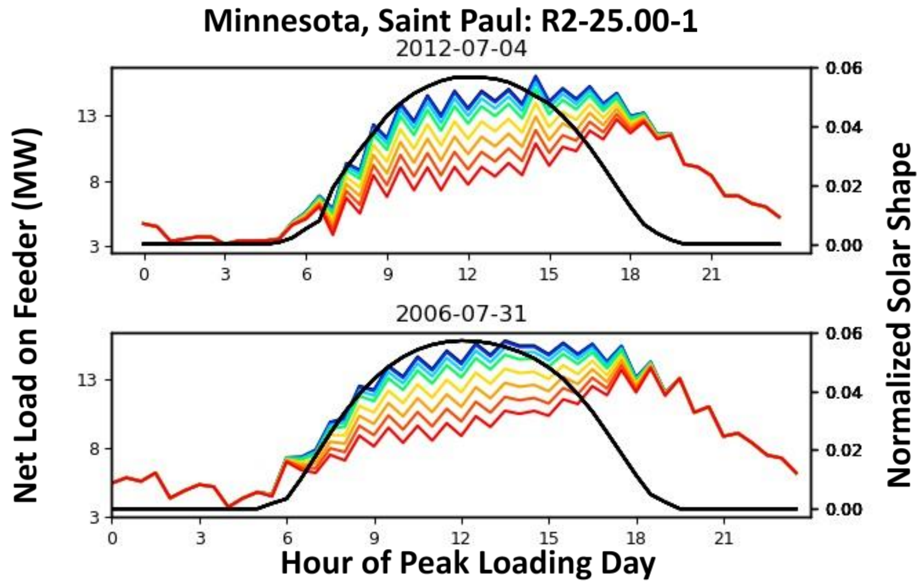

Minnesota, Saint Paul: R2-12.47-1
2016-06-10
2006-07-31
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day



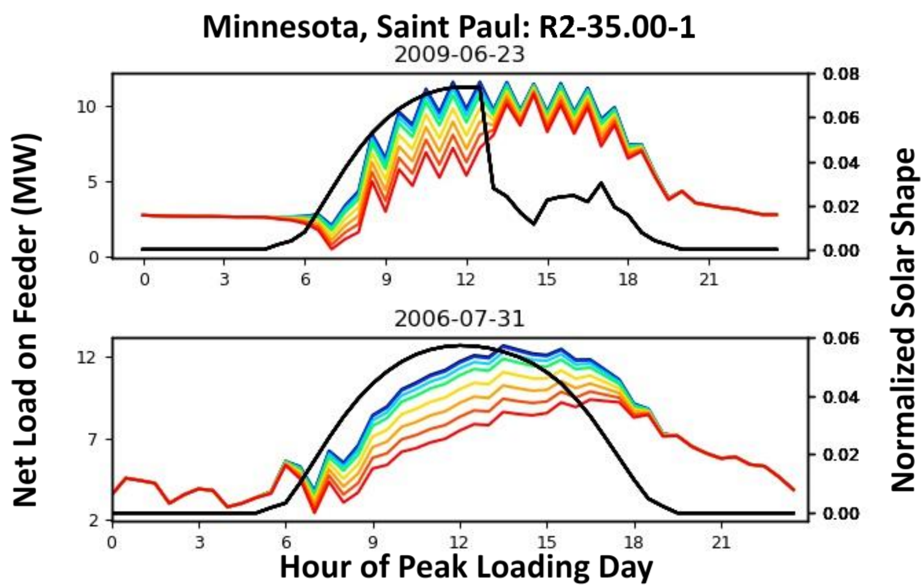
Minnesota, Saint Paul: R2-12.47-2
2003-07-26
2006-07-30
2006-07-31
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day



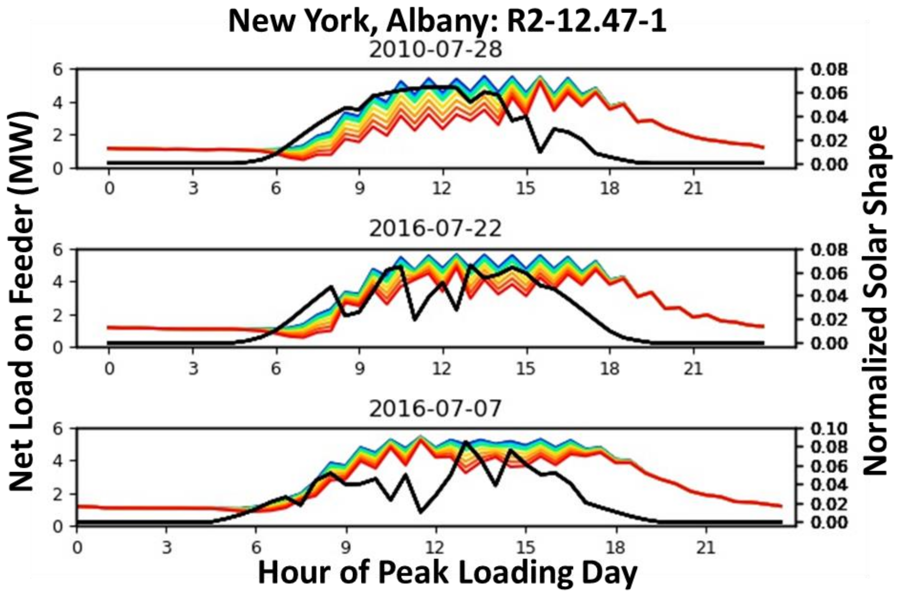
Minnesota, Saint Paul: R2-12.47-3
2003-07-26
2006-07-31
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

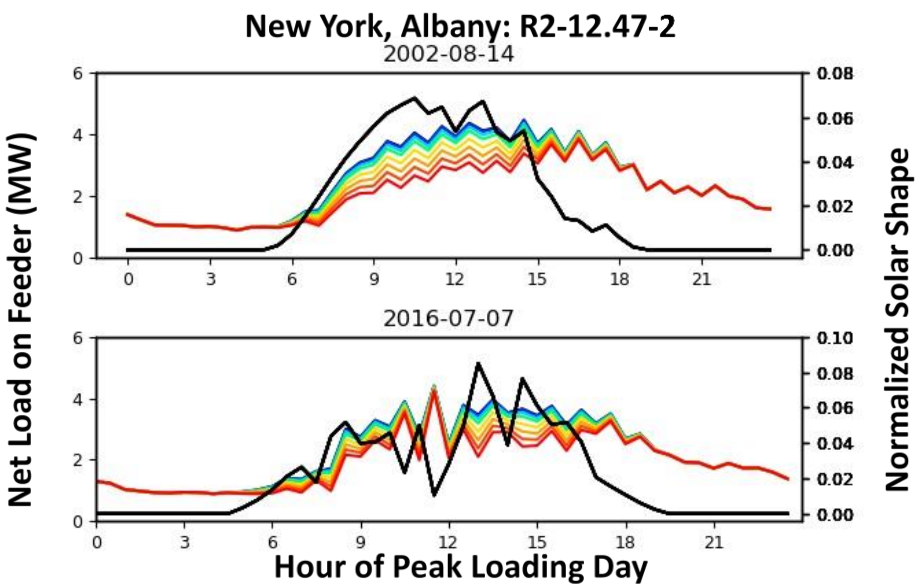


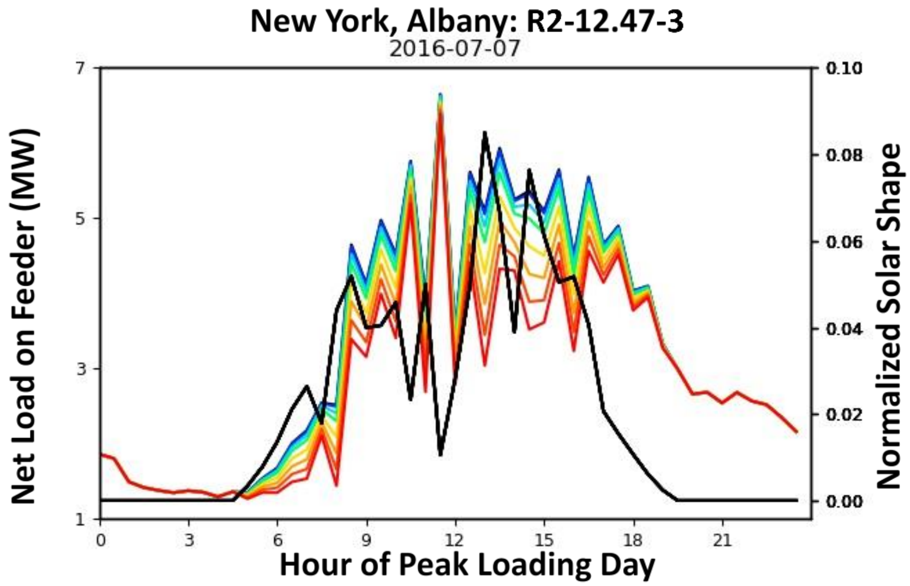
Minnesota, Saint Paul: R2-25.00-1
2012-07-04
2006-07-31
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

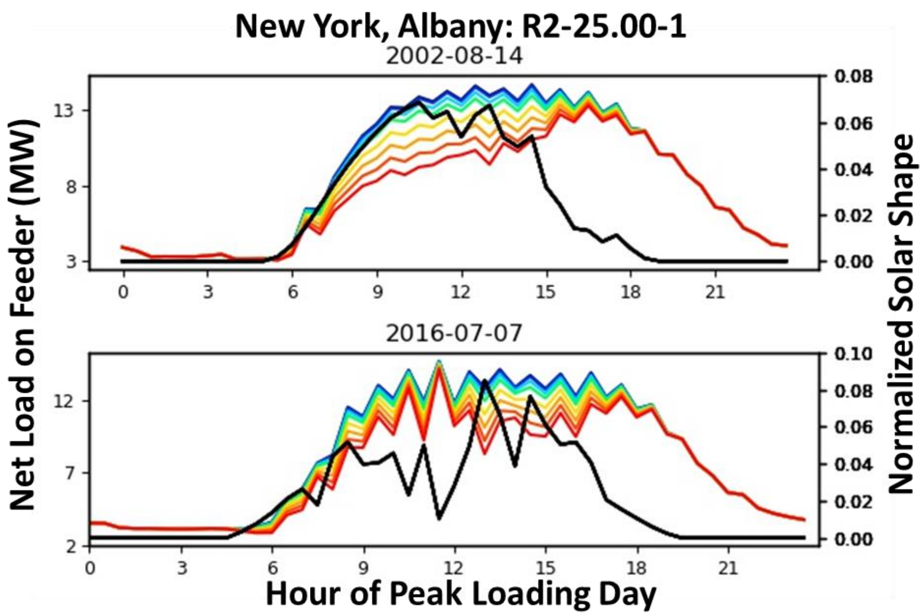


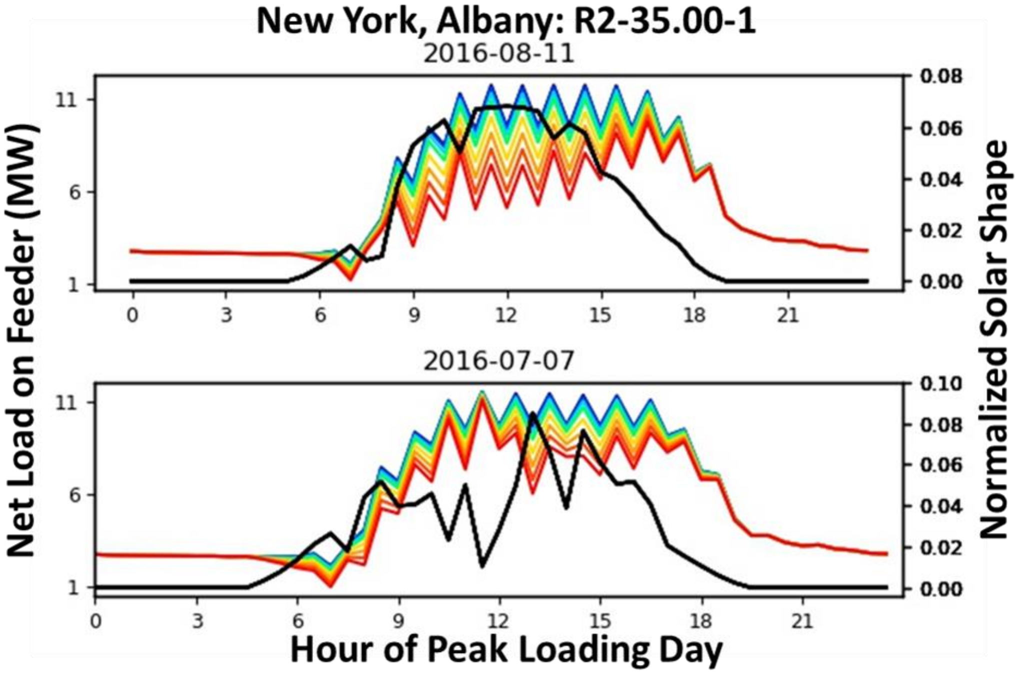
Minnesota, Saint Paul: R2-35.00-1
2009-06-23
2006-07-31
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day


New York, Albany: R2-12.47-1
2010-07-28
2016-07-22
2016-07-07
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

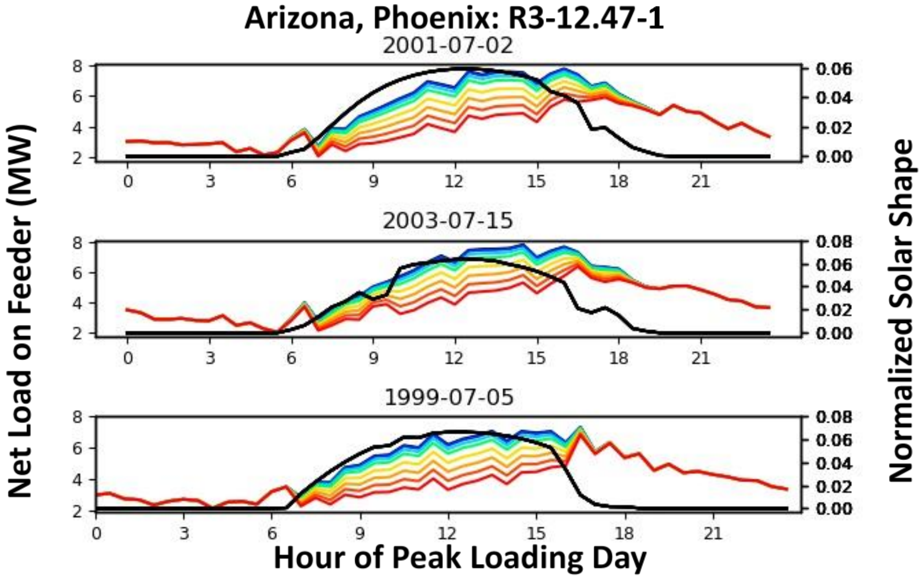

New York, Albany: R2-12.47-2
2002-08-14
2016-07-07
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day


New York, Albany: R2-12.47-3
2016-07-07
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day
1
3
5
7
0.00
0.02
0.04
0.06
0.08
0.10
0
3
6
9
12
15
18
21

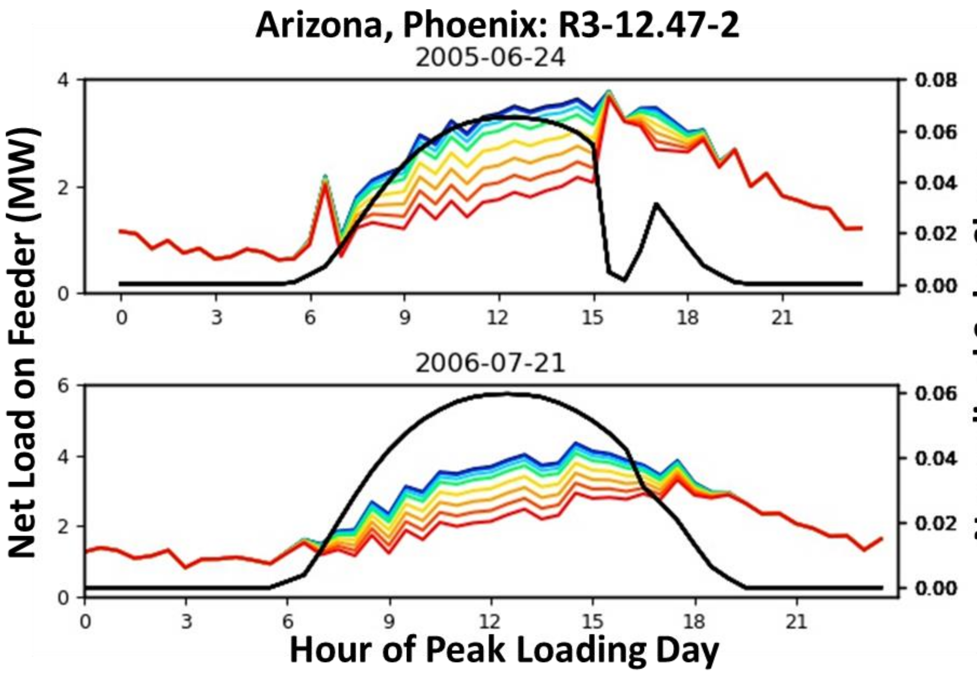

New York, Albany: R2-25.00-1
2002-08-14
2016-07-07
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day
3
8
13
2
7
12
0.00
0.02
0.04
0.06
0.08
0.10
0
3
6
9
12
15
18
21

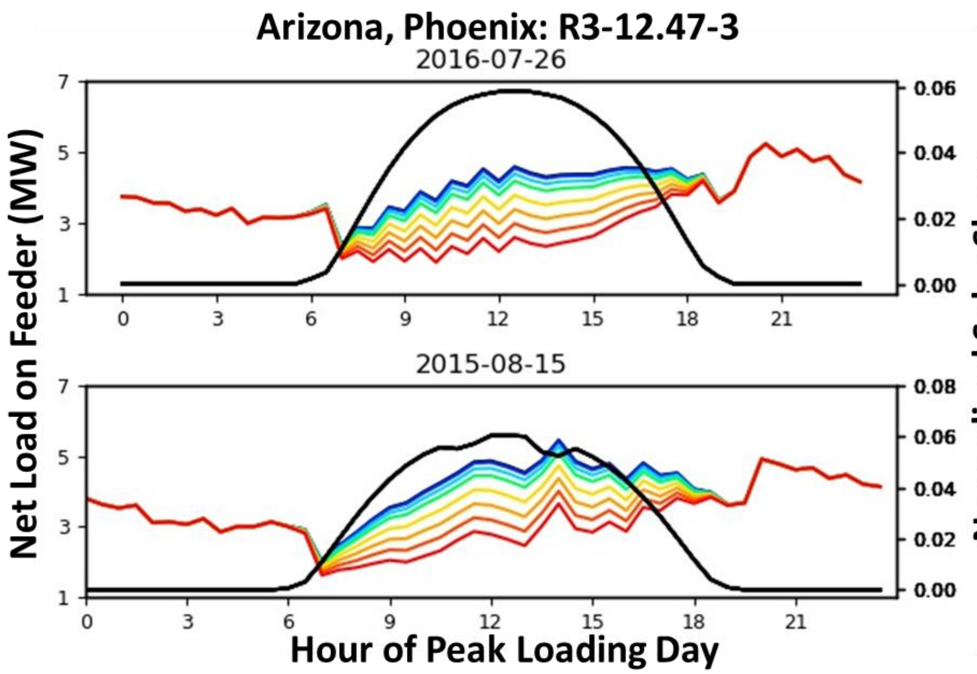


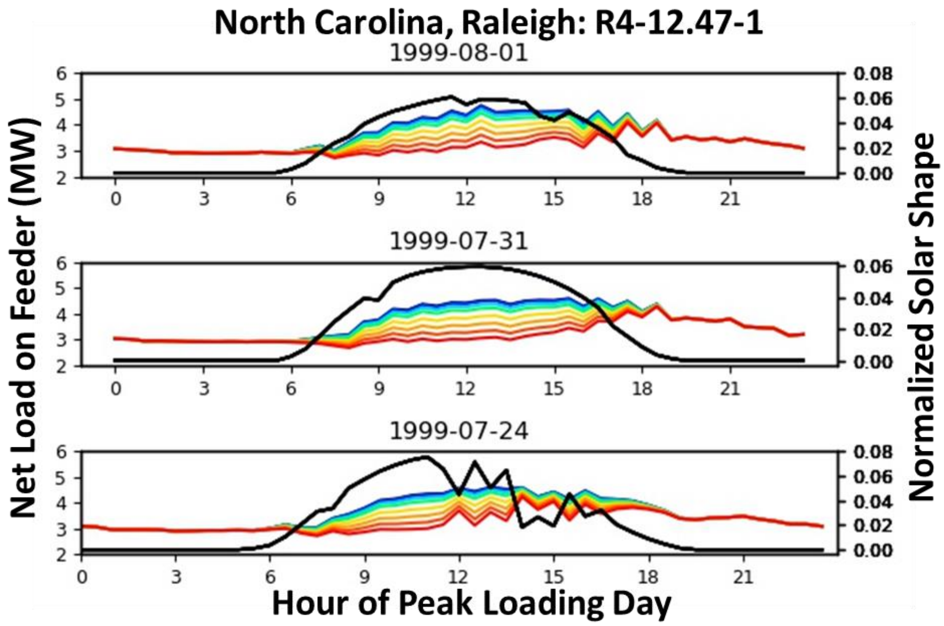
New York, Albany: R2-35.00-1
2016-08-11
2016-07-07
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

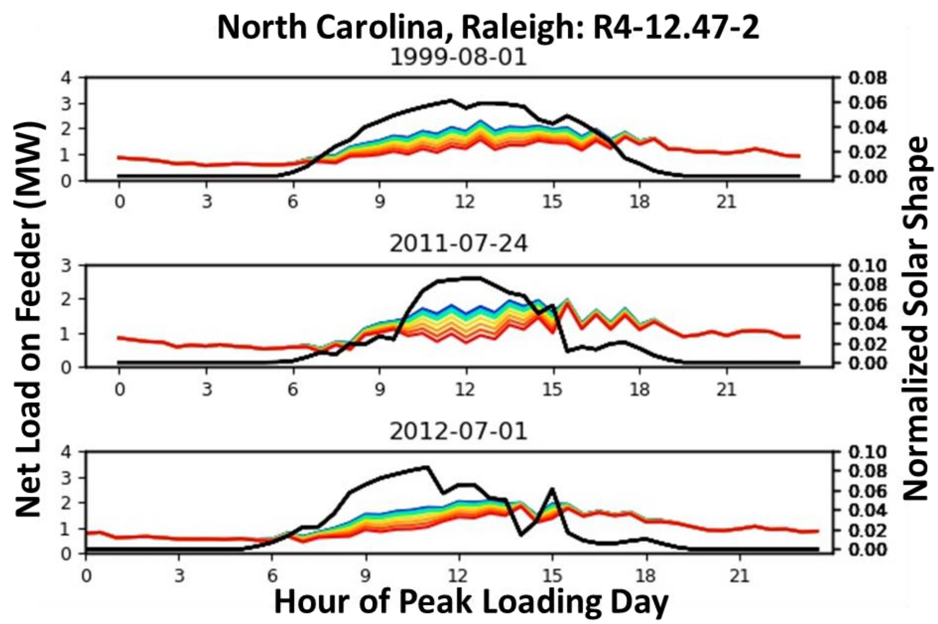


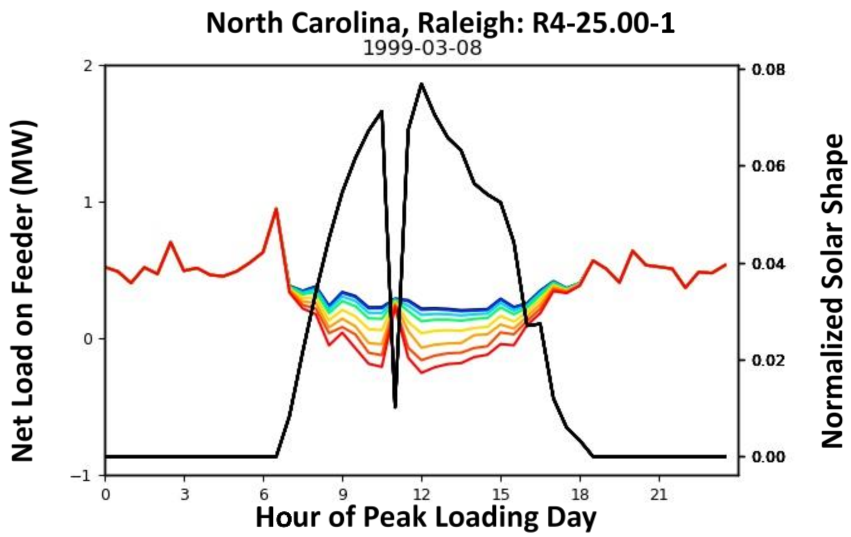
Arizona, Phoenix: R3-12.47-1
2001-07-02
2003-07-15
1999-07-05
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

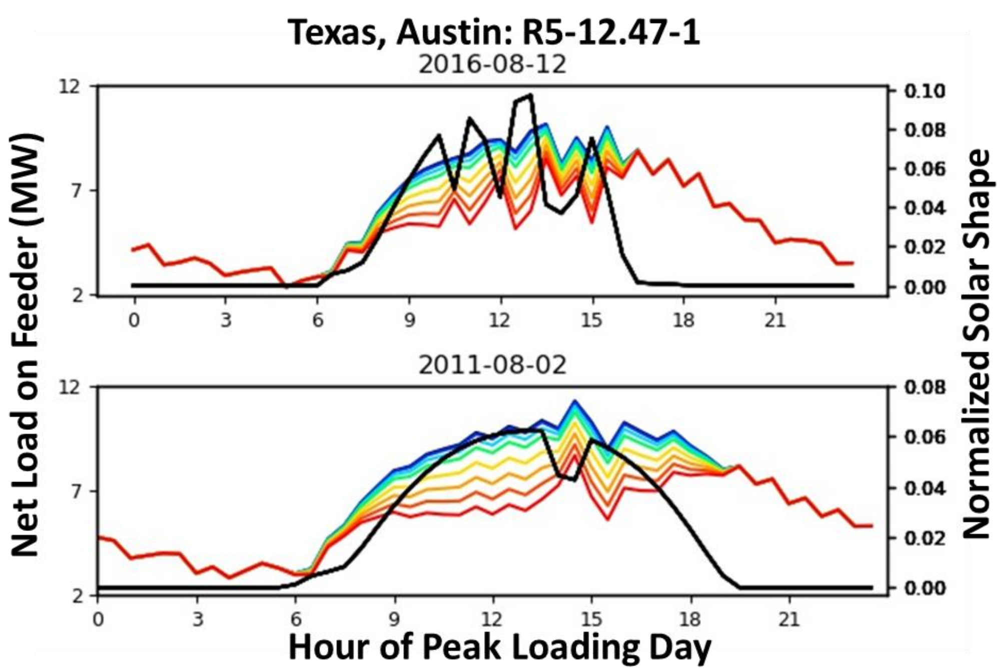

Arizona, Phoenix: R3-12.47-2
2005-06-24
2006-07-21
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

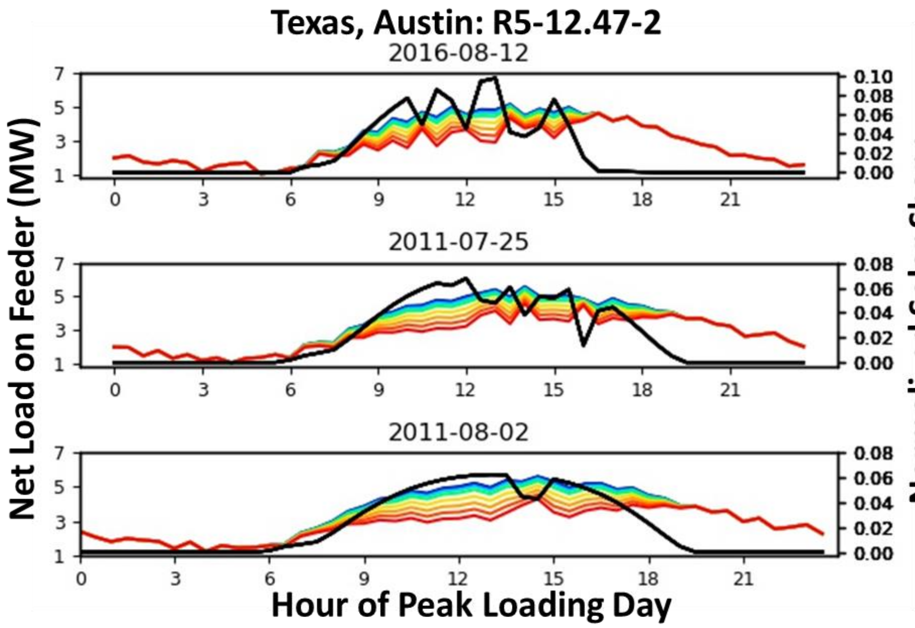

Arizona, Phoenix: R3-12.47-3
2016-07-26
2015-08-15
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day


North Carolina, Raleigh: R4-12.47-1
1999-08-01
1999-07-31
1999-07-24
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

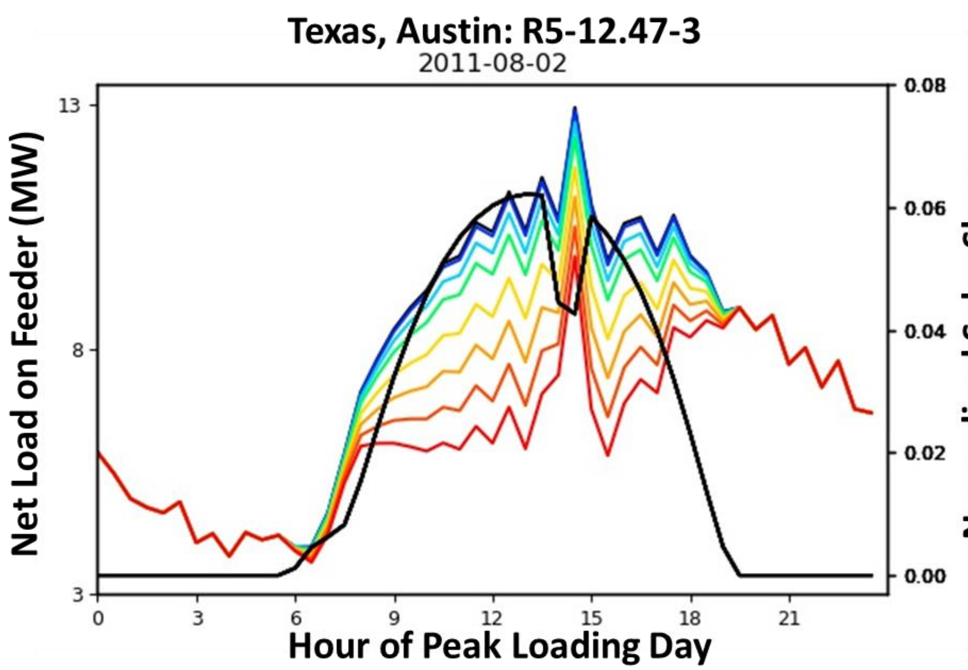

North Carolina, Raleigh: R4-12.47-2
1999-08-01
2011-07-24
2012-07-01
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day


North Carolina, Raleigh: R4-25.00-1
1999-03-08
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

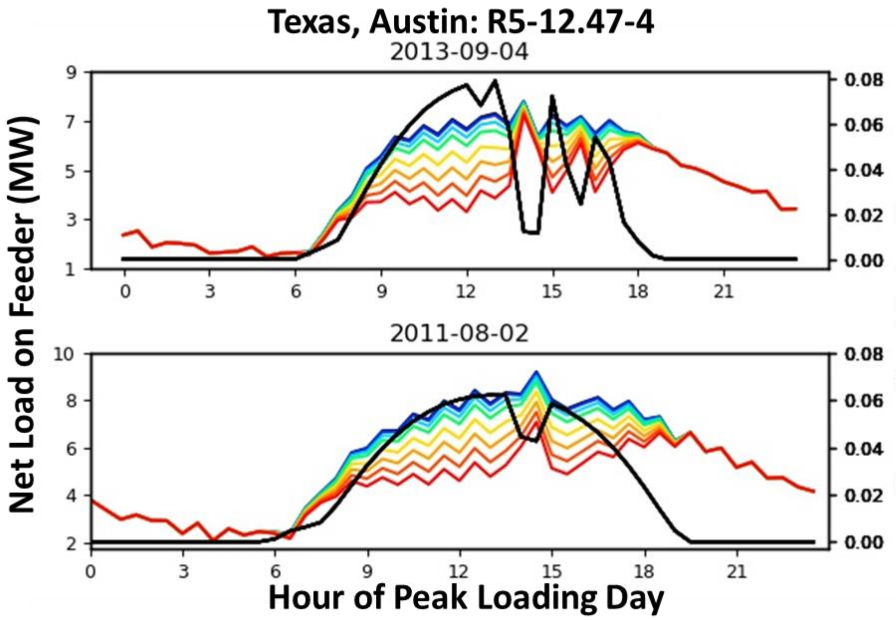

Texas, Austin: R5-12.47-1
2016-08-12
2011-08-02
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

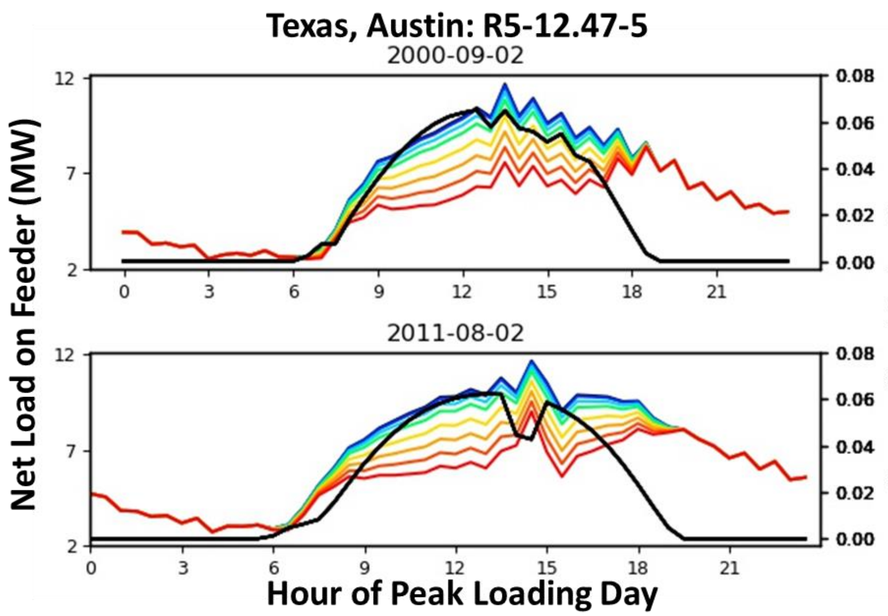


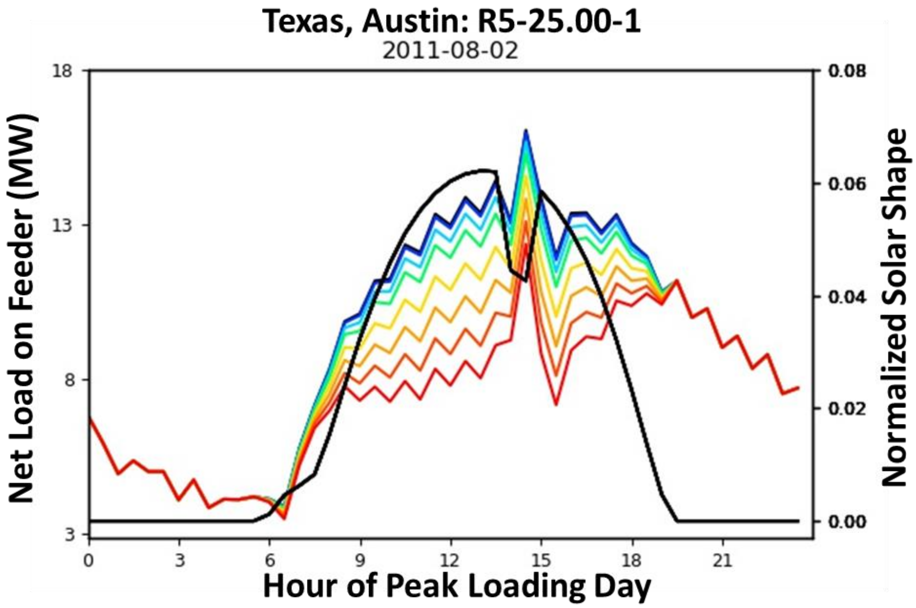
Texas, Austin: R5-12.47-2
2016-08-12
2011-07-25
2011-08-02
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

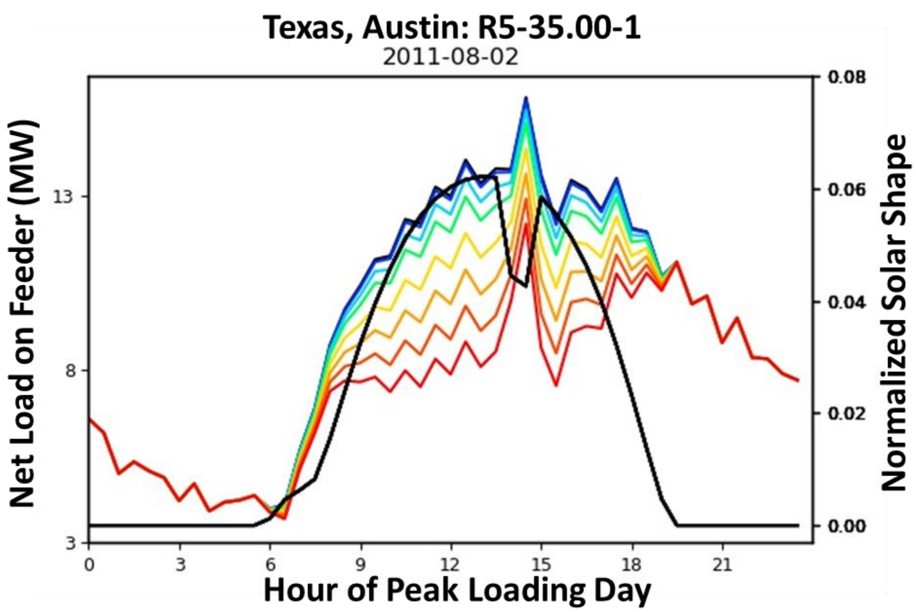


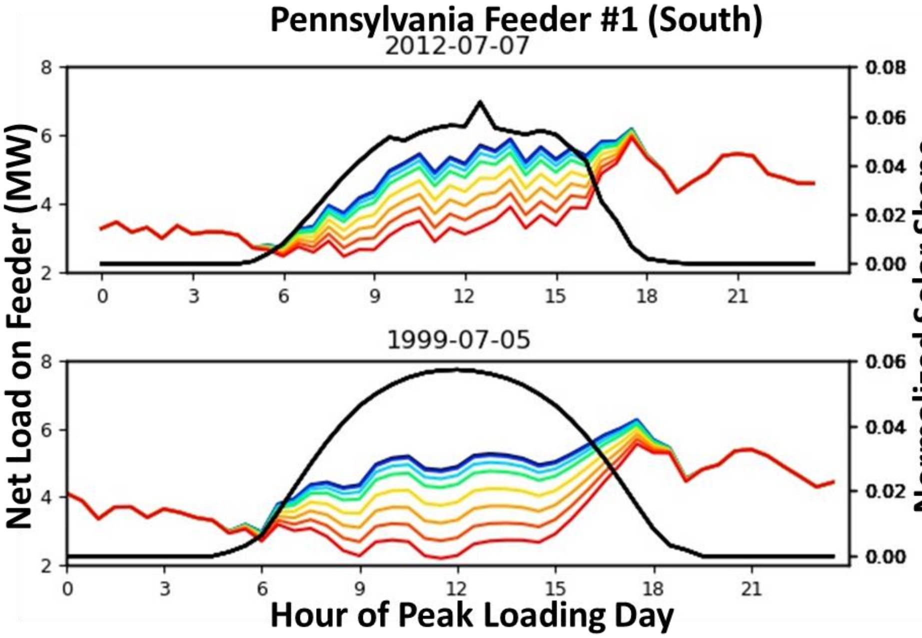
Texas, Austin: R5-12.47-3
2011-08-02
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

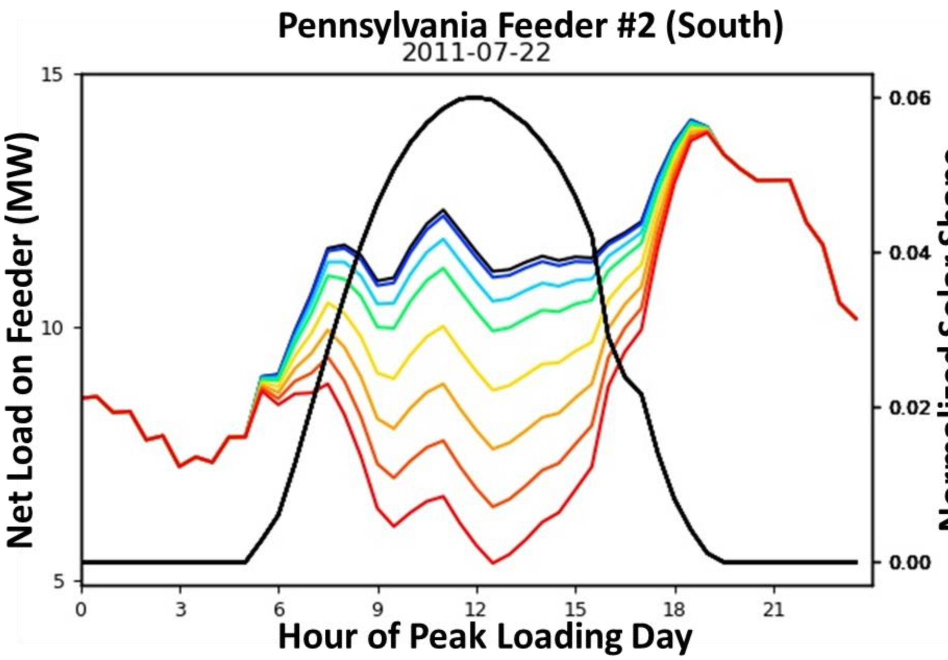

Texas, Austin: R5-12.47-4
2013-09-04
2011-08-02
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day


Texas, Austin: R5-12.47-5
2000-09-02
2011-08-02
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day


Texas, Austin: R5-25.00-1
2011-08-02
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day
18
13
8
3
0.08
0.06
0.04
0.02
0.00
0
3
6
9
12
15
18
21


Texas, Austin: R5-35.00-1
2011-08-02
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day
13
8
3
0.08
0.06
0.04
0.02
0.00
0
3
6
9
12
15
18
21


Pennsylvania Feeder #1 (South)
2012-07-07
1999-07-05
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day


Pennsylvania Feeder #2 (South)
2011-07-22
Net Load on Feeder (MW)
Normalized Solar Shape
Hour of Peak Loading Day

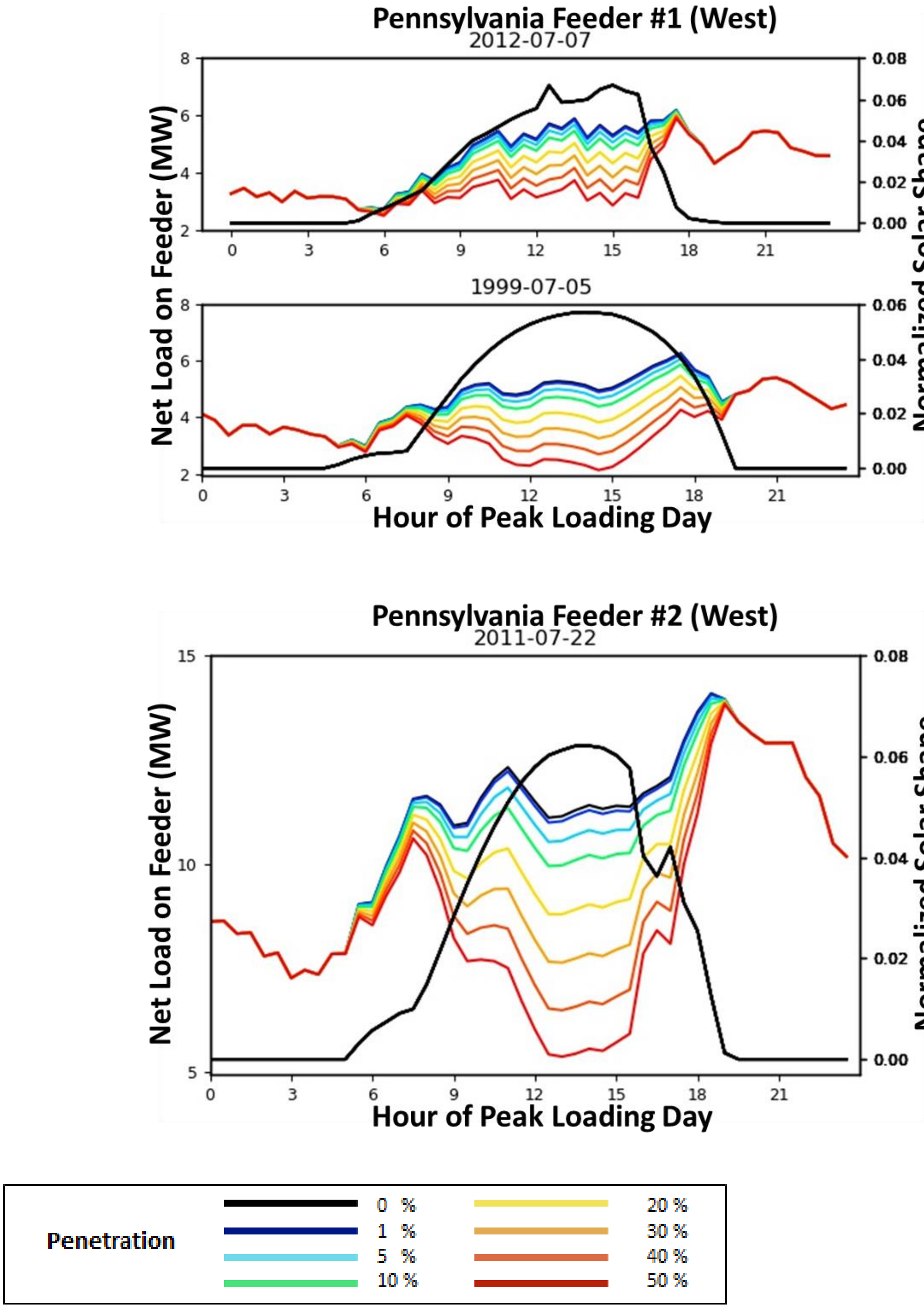


Figure 3-14: Feeder Net Load on Peak Days. Feeder loads are shown without solar (0% penetration) and for varying amounts of solar. Plots include every day where a peak load event occurred over all penetrations. For example, Pennsylvania feeder #2 experiences a 14 MW peak on July 22nd 2011, July 5th 1999 and July 6th 1999. Solar reduces the load on each of these days. On Feeder #1, cloud events reduce solar's performance on July 7th 2012.

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Chapter 4: The value of solar for PECO and its ratepayers

4.1 Abstract

We have developed a utility financial model that describes how the average customer 'all-in-rate' (i.e. the volumetric rate based on the total revenue requirement and kWh sales of all customer classes), will change for different energy penetrations[10] of solar photovoltaic generation in the PECO (Philadelphia Electric Company) service territory if Pennsylvania continues offering net energy metering (NEM) rates. Under a NEM tariff, if the revenue reduction from solar exceeds avoided costs, customer rates will increase. We define the Value of Solar (VOS) as the avoided energy, generation capacity, transmission capacity, and distribution capacity costs associated with solar in avoided dollars per unit of solar generation ($/kWh).

We estimate the value of solar (VOS) in the PECO service territory to be $0.086±0.006/kWh for a 5% penetration of solar rolled out from 2020-2030 with random placement on distribution feeders. This estimate for the VOS is below our estimate of $0.118/kWh for PECO's all-in-rate; so, if Pennsylvania continues with net energy metering, lost revenue will exceed avoided costs and there will likely be a small, 0.9%, increase in rates. The rate increase is relative to the pre-solar expected rates over a time horizon from 2020-2040 and a 5% discount rate. The uncertainty in our estimate arises from weather and load variation in the 10 different historical years (2007-2016) used in the study. Due to the declining value of solar with increasing solar penetration, a penetration of 10% is likely to increase the all-in-rate by

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[10] In Chapter 4, we use solar energy penetration to describe how much solar energy is produced in Pennsylvania. It is defined as the total solar energy relative to total energy consumption.

2.5%.

We find that solar's effect on PECO's business is small. PECO's ROE is insensitive to revenue erosion from solar because of the recent implementation of a Fully Projected Future Test Year (FPFTY). Revenue per customer (RCP) decoupled rates is pending in Pennsylvania and will further protect PECO from volatility in the VOS caused by weather variation. Revenue erosion, however, would still affect PECO through disproportionate changes in the distribution and bulk grid section of customer bills. While the expected increase in the all-in-rate is 0.9%, the distribution portion is expected to increase by 3.3% and the bulk grid portion to decrease by 0.6%.

In this chapter, we estimate avoided T&D capacity expenses assuming that solar is not targeted at overloaded sections of the T&D network. The combination of solar's slow rollout, the rarity of overloaded networks, and the untargeted placement of solar results in a low T&D VOS, a small effect on rates, and minimal impact on PECO's business model. Solar plus utility owned storage can increase the total deferral value by more than a factor of 4 at 5% penetration, but the impact on rates is small. In Chapter 5, we assess the additional value created by targeting solar at overloaded distribution networks.

By displacing fossil fuel generation and reducing criteria pollutant emissions, solar avoids health damages and premature loss of life. These environmental benefits of solar are not included in our model because they do not affect rates, but from a societal perspective have a high value in Pennsylvania due to the state's relatively high proportion of coal and natural gas fired power. Perez et al. (2012) estimate the value of solar at $0.05-0.12/kWh in Pennsylvania. This report can be used by the Pennsylvania PUC to decide whether these large environmental benefits are worth the small rate impact caused by solar.

4.2 Model

4.2.1 Overview

In the year 2021, Pennsylvania will reach the Alternative Energy Portfolio Standard (AEPS) deadline, which includes a 0.5% solar energy penetration carveout. Several other states in the PJM footprint are targeting higher penetrations of solar (Figure 4-1). Recently, Governor Wolf signed an executive order to reduce greenhouse gas emissions 80% by 2050 in Pennsylvania (Wolf 2019) and the Department of Environmental Protection released a report with strategies to achieve 10% solar energy penetration in the state by 2030 (PA DEP 2019).

We have developed a utility financial model that describes how the 'all-in-rate' (i.e. the volumetric rate based on the total revenue requirement and kWh sales of all customer classes) changes for different solar energy penetrations in the PECO service territory if Pennsylvania continues offering NEM rates. We define NEM rates as crediting all solar generation at the retail volumetric ($/kWh) rate and crediting reduced peak demand (kW) at the retail demand change ($/kW).

Due to its solar resource, PECO has the largest amount of residential and commercial solar PV installations in Pennsylvania and is a reasonable choice for a Pennsylvania VOS study. In this study, we consider mandated solar energy penetrations in Pennsylvania that range from 1-30%. We assume that the solar is rolled out linearly from 2020-2030 and remains constant thereafter. In Chapter 5, we assess the targeted placement of solar and allow the penetration to be higher in some locations where reduced loading may defer large capital investments and create value. The benefit of solar plus utility owned storage is considered in both our targeted and untargeted capacity deferral modeling.

The utility financial model estimates how the combination of avoided costs associated with solar and lost revenue associated with NEM ultimately affect rates. First, the model forecasts PECO's revenue requirement (i.e. cost of service including debt and equity payments), including pass-through costs and non-pass-through costs. The model begins with PECO's revenue requirement in the year 2016 and forecasts each revenue requirement component based on the relevant escalation factors. Second, a forecast of volumetric sales, customer charges, and demand charges is used with the revenue requirement to baseline customer rates without solar by assuming a rate case every three years. Third, solar is associated with avoided costs (i.e. a lower revenue requirement) and reduced revenue from volumetric sales and demand charges that will affect PECO rates.

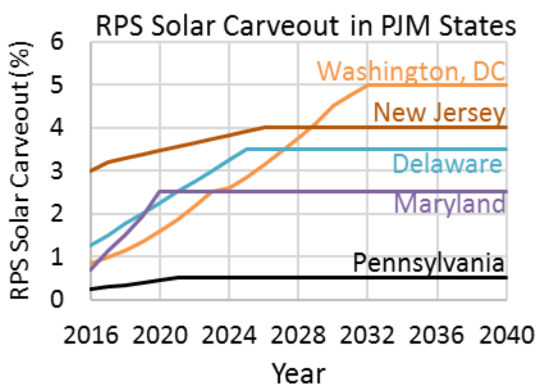


Figure 4-1: Solar Renewable Portfolio Standards in PJM service territory.

4.2.2 Metrics

Throughout this chapter, we use three key metrics defined in Equations 4-1, 4-2, and 4-3. The all-in-rate is a volumetric rate based on the revenue requirement and sales for all customer classes. Figure 4-2 shows the all-in-rate categorized by spending category without any solar. Return on Equity (ROE) is a measure of financial performance showing utility earnings relative to shareholder equity. Solar reduces the revenue requirement by avoiding energy costs, generation capacity costs, transmission costs, distribution costs, and taxes. The VOS is found by estimating the avoided costs and dividing the resulting revenue requirement reduction by all energy generated from solar. Additionally, to evaluate capacity deferral opportunities, we define 'total deferral value' as the numerator of Equation 4-3 when applied to avoided distribution costs. It is the net present value of all capital expense (capex) deferrals created by solar. The size of the total deferral value is useful for determining which policies are appropriate for managing and encouraging capacity deferral opportunities.

$$All - in - Rate[\frac{\$}{kWh}] = \frac{Utility\ Revenue\ \ [\$]}{Volumetric\ Sales\ [kWh]} \tag{4-1}$$

$$Return - on - Equity[\%] = \frac{Utility\ Revenue\ [\$]\ \ - Utility\ Costs[\$]}{Ratebase\ Equity[\$]} \tag{4-2}$$

$$Value\ of\ Solar\ [\frac{\$}{kWh}] = \frac{Change\ in\ Utility\ Costs[\$]}{Solar\ [kWhs]} \tag{4-3}$$

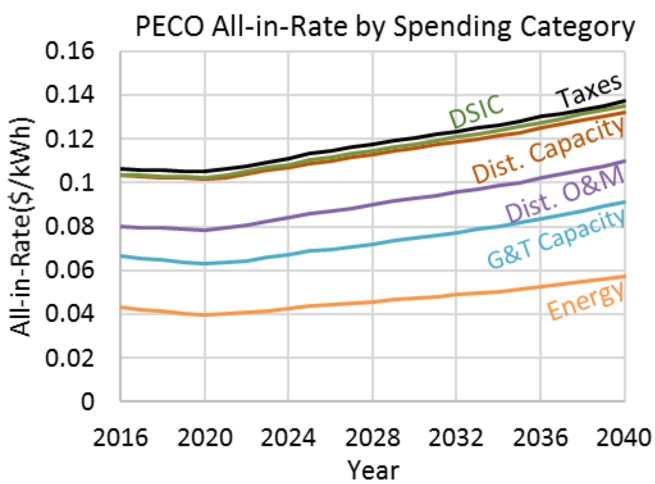


Figure 4-2: All-in-Rate by spending category (stacked). Spending category components are deescalated equally from 2016-2020 to reflect falling bilateral contract and natural gas prices. Spending category components are escalated separately, resulting in a 1.2% cumulative average growth rate for the all-in-rate from 2020-2040. The all-in-rate is a volumetric rate based on the revenue and sales for all customer classes. Energy is the largest percentage of the all-in-rate and includes the load-weighted locational marginal price (LMP), ancillary services, alternative energy credits (AECs), and the risk premium associated with bilateral contracts. Generation and Transmission (G&T) capacity is the next largest component, followed by distribution O&M and distribution capacity. The distribution system improvement charge (DSIC), a recent Pennsylvania policy aimed at improving resiliency and taxes are a very small percentage of the total rate.

4.2.3 Utility Financial Model

Figure 4-2 shows the all-in-rate forecasted by the utility financial model without solar. Spending category components (Energy, generation capacity, O&M etc.) are escalated equally from 2016-2020 to reflect falling bilateral contract and natural gas prices, and separately from 2020-2040 based on Bureau of Labor and Statistics (BLS), PJM Market Data, and EIA Reference Forecasts. Altogether, we forecast a 1.2% cumulative average growth in the all-in-rate from 2020-2040. Figure 4-3 and Figure 4-4 summarize the utility financial model that we use to estimate the metrics defined by Equation 4-1 (all-in-rate), equation 4-2 (return-on-equity), and equation 4-3 (value of solar). First, the utility's revenue requirement and actual revenue from customer charges, volumetric rates, and demand charges are forecast. These billing components are allocated in different proportions to pay for each spending category of the revenue requirement. Details of this allocation can be found in the Supporting Materials (Section 4.6.2). Next, in rate-case years, rates are increased to ensure that the utility earns its full revenue requirement, including a 10% ROE. In non-rate case years, unequal changes in actual revenues and costs lead to changes in the ROE. Typically, if costs increase and decreased sales prevent the utility from achieving the revenue requirement, the actual utility ROE will be less than the target ROE. Pennsylvania utilities may be protected from this effect with a Fully Projected Future Test Year (FPFTY) and revenue per customer decoupling. Modeling details of these policies can be found in the Supporting Materials (Section 4.6.5).

Rooftop solar customers are sometimes criticized for creating a disproportionate loss in revenue relative to the avoided costs associated with solar (EEI 2016). If the revenue reduction is greater than the avoided costs, the utility ROE will decrease, and customer rates will increase. Stated in another way, if the VOS is greater than the all-in-rate, rates will decrease, and if the VOS is less than the all-in-rate, rates will decrease.

The utility financial model was adapted from a spreadsheet model developed by Energy and Environmental Economics (E3) for the National Action Plan for Energy Efficiency (NAPEE 2007) and later work by Satchwell et al. (2014), which focused on solar's effect on a prototypical deregulated northeast utility and southwest vertically integrated utility. Details of changes that we made can be found in Section 4.6.4 of the Supporting Materials.

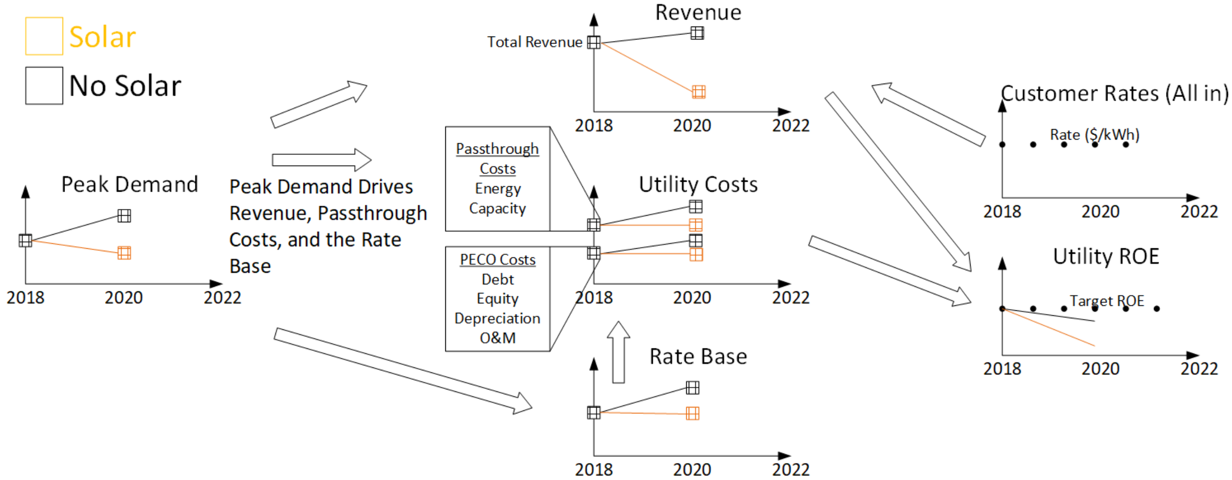


Figure 4-3: The rate base, utility costs, and revenue change on a yearly basis. In 2020 –an off rate-case year- rates stay the same, but the misalignment between revenue and costs are likely to decrease the ROE.

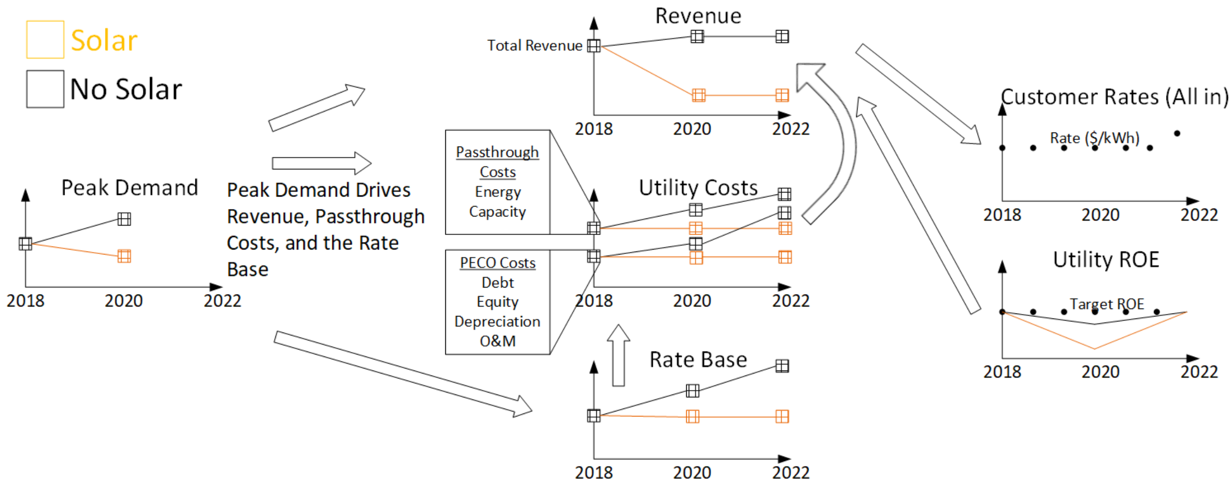


Figure 4-4: The rate base, utility costs, and revenue change on a yearly basis. In 2022 –a Rate case year- rates are increased to ensure that the utility ROE is 'just and reasonable'.

4.2.4 Avoided Costs

Figure 4-2 shows each component of PECO's revenue requirement. Solar can avoid costs and therefore reduce the revenue requirements for four of these components: distribution capacity, transmission capacity, generation capacity, and energy costs. These costs are escalated yearly using historical data and forecasts from the Bureau of Labor and Statistics (BLS), PJM Market Data, and EIA Reference Forecasts. We describe each avoided cost component below.

4.2.4.1 Avoided Energy Costs

Avoided energy costs make up the largest component of the value of solar. Most of the avoided energy costs are based on solar's hourly coincidence with PECO's Locational Marginal Prices (LMPs). We add the cost of alternative energy credits, the Demand Reduction Induced Price Effect (DRIPE), ancillary services and the risk premium associated with PECO's bilateral contracts to the avoided energy cost. These avoided costs also include average line losses of 6.4%. The cost of alternative energy credits is small, and details can be found in Section 4.6.6 of the Supporting Materials.

As solar decreases PJM's net load, LMPs will also decrease and reduce PECO's energy revenue requirement. The reduction in the energy revenue requirement is often treated as a value of solar component and referred to as the market price response or the Demand Reduction Induced Price Effected (DRIPE). We have constructed daily PJM supply curves from public PJM bid data (PJM 2018) to estimate the DRIPE associated with different penetrations of solar. This required several steps. We began with historical hourly LMPs in the PECO Zone (PJM 2018). We next used PJM supply curves (PJM 2018) and PJM hourly loads (PJM 2018) from historical reference years to estimate a PJM wide hourly marginal price. The supply curves were constructed from public bidding data, assuming each generator operates at maximum output. Solar's hourly output for each reference year and energy penetration were calculated using GridLab-D (PNNL 2018) with weather data from the National Renewable Energy Laboratory (NREL)'s Physical Solar Model (NREL 2018). An example of solar's effect on PECO's LMPs are shown in Figure 4-6 for several weeks in July 2016. Further details of the solar profile that we use and the DRIPE can be found in the avoided energy cost section of the Supporting Materials (Section 4.6.6).

The combined avoided cost of ancillary services and the risk premium are assumed to be the remainder of PECO's bilateral contracts after subtracting the load-weighted LMP, generation capacity costs, and cost of Alternative Energy Credits (AEC). The average bilateral contract costs were estimated from the "Purchased Power" page in FERC Form 1 (FERC 2016) and PECO's default service supply procurement website (2019). These are "Fixed Price Full Requirement" bilateral contracts that covers all generation aspects (excluding transmission costs) of serving a portion of load during a fixed period of time. Spot market purchases are only about 1% of PECO's energy costs in. Figure 4-5 shows the cost components of the bilateral contract. Ancillary services and the risk premium are estimated to be $16/MWH in 2016.

Sensitivity

PECO's average bilateral contract costs have been decreasing in recent years (Figure 4-7). We assume all components of PECO's bilateral contract are deescalated to match our base case estimate of PECO's average bilateral contract cost in 2020 ($55/MWH). $50/MWH and $60/MWH are considered in the sensitivity analysis. Beyond 2020, we escalate all cost categories separately. In our base case scenario, LMPs are escalated based on a weighted combination of the EIA reference natural gas and coal forecasts (EIA 2018). The weights for natural gas and coal are 65% and 35%, respectively and are based on the percentage of time that each fuel type is on the margin. Marginal fuel usage was taken from Monitoring Analytics Marginal Fuel Posting in PJM's real-time energy market (2018). In our high and low energy escalation scenarios, we use the EIA forecast for high and low oil prices.

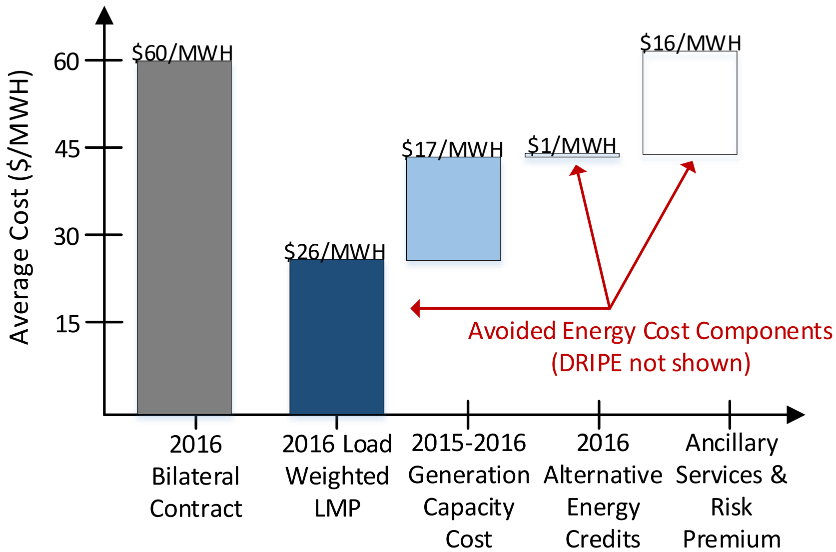


Figure 4-5: The average bilateral contract cost in 2016 and its components. The load-weighted locational marginal price (LMP), generation capacity and alternative energy credit costs are subtracted from the average bilateral contract cost to estimate the cost of ancillary services and the risk premium. Our energy value of solar estimate includes all components of the bilateral contract except the generation capacity cost. The demand reduction induced price effect (DRIPE) is also included in the energy cost but not included in this figure. The average bilateral contract cost has been declining in recent years and is forecasted to be $55/MWH in 2020. All components are deescalated equally from 2016 to 2020 to match this forecast.

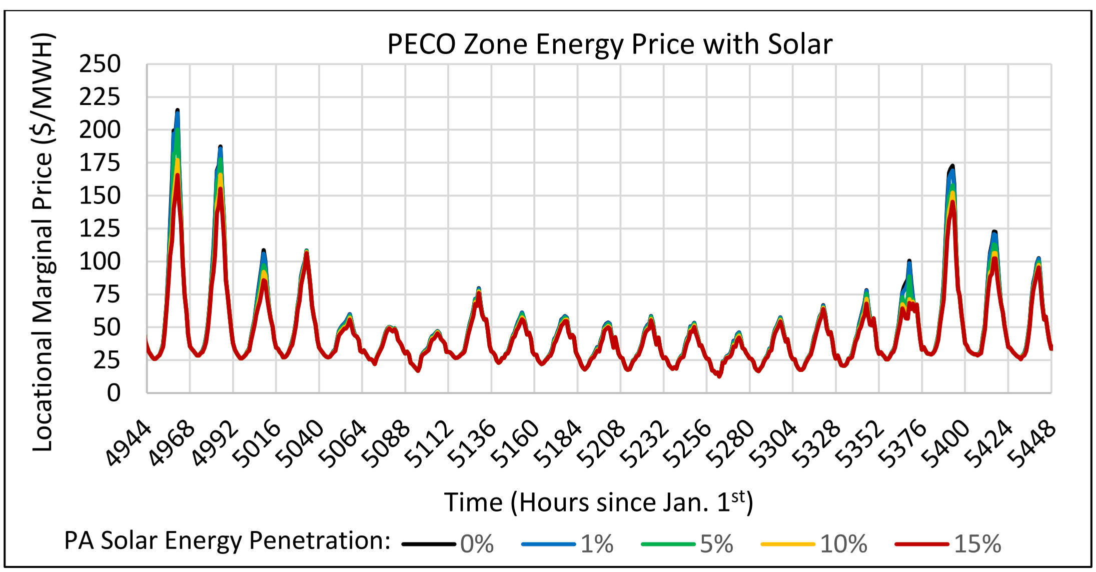


Figure 4-6: PJM market prices decrease when solar reduces demand during the day. PECO LMPs from 2016 are shown for several weeks in July.

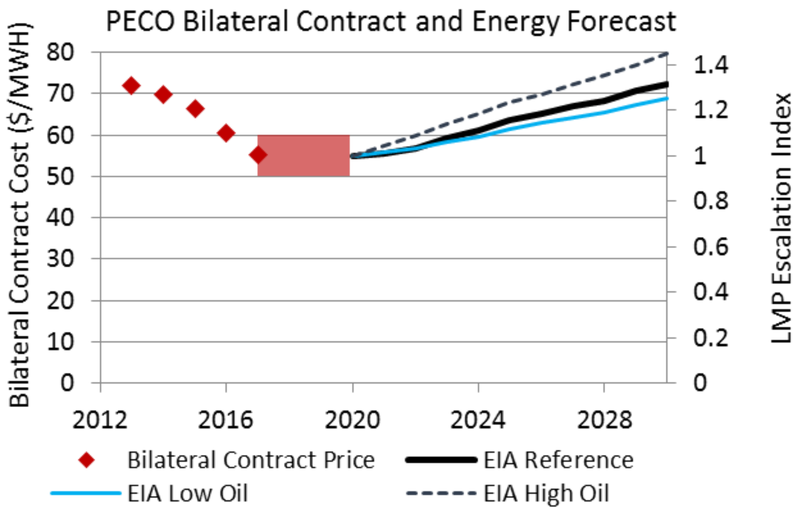


Figure 4-7: PECO's average bilateral contract has been decreasing in recent years as fuel prices have fallen, and the average bilateral contract price in the year 2020 is uncertain (shaded red region). A bilateral contract of $55/MWH is used in 2020 (the start of the solar rollout). After 2020, the locational marginal price (LMP) component of the bilateral contract is escalated based on the EIA reference forecast for natural gas and coal.

4.2.4.2 Avoided Generation Capacity Costs

When solar reduces PECO's load on peak loading days, PECO's capacity obligation in PJM's capacity market (i.e. the reliability pricing model or RPM) is reduced. The avoided generation capacity cost is the product of the generation capacity credit, the RPM capacity price, and reserve margin. We use $164/MW-day for the capacity price and a reserve margin of 20.5%, all based on PJM's base residual auction (PJM 2018).

The generation capacity credit is based on solar's ability to reduce PJM's weather normalized forecast, which is a key input for calculating PECO's capacity obligation and is described in PJM's Manual 19 (2017). In Figure 4-8, we show our estimate of the generation capacity credit. The generation capacity credit is defined in Equation 4-4.

$$Generation\ Capacity\ Credit = \frac{Div.Factor * (Peak\ Load_{WN}(p=0) - Peak\ Load_{WN}(p))}{Nominal\ Solar\ Capacity} \tag{4-4}$$

The diversity factor is defined by PJM as PECO's coincident peak divided by PECO's noncoincident peak (Reynolds 2017). We use a diversity factor of 0.97, which is an average over all 10 reference years. The weather normalized peak (Peak $Load_{WN}$) is based on a statistical regression using 3 years of weather and demand data (2014-2016). In Figure 4-9, we show a scatter plot of weather, expressed as Weighted Temperature Humidity Indexes (WTHI's) and demands. The demand values are regressed on the WTHIs and solved at the weather standard (an average of WTHIs on peak load days) to find the weather normalized load. High solar penetrations decrease the demand. Finally, the weather normalized load is scaled by PJM's zonal load forecast and reserve margin, found in PJM's yearly base residual auction.

Sensitivity

The cost of generation capacity has been very volatile and has not shown a clear trend since the beginning of PJM's RPM auction. We use the average capacity market clearing price over the 2015-2016 and 2016-2017 delivery years for the PECO zone for our best estimate ($164/MW-day) in 2016. We reduce the price by one standard deviation for our low estimate ($124/MW-day) and increase it by one standard deviation for our high estimate ($203/MW-day).

For our best estimate of the generation capacity escalation rate, we assume 0% escalation. For our low estimate, we assume -2%, the escalation rate reported by the BLS (2018) for "non-utility" owned generation. For our high estimate, we assume +2%, an escalation rate more typical of escalation rates in the rest of the power sector.

We define the reserve margin as the excess capacity in PECO's 2018 capacity obligation relative to their actual 2018 peak load. Using market data from the base residual auction (PJM 2018), our best estimate of PECO's reserve margin is 20.5%. We use 16% for the low estimate, which is PJM's required reserve margin (PJM 2018). We use 28% for our high estimate, which is the most recent reserve margin for PJM's entire service territory (PJM 2018).

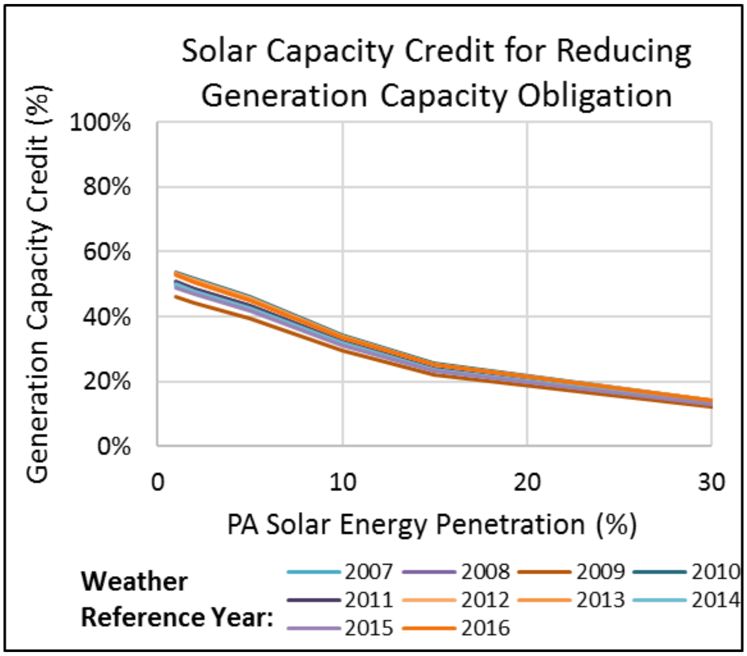


Figure 4-8: Generation Capacity Credit using 2016 load data. The ability of solar to reduce PECO's coincident weather normalized peak and PJM capacity market obligation diminishes with penetration.

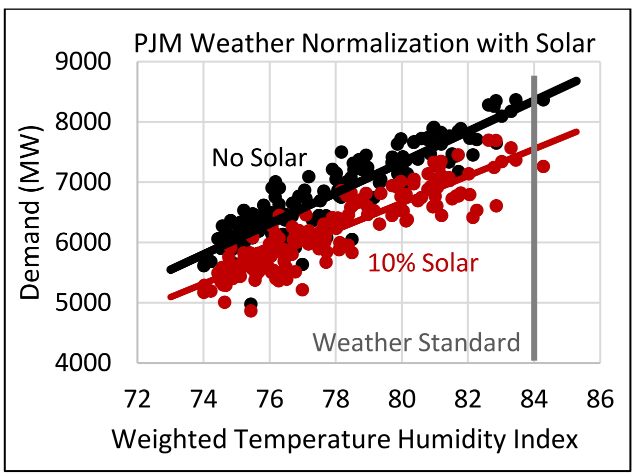


Figure 4-9: The weather normalized demand is found by regressing PECO's demand on corresponding Weighted Temperature Humidity Indexes and solving at the Weather Standard. The weather normalized demand is lower under the 10% solar penetration scenario.

4.2.4.3 Avoided Distribution Capacity Costs

The distribution capacity deferral value of solar is the value that solar creates by reducing overloaded equipment and deferring capital investments to later years. The investment deferral avoids costs in the form of debt and equity payments. We assume that solar is randomly placed throughout PECO's service territory and estimate the deferral value created by the solar that accumulates on overloaded feeders.

We model constant yearly capacity investments caused by overloading, reflecting the relatively constant yearly pipeline of projects experienced by most utilities. Solar is rolled out linearly from 2020-2030 and enough solar must accumulate by the year of the planned capacity project for the deferral to take place. If a project is deferred to a later year, solar can accumulate more and defer the project again. Frequently, at low solar energy penetration targets and for projects planned for earlier years, enough solar has not accumulated to defer the project by at least one year. It is possible that these capacity projects could have been deferred if solar was targeted at the capacity project locations. In Chapter 5, we consider targeted placement of solar and the additional value it can create.

The distribution capacity deferral value of solar is very sensitive to the cost of replacing or augmenting overloaded capacity, the ability of solar to reduce peak loading, and the growth rate in locations with overloaded capacity. We use the marginal cost of service (MCOS) to estimate the cost of replacing or augmenting overloaded capacity. We estimate PECO's MCOS to be $600/kW, based on 4 growth related projects planned for the next five years (PECO 2018). This estimate is close to other distribution capacity cost estimates in California (E3 2018) and New York (NYSERDA 2015).

If the load growth is very low, the deferral will be longer. At typical utility costs of capital, a few additional deferral years can create a lot of value. We estimate that the average load growth is 1%, based on four PECO growth-related projects planned for the next 5 years.

We call the ability of solar to reduce peak loads the distribution-effective load carrying capability (D-ELCC). This metric is described in detail in Chapter 3. We use two estimates of the D-ELCC, shown in Figure 4-10. Both are based on 19 years of solar and loading profiles, and the average of two PECO feeders. D-ELCC$_{worst}$ describes how much solar can reduce the largest net peak load over 19 years for each penetration. It does not allow any overloading.

For capacity deferral projects where transformer overloading is the main constraint, relying on the inherent overloading flexibility of transformers, rather than currently costly energy storage, can also increase the D-ELCC. Our D-$ELCC_{age}$ allows occasional overloading but limits the total transformer aging (i.e. deterioration of insulation) to the aging incurred during typical weather normalization planning processes. D-$ELCC_{worst}$ is low because it is based on evening peaking feeders. As a first order approximation, D-$ELCC_{age}$ can be viewed as the D-$ELCC_{worst}$ on afternoon peaking feeders in regions with a good solar resource (see Figure 3-5 in Chapter 3).

In Figure 4-10, we show the amount of energy storage required at varying penetrations to ensure a D-ELCC of 50%. Below 10% penetration, the energy storage requirements are very low because the energy storage is compensating only for solar variability and does not require peak shifting. Storage creates more deferral value by increasing solar's effective capacity, but it also has a cost. We use installed battery costs reported by the EIA (2018). Storage with durations less than 0.5 hours costs $2600/kWh, between 0.5-2 hours costs $1400/kWh, and storage greater than 2 hours costs $400/kWh. We describe our method for estimating the energy storage duration and size in Chapter 3. Estimates of the energy storage and duration are shown in Chapter 3, Figure 3-6. All estimates of the value of solar and total deferral value in this chapter include these storage costs.

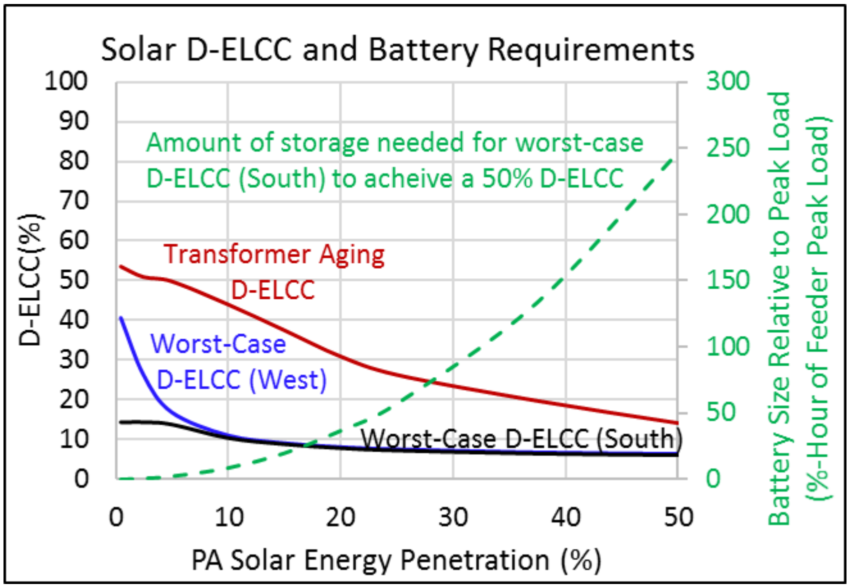


Figure 4-10: Distribution Effective Load Carrying Capability (D-ELCC). The worst-case D-ELCC does not allow any overloading over the 19 years. The worst-case D-ELCC is shown for South and West facing panels. The energy storage requirement to achieve a 50% worst-case D-ELCC over all penetrations is shown. The transformer aging D-ELCC allows occasional overloading but limits the total transformer aging (i.e. deterioration of insulation) to the aging incurred during typical weather normalization planning processes.

4.2.4.4 Avoided Transmission Capacity Costs

PECO's revenue requirement includes two kinds of transmission costs: non-pass-through PECO owned transmission capacity that is included in PECO's rate base and pass-through regional transmission with costs allocated to multiple load serving entities as dictated by PJM's regional transmission expansion plan (RTEP) and schedule 12 of the Open Access Transmission Tariff (OATT) (PJM 2019). To estimate the avoided transmission costs, we use a method similar to that in the "avoided cost calculator" designed by E3 and used by the California PUC (E3 2018). We first multiply yearly growth-related capex by the reduction in growth caused by solar. While E3 uses the Peak Capacity Allocation Factor (PCAF), we estimate the reduction in growth from the transmission effective load carrying capability. The PCAF and ELCC method are compared in Chapter 3, and the differences should not affect the results in this chapter. In Figure 4-11, we show the effective load carrying capability that defines the peak load reduction caused by varying penetrations of solar. It is based on the worst-case loading associated with 10 years of historical and solar and loading in the PECO service territory.

We apply a deferral saving factor that accounts for the net present value savings of a deferred capital investment. Based on a 5 year deferral and a 7% discount rate, we use a savings factor of 30%. We estimate PECO and PJM's growth-related capex from project descriptions in PJM's Transmission Cost Information Center (PJM 2019). A description of our criteria for estimating transmission growth-related capex is in the Avoided Transmission Costs Section 4.6.6 of the Supporting Materials.

Sensitivity

Transmission costs have been increasing rapidly. Our best estimate of the transmission escalation rate is 4.3% based on the average Bureau of Labor and Statistics (BLS) Power Purchasing Index (PPI) growth over the last 10 years (Bureau of Labor Statistics 2018). Our low estimate is 2% which is approximately one standard deviation below the BLS average and more typical of escalation rates for distribution. Our high estimate is 6.6%, which is one standard deviation above the BLS average.

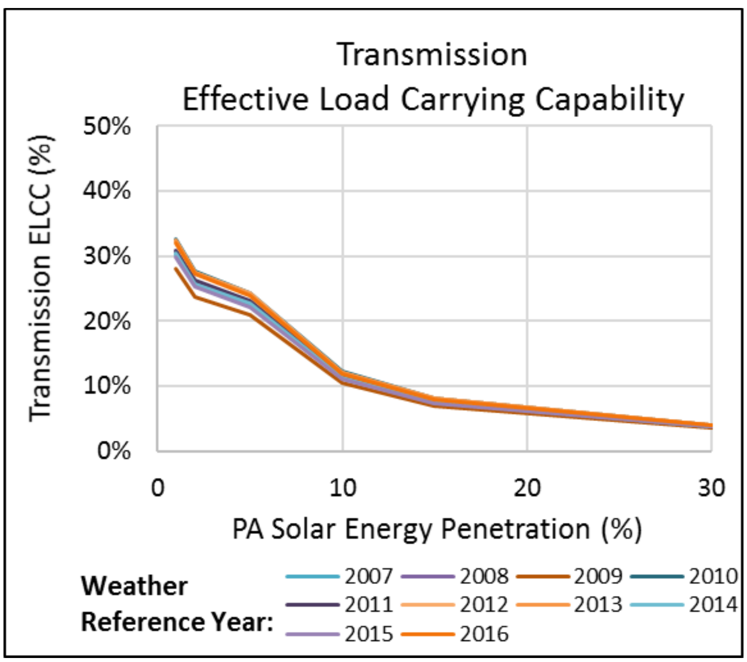


Figure 4-11: Transmission capacity credit for PECO using 2016 load data. The ability of solar to reduce PECO's coincident peak (with PJM) and transmission demand charge diminishes with penetration.

4.2.5 Solar Integration Costs

PECO charges application and interconnection fees to solar owners to cover administrative and integrations costs. Because costs associated with these fees are paid for by solar owners, they will not affect the rates for other customers and are omitted from this study. We assessed when high penetrations may cause additional distribution interconnection costs that could be passed to other customers.

In 2012, Southern California Edison studied integration costs on four feeders in response to a state policy to install 4,800 MW of renewable DER in the service territory by 2020 (Southern California Edison 2012). The study found that the cost of integrating renewable DER would be approximately $4.5 Billion but could be reduced to $2.1 Billion if the DER were "guided" towards stronger grid locations that are less affected by DER. Specifically, the study cites long rural feeders and low voltage feeders (e.g. 4 kV) that are particularly prone to high integration costs. Assuming an 18% AC solar capacity factor, these costs equate to approximately $0.007-0.04/kWh-solar depending on whether solar was placed predominantly in urban or rural feeders. Notably, the study focused on large solar installations in the 1 to 3 MW range, which are common in rural California where land is cheaper, and the solar resource is stronger. The integration costs include distribution upgrades, transmission upgrades and interconnection facility costs.

We examined four PECO feeders and found that the number of voltage violations on these feeders are low at low solar energy penetrations. Depending on the feeder, the number of voltage violations begins to increase rapidly when energy penetrations reach 10%. We did not find distribution system reconductoring to be very effective at reducing voltage violations. Volt/Var smart inverters with reactive power priority was the most effective and we found the costs of real power curtailment associated with this inverter to be negligible (less than a 0.01 ₵/kWh). Beyond penetrations of 5-10%, more expensive interconnection costs, such as those described by Southern California Edison, may be incurred. Modeling details of this study are described in the Section 4.6.7 of the Supporting Materials.

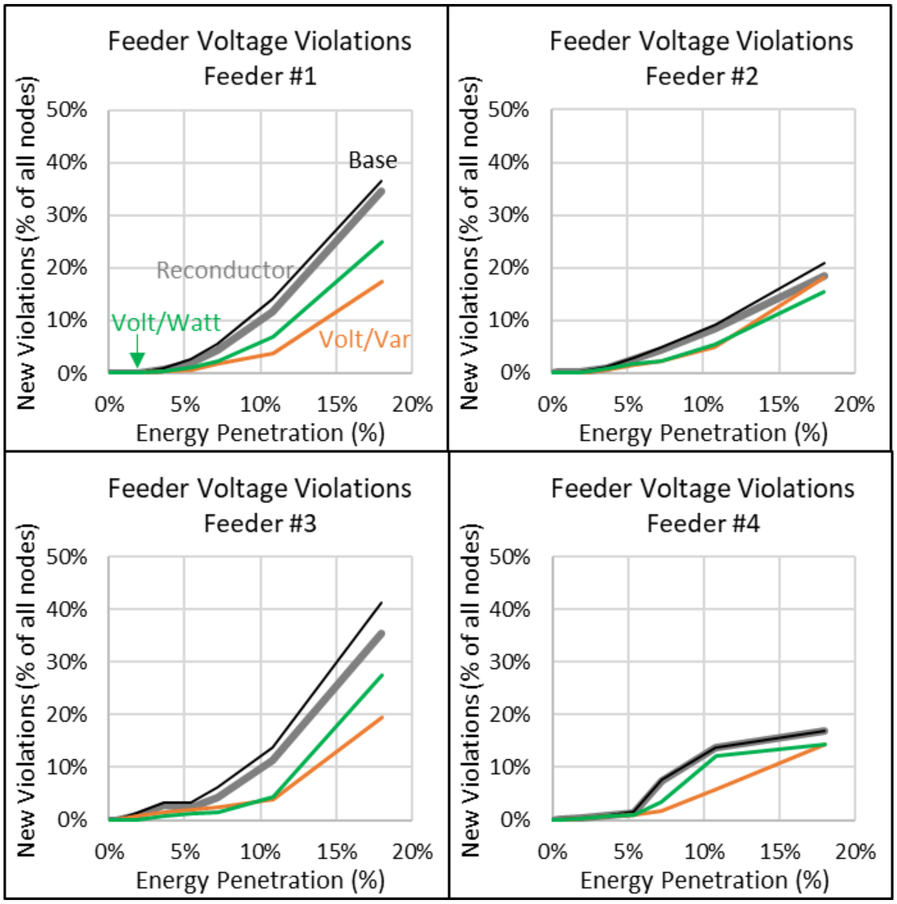


Figure 4-12: The number of voltage violations are small below 5% energy penetration but begin to increase quickly for penetrations ranging from 5-10%.   Volt/Var is a smart inverter with reactive power priority. We found Volt/Var smart inverters to be most effective and the least-cost method for mitigating voltage violations.

4.2.6 Base-Case Input Assumptions

Table 4-1 summarizes our base-case assumptions. The data comes primarily from PJM market data, PECO's 2015 rate case, Pennsylvania's Alternative Energy Portfolio reports, FERC Form 1, Pennsylvania Electric Power Outlook Reports, and internal PECO data. The utility financial model uses hourly historical PJM loads, PECO loads, solar insolation, and PECO zone LMPs. To account for yearly variability in the VOS caused by these hourly values, we do sensitivity analysis on the years 2007-2016. Further details on these historical reference years can be found in Section 4.6.1 of the Supporting Materials.

Table 4-1: Base case assumptions for utility financial model. Solar is installed randomly throughout the service territory and solar owners are compensated at the retail rate (i.e. with Net Energy Metering).

Input	**PECO Input**
Study Period	2016-2040. Solar deployed 2020-2030
Solar PV Compensation	Net Energy Metering (NEM)
Peak Load, Growth	8,364 MW, 0.7%
Load Factor	48.6%
Forecast Sales Growth	0.6%
Customer Count, Growth	1.6 Million, 0.52%
Customer Growth	0.52%
Average, Peak Losses	6.4%, 8%
Rate Base Assets	$4,100 MM
Avg. Asset Book Depreciation	30 years
Capex, Escalation	$398MM at 2% escalation
LTIIP Capex	$55 Million
O&M, Escalation	$829MM at 0.5% escalation
Rate Case Trigger	Every three years
Test year	“Fully Projected Future Test Year” (2 years)
Regulatory Lag	1 year
Target Return on Equity	10%
Debt Cost, percentage	5.04%, 46.64%
Weighted Average Cost of Capital	7.4%
Federal Tax Rate	20%
State Tax Rate	9.99%
Average Bilateral Contract	$45/MWh in 2020 (includes load-weighted LMP, capacity market, ancillary services, AEPS costs, and the risk premium)
Energy Escalation Rate	Indexed to EIA reference forecasts for coal and natural gas
Generation Capacity, Escalation	164/MW-day, 0%
Reserve Margin	20.5%
PJM Transmission Unit Cost, Escalation	$27.3/kW-year, 4.3%
PJM Transmission Growth Capex	$46MM/year
PECO Transmission Growth Capex	$6MM/year
REC Price	$8/MWH
Growth Related Capex	1% of distribution capex or $3MM per year
Distribution Marginal Cost of Service	$600/kW
D-ELCC	Based on worst case loading over 19 years and two PECO feeders. See Figure 4-10.
Solar Placement Strategy	No placement strategy. Solar is placed randomly.

4.3 Results

4.3.1 Ratepayer Impact

Figure 4-13 shows the revenue requirement by spending category without solar and with 5% solar energy. Reductions in the revenue requirement are concentrated among the generation capacity, PJM transmission capacity, and energy pass-through costs. Changes in PECO's T&D capacity revenue requirements are small because few capacity deferral opportunities exist.

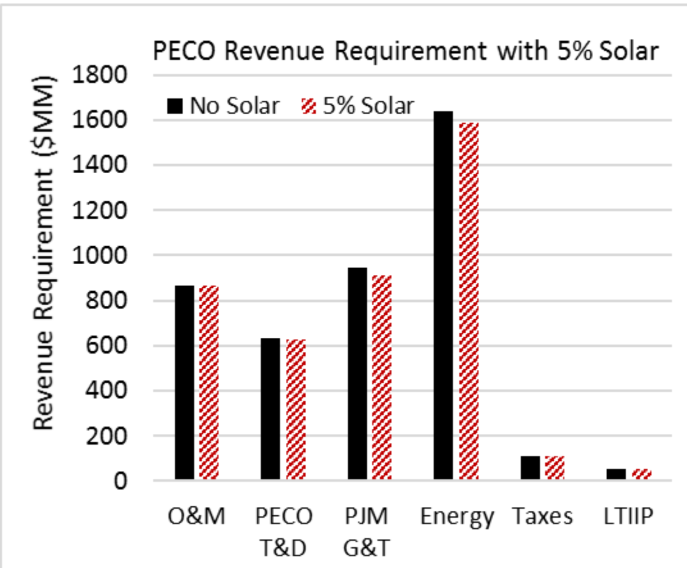


Figure 4-13: PECO Revenue Requirement with 5% Solar energy in the base case scenario. Generation and Transmission (G&T) and energy are pass through costs. O&M and Distribution Capacity are non-pass through costs. The Long-Term Infrastructure Improvement Plan (LTIIP) refers to capex allowed in Pennsylvania to improve resiliency.

In Figure 4-14, we show the combined VOS for the energy component, generation capacity, transmission and distribution capacity component. Altogether, the VOS averages \$0.086±0.006/kWh at 5% penetration. The uncertainty is caused by variations in the weather and load profiles during the 2007-2016 reference years. Because our best estimate of the energy, generation, and transmission VOS is below the all-in-rate, we expect that NEM will very slightly increase customer rates.

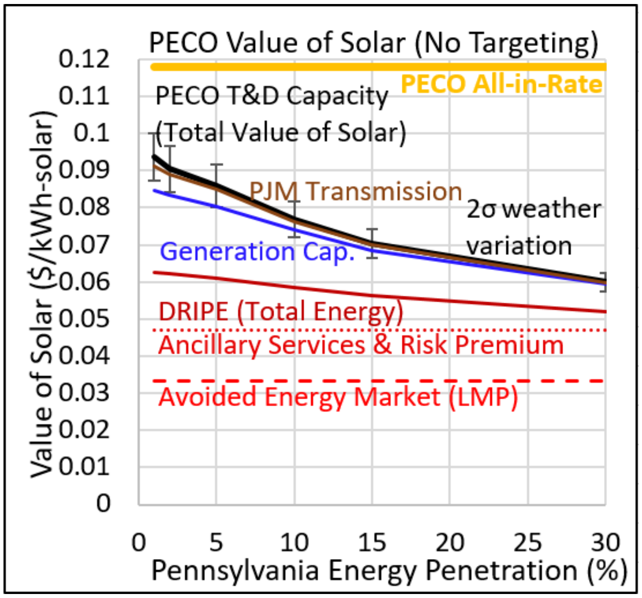


Figure 4-14: Energy, generation capacity, and transmission value of solar. The untargeted distribution capacity value of solar is very small. The total value of solar falls below PECO's all-in-rate, so rates are likely to increase.

Figure 4-15 compares the all-in-rate (without solar) to the value of a 5% solar energy target over time and shows the resulting increase in the all-in-rate (with solar). In 2020, the VOS is high because the penetration is very low resulting in a relatively high effective capacity of solar for generation and transmission capacity. As the penetration increases over time to meet the 5% solar energy target, the VOS decreases. After 2030, the solar energy penetration remains constant and the VOS increases as generation, transmission, and distribution costs increase.

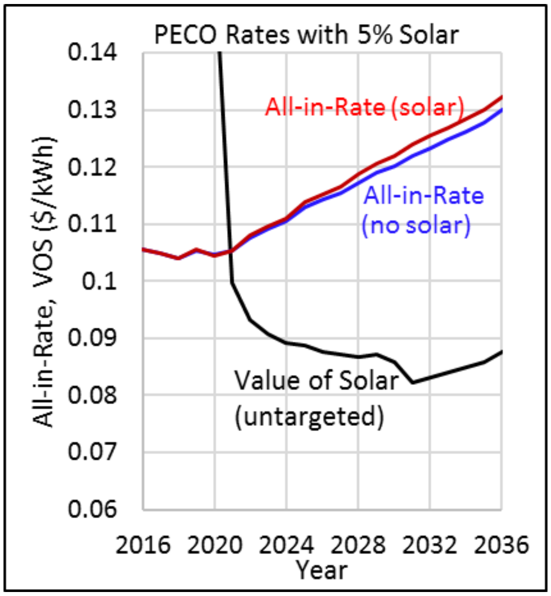
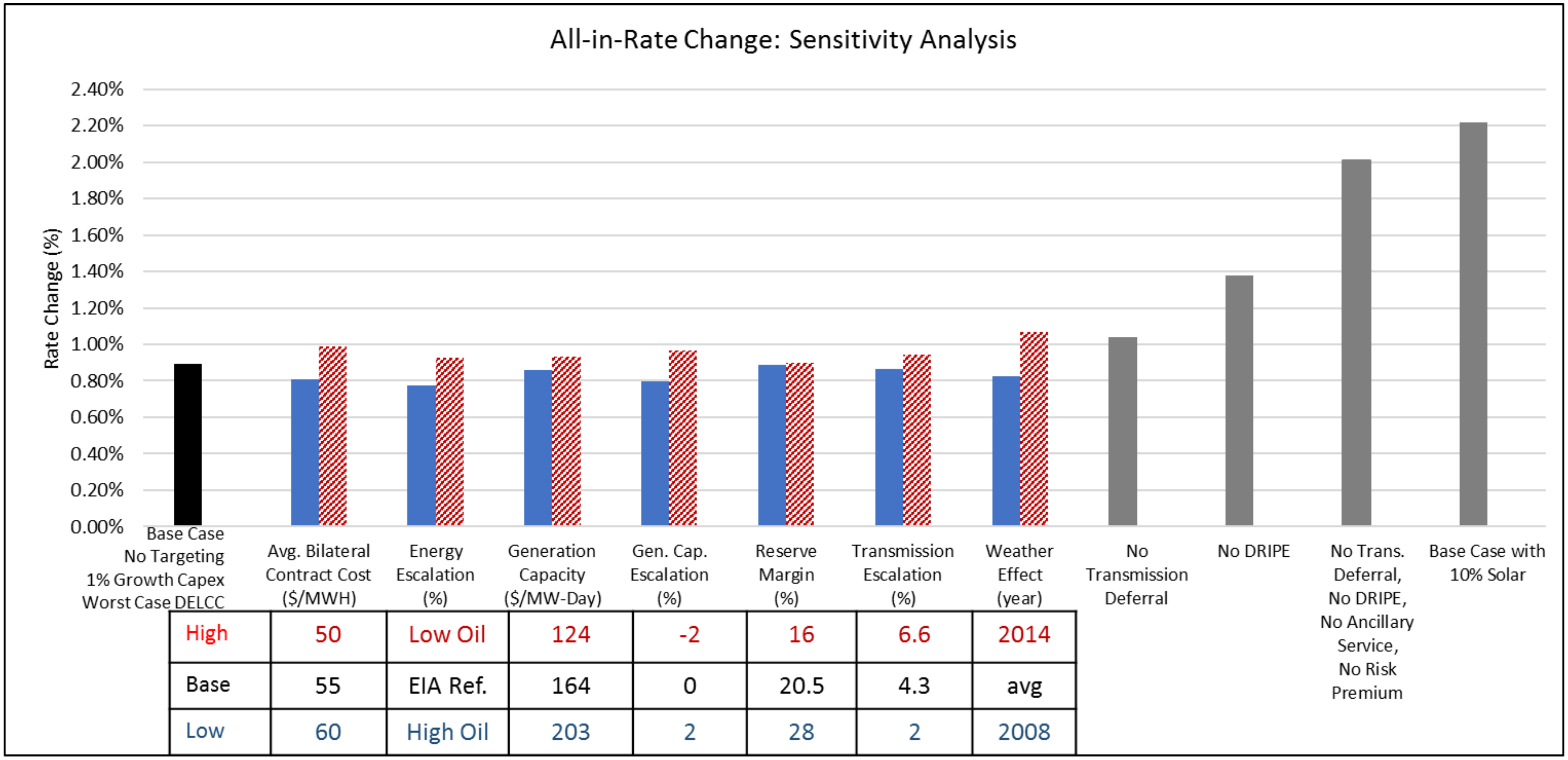


Figure 4-15: Value of 5% solar energy over the study period and its effect on rates. There is a 0.9% increase in the all-in-rate with solar relative to the all-in-rate without solar. In 2020, the VOS is high because the penetration is very low resulting in a relatively high effective capacity of solar for generation and transmission capacity. As the penetration increases over time, the VOS drops rapidly.

In Figure 4-16, we perform sensitivity analysis on several key assumptions. In the "Base Case" scenario, we assume NEM rates for solar owners, a 5% solar energy penetration target by 2030, no solar targeting at overloaded feeders and the worst-case D-ELCC. Detailed base case assumptions are shown in Table 4-1 and sensitivity assumptions are shown in the table below the bar chart of Figure 4-16. We find that a 5% solar energy penetration is most likely to cause a 0.9% increase in the all-in-rate (or a 0.2₵/kWh increase by the year 2040). The all-in-rate is very sensitive to the inclusion of the DRIPE, ancillary services, and the solar penetration. Overall, most of the sensitivity scenarios are consistent with 5% solar leading to a very small increase in rates.



	Avg. Bilateral Contract Cost ($/MWH)	Energy Escalation (%)	Generation Capacity ($/MW-Day)	Gen. Cap. Escalation (%)	Reserve Margin (%)	Transmission Escalation (%)	Weather Effect (year)
High	50	Low Oil	124	-2	16	6.6	2014
Base	55	EIA Ref.	164	0	20.5	4.3	avg
Low	60	High Oil	203	2	28	2	2008

Figure 4-16: Estimated change in the all-in-rate from solar and sensitivity analysis. In our base case, we estimate that a 5% solar penetration will increase the all-in-rate by 0.9%. While the rate impact is sensitive to which components are included in the value of solar, the largest rate impact would be caused if Pennsylvania had a 10% solar energy penetration rather than a 5% solar energy penetration.

4.3.2 Utility Impact

Although solar is likely to very slightly increase customer rates, current Pennsylvania regulations make PECO mostly financially indifferent to solar. In Figure 4-17, we show PECO's ROE with and without solar, and under different test-year and decoupling scenarios. As before, we assume the base case described in Table 4-1. Without decoupling or the FPFTY, solar causes a consistent reduction in PECO's ROE. Assuming a historical test year, PECO's average ROE from 2020-2040 would be 9.5% without solar but would drop to 9.3% with 5% solar. With the FPFTY, PECO's FPFTY remains at 10% with or without solar. Revenue decoupling further improves PECO's ROE beyond the allowed 10%. These overearnings may be limited by the PA PUC.

Revenue erosion may indirectly affect PECO through disproportionate changes in the distribution and bulk grid section of customer bills. Table 4-2 shows the 20 year average rate impact for distribution (non-pass-through) and bulk grid (pass-through) portions of customer bills by billing determinant and the all-in-rate for a 5% solar energy penetration and no solar. While the increase in the all-in-rate is just 0.9%, the distribution portion increases by 3.3% and the bulk grid portion decreases by 0.6%.

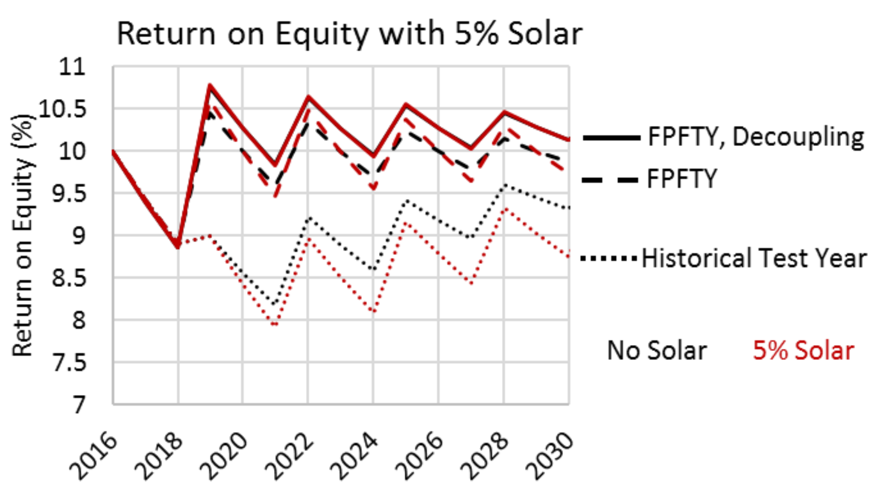


Figure 4-17: PECO Return on Equity (ROE). With the Fully Projected Future Test Year (FPFTY), PECO's ROE average 10% regardless of the solar penetration.

Table 4-2: 20 year average rate impact for distribution (non-pass-through) and bulk grid (pass-through) portions of customer bills by billing determinant and the all-in-rate for a 5% solar penetration and no solar targeting. Solar avoids more costs on the bulk grid than on distribution networks and would cause a disproportionate increase in distribution network rates.

	All-In-Rate (%)	Volumetric (%)	Customer (%)	Demand (%)
non-pass through	3.31%	3.31%	-0.17%	2.19%
pass through	-0.58%	-0.56%	n/a	-0.77%
combined	0.89%	0.59%	-0.18%	0.91%

4.3.3 Distribution Capacity Deferral

Figure 4-18 shows the value of solar for distribution capex deferrals and the total deferral value for both transmission and distribution. The value of solar is not high enough to significantly affect rates. Furthermore, the combined T&D deferral value at 5% solar energy penetration is $10-15MM from 10 years of solar deployment, and it probably does not justify large administrative efforts to capture that value. The effective capacity of solar, MCOS, and growth rate all affect the value created by solar. These results are also very sensitive to the total amount of deferrable capex, which is not well documented and may vary considerably between utilities. Figure 4-19 show the rate impact, total deferrable value, and earnings reduction if 10% of PECO's capex were deferrable each year. Under this higher deferrable capex scenario, more deferrable value is created. In Chapter 5 we revisit these estimates assuming that solar can be targeted at overloaded locations.

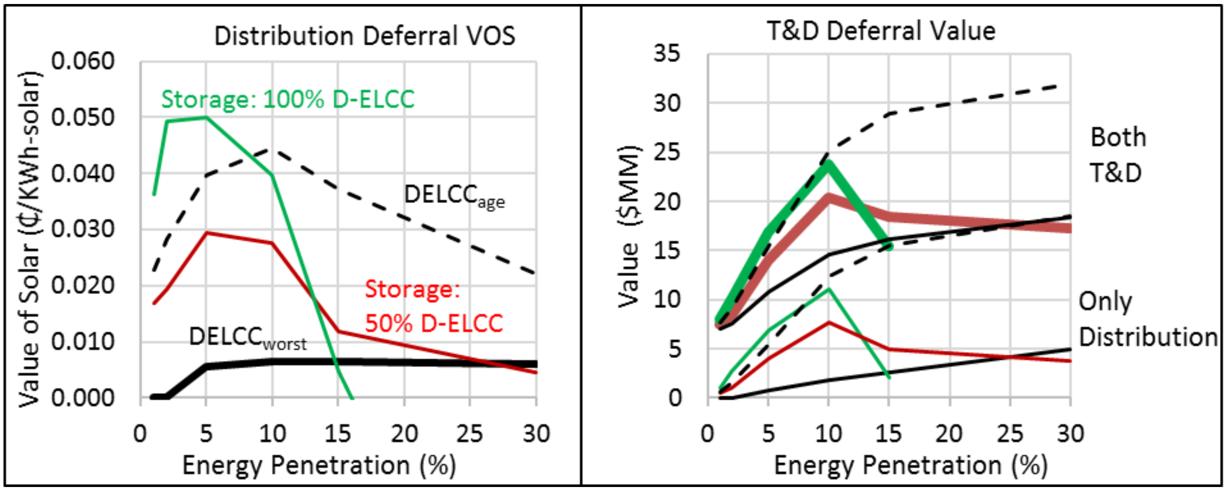


Figure 4-18: Distribution VOS, and the T&D total deferral value. Under the assumption of 1% growth related capex deferral opportunities, $3MM in distribution capex can be deferred each year. The T&D deferral value and T&D VOS are low.

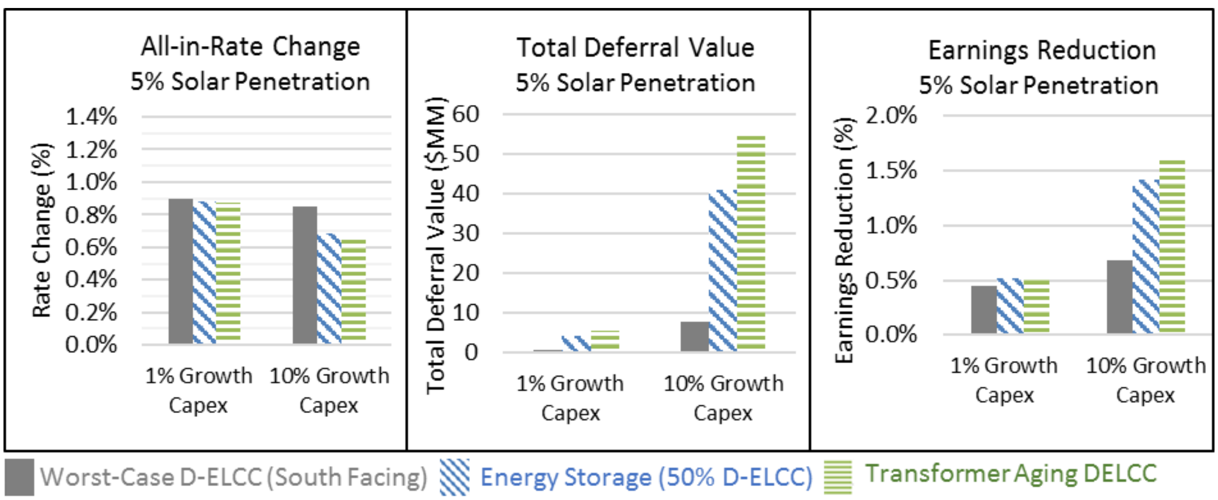


Figure 4-19: The all-in-rate change, total deferral value and earnings reduction assuming that 1% and 10% of PECO's distribution capex is deferrable. PECO's best estimate is that 1% of distribution capex is deferrable ($3MM per year). The 1% deferrable capex scenario probably does not justify large administrative efforts to capture the deferral value.

4.3.4 Comparison with Previous Value of Solar Research

Our findings are consistent with other value of solar studies and rate impact tests. A study by Perez et al. (2012) prepared for the Mid-Atlantic Solar Energy Industries Association (MSEIA) estimated a $0.33/kWh value of solar for Philadelphia at a 7% energy penetration of solar. The MSEIA reported estimated the VOS from energy, generation capacity, and T&D at $.081/kWh. The MSEIA estimate for DRIPE added another $0.051/kWh, which is higher than our estimate and other estimates for the DRIPE that we have reviewed. The remainder of the avoided costs is from environmental, security enhancement, long term societal, fuel price hedging, and economic development value. A thorough review of the value of solar findings in other states is provided by E3 in their report for the New York State Energy Research & Development Authority (2015), and by the Rocky Mountain Institute (2013). A challenge of interpreting these studies is that VOS estimates cover more than an order of magnitude, from $0.03/kWh to $0.35/kWh.

Unique features of our study include a rate impact assessment and detailed modeling of the distribution capacity deferral value of solar. Using an earlier version of the utility financial model applied to a typical Northeastern utility, Satchwell et al. (2014) of Lawrence Berkeley National Lab (LBNL) estimate that a 5% penetration of solar will increase rates by 0.7%. This estimate is very close to our own estimate of a 0.9% increase in rates. Our estimate for the value of solar is lower than the LBNL report because energy costs have declined and because we estimate a lower distribution deferral value of solar.

Our estimate of the T&D capacity deferral value of solar is most like Cohen et al. (Cohen, Kauzmann and Callaway 2016). They estimate a distribution deferral value of solar in California ranging from 0.05-0.20 ₵/kWh without targeting, which is higher than the estimates we provide in Figure 4-18. We use a similar method to estimate capacity deferral and our lower estimate may be caused by PECO's low estimate for growth related capex deferral opportunities. Cohen et al. (2016) also estimate a targeted VOS at 0.25-1 ₵/kWh, but their targeting definition does not place more solar in overloaded networks. Solar is placed randomly on all networks and the deferral value is distributed only among solar owners in overloaded networks. We assess the targeted placement of solar in Chapter 5.

4.4 Conclusion

We find that Pennsylvania can offer Net Energy Metering (NEM) rates up to 5% solar energy penetration with only a small (0.9%) increase in rates. Our result is similar to a Lawrence Berkeley National Lab (LBNL) report estimating a 0.7% increase in rates for a 5% penetration on a “typical Northeastern” utility (Satchwell, et al. 2014). Because of the recent implementation of the Fully Projected Future Test Year and pending implementation of revenue per customer decoupling, a 5% energy penetration of solar is unlikely to negatively affect Pennsylvania utilities. Additionally, solar has benefits that are not included in this rate impact test. By displacing fossil fuel generation and reducing criteria pollutant emissions, solar avoids health damages and premature loss of life. A study by Perez et al. (2012) estimates this value of solar at $0.05-0.12/kWh. This chapter can be used by the Pennsylvania PUC to decide whether these large environmental benefits are worth the small rate impact caused by solar.

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4.6 Supporting Materials

4.6.1 Historical Reference Years

The utility financial model uses hourly historical PJM loads, PECO loads, solar insolation, and the PECO zone LMPs. The years 2007-2016 are used for these inputs, and we refer to them as historical "reference years". The model is run for each reference year for the full duration of the model time span (2016-2040) and the results are averaged over all reference year results. When there are discrepancies between reference year attributes and inputs from the year 2016, we multiplicatively scale the reference year. For example, the 2008 load weighted LMP is $81/MWH while the entire 2016 bilateral contract cost is just $60/MWH, so we scale the 2008 hourly LMP downwards. Similarly, PECO's yearly loads do not perfectly match our input load factor for PECO and are scaled accordingly. Our motivation for this treatment is to remove the effect of trends (e.g. load growth) over the reference years while still capturing the variation in load, solar, and LMP profiles that cause variation in the value of solar.

4.6.2 Billing Determinants

The utility earns revenue from three billing determinants: fixed charges ($/customer), demand charges ($/kW), and volumetric charges ($/kWh). The revenue earned from the billing determinants is allocated to several different spending categories, shown in Table 4-3 and based on PECO's accounts (PECO 2016). We assume this allocation stays constant for varying energy penetrations of solar. If solar, for example, reduces the volume of sales without reducing peak demand and distribution capacity revenue requirements, there will be an increase only in customer volumetric rates. A newer source of revenue in Pennsylvania comes from the LTIIP (Long Term Infrastructure Improvement Plan). The LTIIP allows utilities to recover investments in aging infrastructure through a Distribution System Improvement Charge (DSIC)-a volumetric rate that can change quarterly. The LTIIP is unaffected by solar.

Table 4-3: Revenue from the billing determinants are allocated to the major utility spending categories based on PECO's accounts.

	Billing Determinant		
Spending Category	**Fixed Charge (%)**	**Demand Charge (%)**	**Volumetric Charge (%)**
O&M	16	21	63
Distribution	16	21	63
Generation	0	50	50
Transmission	0	50	50
Energy	0	0	100
Taxes	16	21	63
LTIIP	0	0	100

4.6.3 Customer Class and Net Energy Metering Model

Net Energy Metering (NEM) compensates solar owners at the retail rate. In our model we aggregate all customer classes and expand the NEM definition to include both volumetric and demand charges. This was a necessary simplification to limit data requirements but does prevent us from estimating cross-subsidies between classes. We do not think it will significantly change the metrics used in this chapter because solar capacity is distributed among the commercial and residential classes in PECO's service territory similarly to PECO's revenue from those same classes. This assumption would be less tenable if solar was installed in one customer class. For example, if PECO only had solar customers in the commercial class, the model would overpredict a loss in volumetric sales that may differ from revenue associated with a loss in demand charge revenue.

4.6.4 Utility Financial Model: Version History

The utility financial model was adapted from a NAPEE spreadsheet model (2007) and later work by Satchwell et al. (2014), which explored a variety of policy options to mitigate the negative effects of rooftop solar for a typical Northeast utility. We replicated key results of this work in Analytica™ and have made several changes to better represent Pennsylvania and PECO. Major changes include:

- Adapting the model to PJM rules and rates.
- Adapting the model to Pennsylvania regulatory and ratemaking processes, such as the FPFTY and Revenue Per Customer (RPC) decoupling.
- Hourly modeling of Locational Marginal Prices (LMPs), solar insolation, and loads to estimate avoided costs and the declining value of solar with increasing penetration.
- 10 historical reference years to capture the changing value of solar with different weather, load, and market prices.
- Explicit modeling of transmission and generation capacity credits, especially as a function of increasing solar and historical reference years.
- Explicit modeling of the Demand Reduction Induced Price Effect (DRIPE), especially as a function of increasing solar and historical reference years.
- Forecasts of solar in other PJM states based on RPS standards.
- Detailed modeling of the distribution capacity deferral process.

Figure 4-20 through Figure 4-23 show several key modules from our adaptation of the utility financial model in Analytica®.

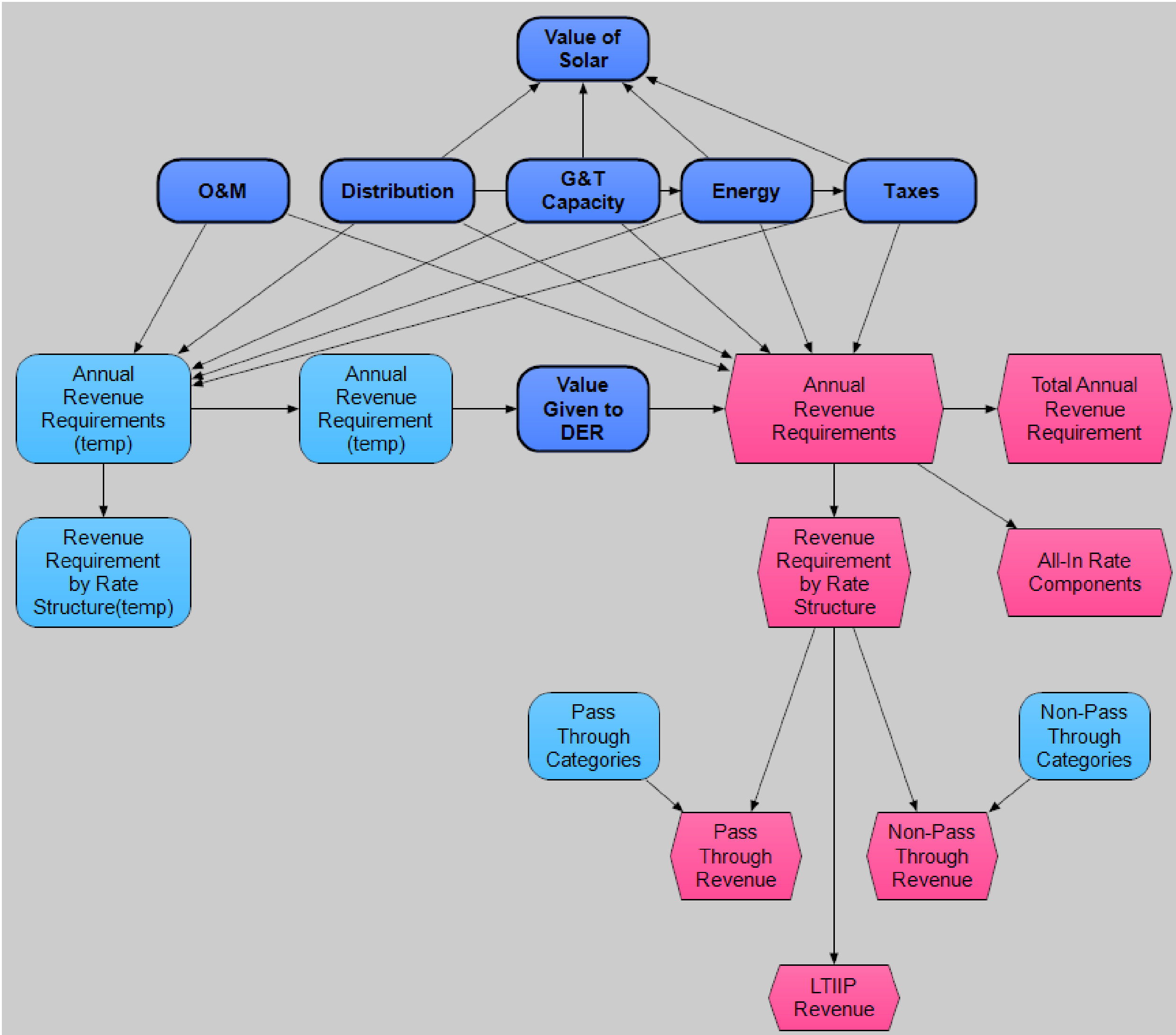


Figure 4-20: Utility Financial Model: revenue requirement and value of solar module

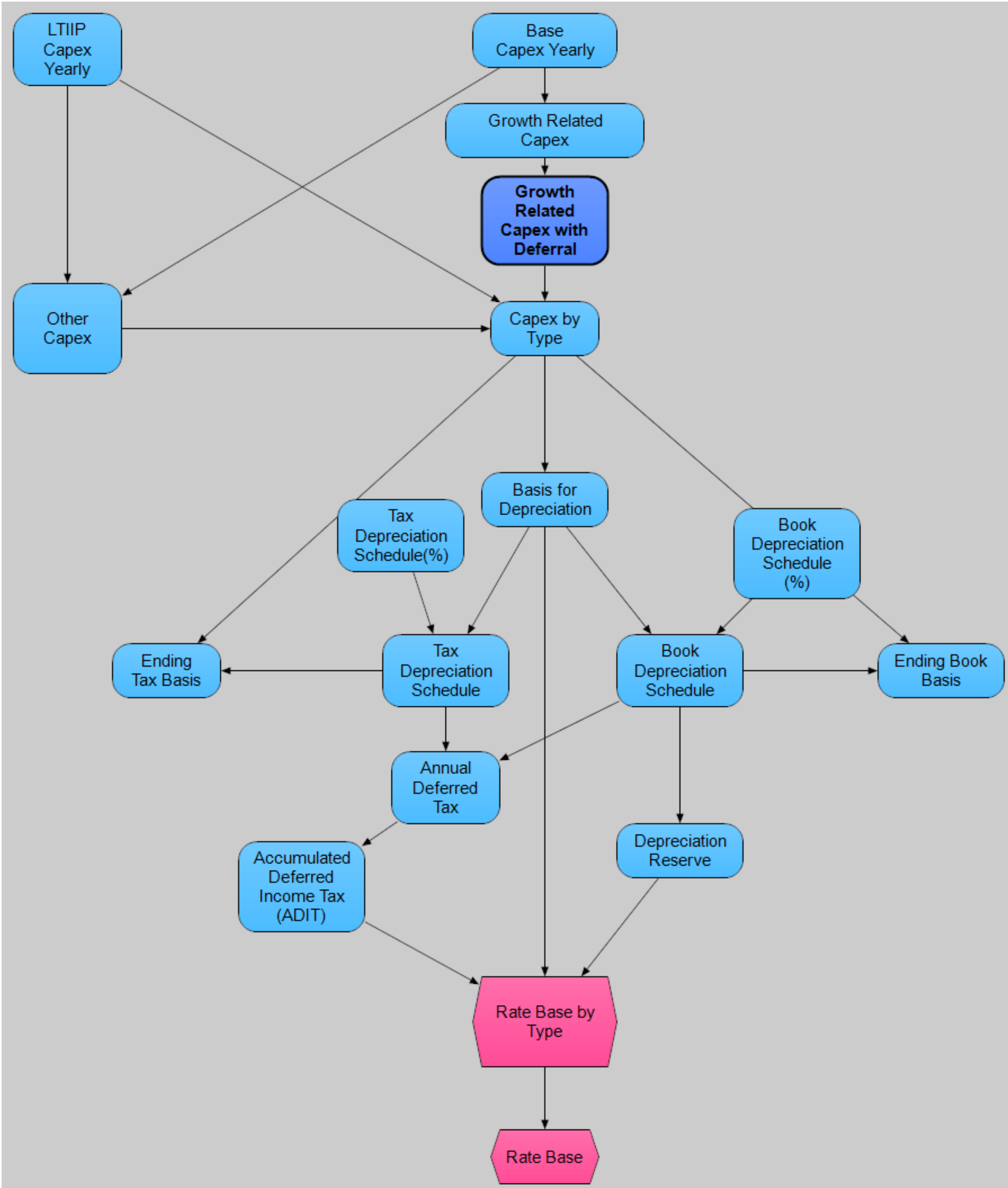


Figure 4-21: Utility Financial Model: rate base module

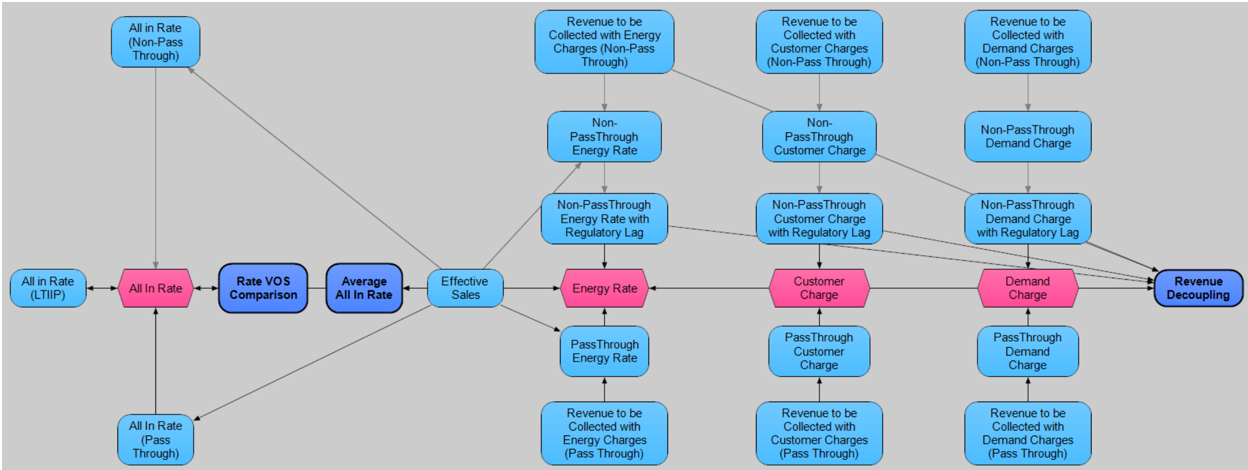


Figure 4-22: Utility Financial Model: Billing determinants module

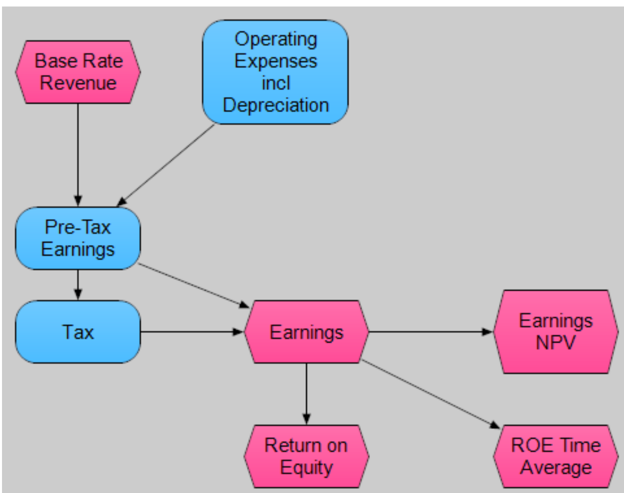


Figure 4-23: Utility Financial Model: Return on equity module

4.6.5 Rate Case Modeling

Utilities are permitted to charge high enough rates to earn a reasonable return on equity (ROE), typically around 10%. In practice, changing costs and revenue between rate cases cause fluctuations in the ROE. Several factors complicate utility revenue collection and thus, their achieved return-on-equity. There is typically a delay between when rates are set and the year they take effect. This is known as “regulatory lag”. We use a regulatory lag of 1 year, which is typical for Pennsylvania and most utilities. Furthermore, Public Utility Commissions, like the PA PUC, typically, do not set rates based on data in the rate case year. Instead, they use data from a “historical test year”, usually one year before the rate case. Together, regulatory lag and the use of a historical test year can significantly reduce a utility's achieved ROE relative to the target ROE. This difference occurs when costs increase at a faster rate than revenue. Assuming a 1 year historical test year and a 1 year regulatory lag, there is an effective 2 year delay between the data used to set rates and the year rates go into effect. During this time, increasing costs decrease the utility's profit and therefore, decrease the return on equity. Solar and Net Energy Metering is often associated with a further reduction in utility revenue that is not fully counteracted by equivalent reductions in costs. Consequently, with increasing solar penetrations, under Net Energy Metering, historical test years, and regulatory lag, many utilities are concerned with large reductions in their return-on-equity.

In recent years, Pennsylvania has implemented several policies effectively eliminating regulatory lag. These policies are the fully projected future test year (FPFTY), Distribution System Infrastructure Charge (DSIC) (PA PUC 2012) under docket number M-2012-2293611, and the pending implementation of revenue per customer decoupled rates (PA PUC 2018).

The FPFTY sets rates on projected revenue requirements, costs, and sales two years into the future. There is still one year of regulatory lag following the rate case, so one year after the rate case, the utility over collects. Assuming costs are increasing, rates are set to allow more revenue in the first year than the expected revenue requirement. In the second year after the rate case, assuming cost projections were accurate, the utility earns the target return-on-equity. In the third year after the rate case, increasing costs result in under-collection and a return-on-equity below the target. It is typical for the Pennsylvania PUC to allow rate cases every three years, so the utility can expect the cycle to repeat in the following year with over-collection. Figure 4-24 illustrates how the utility ROE changes with a historical test year and with the FPFTY.

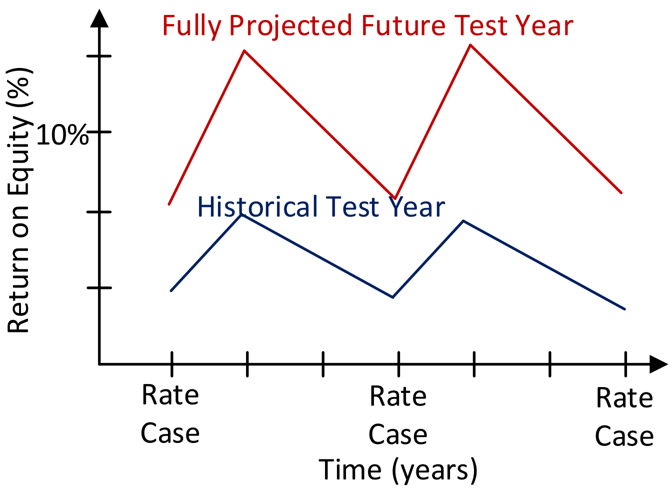


Figure 4-24: Comparison of utility ROE with Fully Projected Future Test Year (FPFTY) and a historical test year. Regulator lag prevents utilities from earning the target return on equity (10%). The FPFTY sets rates based on forecasted costs two years in advance, resulting in overcollection in the first year after the rate case.

The purpose of the DSIC is to encourage utilities to invest in aging infrastructure and to improve resiliency, but it also decreases regulatory lag. Utilities are permitted to submit Long Term Infrastructure Investment Plans (LTIIP) for replacing aging infrastructure. If approved, utilities pass costs related to these investments through to customers on quarterly basis, effectively bypassing the rate case process and eliminating any regulatory lag. One exception to this rule is that Pennsylvania utilities cannot collect the DSIC if they have already collected more than the revenue requirement allowed under the FPFTY.

Revenue decoupling takes a more direct approach to eliminating over and under collection. After estimating the revenue requirement in the rate case year, a projected revenue requirement is found for future years. Different mechanisms exist to project the revenue requirement (RAP 2011). Based on discussions with the Pennsylvania PUC, we assume the projected revenue is based on customer growth, also known as revenue per customer (RPC) decoupling and only revenue from the volumetric billing determinant is considered. We model RPC decoupling as yearly changes in customer volumetric rates to allow the actual revenue to meet the projected revenue. That is, if the volumetric revenue is below the projected revenue allowance, volumetric rates are adjusted to meet the allowed revenue. If revenue is above the projected revenue allowance, rates are decreased. In practice, decoupling is performed with balancing accounts to reduce frequent changes to customer rates.

4.6.6 Avoided Costs

Avoided Energy Costs

Pennsylvania Alternative Energy Portfolio Standards

Pennsylvania has an Alternative Energy Portfolio Standards (AEPS) composed of two tiers of energy products. Tier 1 is composed mostly of renewable energy resources such as wind, hydro, biomass and geothermal. It includes a solar carve out that reaches 0.5% in 2021 (PA Public Utility Commission 2016). Tier 2 is composed of waste coal, municipal solid waste and other alternative energy resources. (PA Public Utility Commission 2016). In 2016, the average AEC price of all tiers is $8/MWh, and the AEPS obligation is 13.7% of sales (PA Public Utility Commission 2016). The AEPS grows 0.5 percentage points per year until 2021 and we assume the AEC price stays constant. We do not model any effect of higher solar penetrations on the AEPS AEC price, although it is possible that AEPS targets could be one mechanism to achieve higher penetrations, or that higher solar penetrations could reduce AEPS REC prices.

Demand Reduction Induce Price Effect (DRIPE)

Figure 4-6 shows modeled price suppression of LMPs for several weeks in in the PECO Zone in the summer. Figure 4-25, below, shows the DRIPE for a full year. The reduction in price is small reflecting the relatively small portion of demand that Pennsylvania (~ 30 peak GW) is of the entire PJM service territory (~ 160 GW). Initially, reduced demand and the price suppression will avoid energy costs and contribute to a relatively high VOS. As the penetration increases and as the LMPs diminish during times of solar output, the energy VOS will also diminish.

Strictly speaking, the DRIPE is not an avoided cost but rather a wealth transfer from producers to consumers. The energy VOS, for example, includes avoided fuel costs and reflects a reduction in consumption. In contrast, the DRIPE does not reflect a reduction in fuel consumption. It only affects the price we pay for that fuel and will make generator operations less economic. PECO does not own generation, so from their perspective and from their ratepayers' perspective, energy costs are reduced. In the long run, however, downward pressure on LMPs may result in higher capacity market prices or ancillary services. We do not model these market dynamics, but we do include scenarios without the DRIPE in our sensitivity analysis.

A better approximation DRIPE would entail running optimal powerflow for different solar penetrations so that the PECO Zone LMP (and not the PJM wide marginal price) could be used to calculate the DRIPE. This method is beyond the scope of the study.

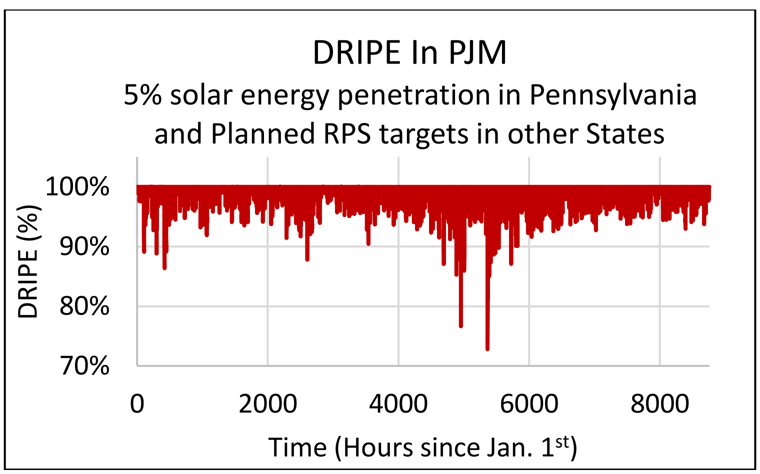


Figure 4-25: Hourly Demand Reduction Induced Price Effect (DRIPE) after solar rollout is complete (in 2030) using 2016 loading and solar profiles.

Using NREL's Physical Solar Model, a combination of several locations throughout Pennsylvania and PJM (Harrisburg International Airport, Pittsburgh International Airport, Philadelphia International Airport, Delaware, Maryland, New Jersey, and Washington DC) are averaged to find a representative PJM solar profile. The PJM solar profile is used to estimate how solar will reduce PJM's load profile. The hourly marginal price is recalculated with the demand reduction caused by solar. We estimate the DRIPE as the fraction of PJM wide marginal price with solar and without solar. The DRIPE is calculated for several penetrations. Interpolation is used to estimate the various yearly penetrations as solar is rolled out to meet the 2030 target. Figure 4-25 shows the DRIPE at a 5% energy penetration of solar in Pennsylvania using weather and loading profiles from the year 2016.

Avoided Transmission Costs

Growth Related Transmission Capex

We estimate yearly growth-related transmission capex from PJMs Transmission Cost Information Center (TCIC) spreadsheet (PJM 2019). To be considered as growth-related, transmission projects must fall under the following project drivers: Baseline Load Growth Deliverability & Reliability, Generator Deactivation. Additionally, the project description must include a reference to adding new equipment or increasing the rating on equipment. We did not consider projects with other drivers: Congestion Relief Economic, Customer Service, Equipment Material Condition, Performance and Risk, Operational Performance, and Short Circuit. Although Congestion Relief Economic is related to growth, we assume that the transmission value associated with these projects is already embodied in PECO's LMPs. Overall, we estimate that PECO has $6MM of growth-related projects per year that are included in its rate base and PECO pays PJM for an additional $46MM of growth-related projects per year (20% of annual transmission expenses).

Solar Profile

The Transmission capacity credit describes the ability of solar to reduce PECO's yearly non-coincident peak Using NREL's Physical Solar Model, a combination of locations in PECO's service territory (Peach Bottom, Doylestown, Philadelphia International Airport) are averaged to find a representative solar profile and to estimate how solar will reduce PECO's load profile.

4.6.7 Distribution Interconnection Model

We modeled four PECO feeders with varying solar penetrations and different smart inverter options. Modeling PECO's feeders required several steps. First, PECO selected four feeders that are representative of their service territory. Second, we converted PECO's feeder models from CYMDIST, which performs only static powerflow analysis, to GridLab-D, which can also do sequential time-series powerflow analysis. Third, we populated the GridLab-D feeder models with representative secondary networks and weather dependent building models, ensuring that the total simulated substation load was similar to SCADA readings and that the maximum simulated spot loads were similar to the spot load values in PECO's models. Fourth, we populated the GridLab-D feeder models with residential and commercial solar PV by drawing from a probability distribution of the nominal capacity (kW_{AC}) of recent solar installations. Fifth, we simulated varying penetrations of solar on the models with different voltage excursion mitigation scenarios. In our reconductoring scenario, if a solar installation caused a voltage excursion, the capacity of the service drop conductor connecting the solar installations was increased by 100 amps. In our smart inverter scenario, we connected smart inverters to all solar installations. These steps are described in more detail below.

4.6.7.1 Feeder Selection

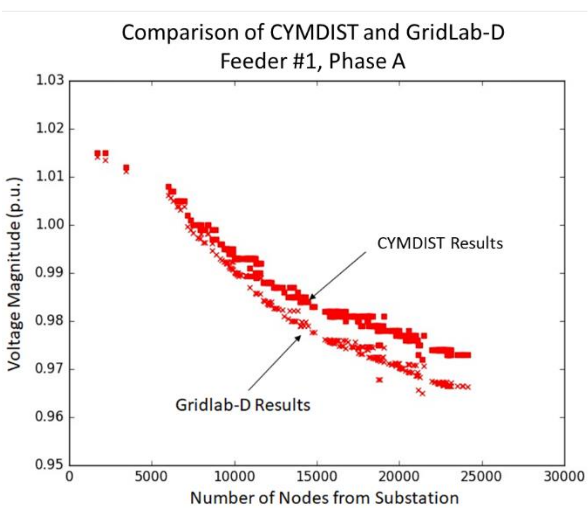
We used four feeders that are representative of the PECO service territory. Feeders were chosen with features common to the PECO service territory that may make it harder to integrate high penetrations of solar. Key features of the feeders are summarized in Table 4-4.

Table 4-4: Summary of PECO feeders used in analysis.

Feeder Name	Voltage Level	Max Length	Number of Nodes	Peak Load	Losses at Peak
Feeder 1	13.2 kV	4.7 miles	473	6.2 MVA	9.4%
Feeder 2	33 and 4 kV	14 miles	3400	17 MVA	10%
Feeder 3	4kV	2.9 miles	200	2.1 MVA	8.6%
Feeder 4	4 kV	5.4	800	2.3 MVA	6%

4.6.7.2 Feeder Conversion

We used the National Rural Electric Cooperative Association's (NRECA)'s Open Modeling Framework (OMF), a suite of open source analysis tools for distribution networks to convert PECO's CYMDIST models to an equivalent GridLab-D static powerflow snapshot. Figure 4-26 shows a comparison of the cyme voltages with the converted GridLab-D voltages. The maximum difference between the results is approximately 3%.



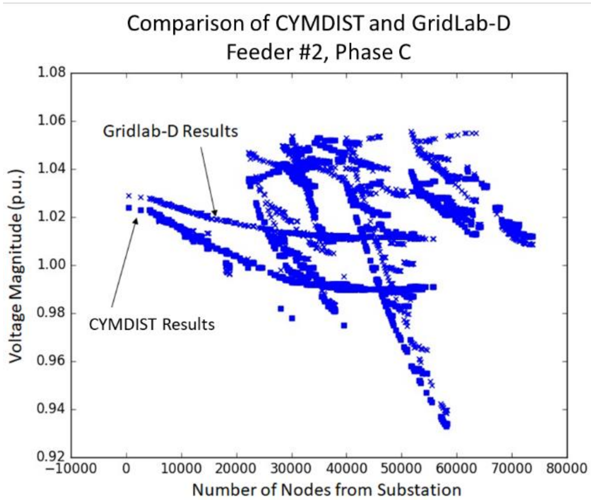


Figure 4-26: Comparison of GridLab-D and CYMDIST Results.

4.6.7.3 Secondary Network Modeling

Figure 4-27 shows the secondary network used in our analysis. A distribution transformer feeds several customers. In PECO's CYMDIST model, all loads connected to the distribution transformer are modeled as a single non-time varying spot load. In our model, the customers are connected to the transformer in a daisy chain sequence with secondary conductors and service drops. The secondary conductors are sized based on the spot load in PECO's CYMDIST models. The service drops are sized based on the peak building load. Table 4-5 shows the parameters used for the secondary and service drop conductors. The minimum secondary conductor rating is 299 amps and the minimum service drop conductor rating is 90 amps.

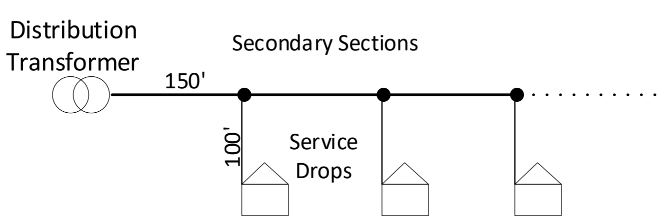


Figure 4-27: Representative Secondary Model

Table 4-5: Secondary and service drop conductors. The default secondary rating is 299 amps and is 150 feet. The default service drop rating is 90 amps and is 100 feet.

Current Rating	Size	Stranding	Material	Diameter (in.)	GMR (ft)	Resistance (ohms/mile)

90	4	Class A	AA	0.152	0.007	2.61
202	1/0	Class A	AA	0.368	0.0111	0.97
299	4/0	Class A	AA	0.422	0.0158	0.528
420	3/0	12 STRD	Copper	0.464	0.01559	0.382
500	300,000	30/7	ACSR	0.7	0.0241	0.342
750	605,000	54/7	ACSR	0.953	0.0321	0.1775
1090	750,000	37 STRD	AA	0.997	0.0319	0.0888

To create time-varying loads, we populated the secondary networks with temperature and humidity dependent building models originally made available to the public by Fuller et al. (2012) as part of the PNNL feeder taxonomy. Residential buildings parameters were based on the Energy Information Administration's (EIA) Residential Energy Consumption Survey (EIA 2018). Parameters include: the percentage of homes with air conditioners, HVAC equipment fuel type, hot water heater fuel type, and building R values. Non-weather-dependent load profiles were based on the Bonneville Power Administration's End-Use Load and Consumer Assessment Program (Prat, et al. 1989), and show the characteristic morning and evening peak typical for most residential customers. Commercial buildings were modeled off building codes and end-use metering studies (Fuller, Kumar and Bonebrake 2012). All commercial buildings are modeled as office buildings, big box stores, and strip malls.

To create time-varying loads, the feeder taxonomy was populated with temperature and humidity dependent building models and made available to the public by Fuller et al. (2012). Residential buildings parameters were based on the Energy Information Administration's (EIA) Residential Energy Consumption Survey (EIA 2018). Non-weather-dependent load profiles were based on the Bonneville Power Administration's End-Use Load and Consumer Assessment Program (Prat, et al. 1989), and show the characteristic morning and evening peak typical for most residential customers. Commercial buildings were modeled off building codes and end-use metering studies (Fuller, Kumar and Bonebrake 2012). All commercial buildings are modeled as office buildings, big box stores, and strip malls.

We used a genetic algorithm to adjust residential and commercial building parameters so that the simulated feeder load time-series matched hourly SCADA readings. Our objective function minimized the difference between the simulated and SCADA load profiles from May-September 2016. The decision variables were the air conditioning coefficient of performance, insulation R values, cooling set points, floor areas, scaling factors for predefined temperature independent ZIP load profiles, the proportion of commercial buildings modeled as strip malls, office buildings, and big box stores, the percentage of residential homes with air conditioners, and the percentage of residential homes with hot water heaters.

Figure 3-1 compares our simulated load with SCADA load in the year 2016 for both feeders. Simulated loads and SCADA readings are close on Feeder #1. On Feeder #2, the simulated load profiles underestimate the peak load, but the peak simulated hour, which is important for estimating solar's effective capacity, is still close to the observed hour using SCADA data. Feeder #2 is an industrial feeder and the error is likely caused by exogenous effects, such as shifting factory production schedules. These exogenous effects are difficult to include in GridLab-D's weather-dependent models.

We did not have hourly SCADA readings for Feeder #3 and Feeder #4, so the building parameters in these feeders were populated with the same parameters in Feeder #1 and Feeder #2. After matching the simulated substation load with the SCADA substation load, we scaled the floor area and ZIP load parameters so that the maximum time varying loads matched PECO's spot loads. Deviations in the floor area was limited to 30%.

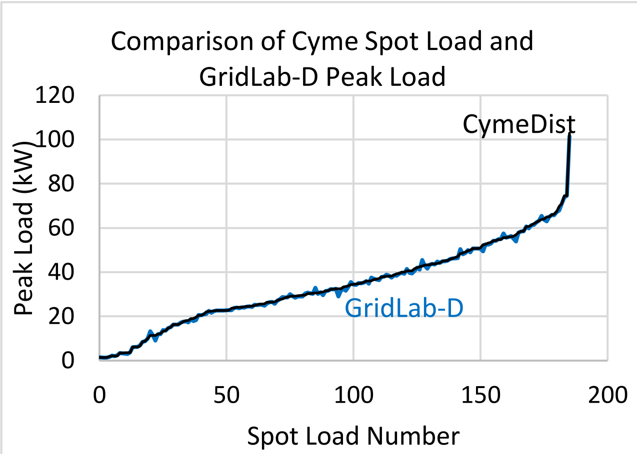


Figure 4-28: Comparison of CYMDIST non-time varying spot load with the maximum GridLab-D peak.

4.6.7.4 Solar Modeling

Each feeder was populated with solar panels to create peak solar penetrations (solar nominal AC capacity divided by the peak feeder load) ranging from 1% to 50%. The nominal capacity(kW_{AC}) of the solar installations were found by sampling from the capacity distribution of recent residential and solar installations. These distributions are shown in Figure 4-29. We used the stats package in the Python™ SciPy[11] library to fit each distribution. The distribution of residential installations is modeled with a lognormal distribution and the commercial installations is modeled with a gamma distribution. For the residential lognormal distribution, the shape, loc, and scale parameters are 0.43, -0.74 and 6.9. For the commercial gamma distribution, the shape, loc, and scale parameters are 0.58, 0, and 117. 96% of installations are on residential loads.

[11] https://www.scipy.org/

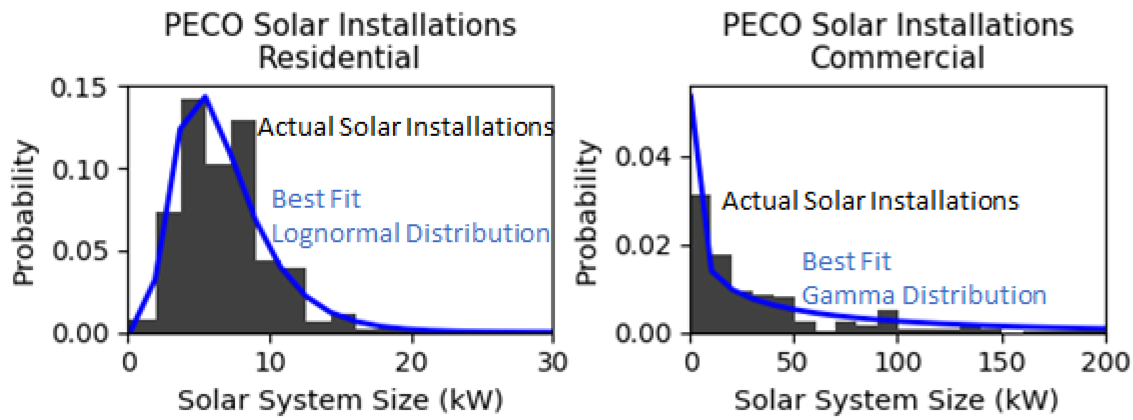


Figure 4-29: Histogram and probability distributions for recent nominal solar capacity (kW_{AC}) installations in the PECO service territory. For the residential lognormal distribution, the shape, loc, and scale parameters are 0.43, -0.74 and 6.9. For the commercial gamma distribution, the shape, loc, and scale parameters are 0.58, 0, and 117.

Each solar installation was drawn from the probability distribution and placed on a building with the closest matching roof size. Floor area was used to estimate total roof space using the method proposed by Butler (2018). The available roof space was found by scaling the total roof space by 40%. All panels are flat plate and monocrystalline with a 30 degree tilt. Inverters have an efficiency of 96% and a sizing factor of 1.4

We used solar radiation and weather data from NREL's National Solar Radiation Database, Physical Solar Model-Version 3 (PSM-V3) (NREL 2018). PSM-V3 estimates solar irradiance from satellite data from 1998-2016 with a geographic resolution of 4-km by 4-km and a 30-minute time resolution (Habte, Sengupta and Lopez 2017). Compared to ground measurements, mean bias errors are approximately ±5% for GHI and ±10% for DNI. RMS errors are as high as 20% for GHI and 40% for DNI.

4.6.7.5 Voltage Violation Mitigation Strategies

We tested several methods for mitigating voltage excursions. PECO currently reconductors service drops when solar installations cause high voltages. To model this practice, when a high voltage was detected we replaced the conductor with the conductor with the next largest ampacity (shown in Table 4-5). In the smart inverter scenarios, we placed smart inverters on every solar installation. Volt/Var with real power priority, Volt/Var with reactive power priority, and Volt/Watt were considered. Figure 4-30 shows the set points for both Volt/Var smart inverters and the Volt/Watt setting.

Figure 4-31 and Figure 4-32 demonstrate the effectiveness of the smart inverters. In Figure 4-31 the solar profile is compared to the total number of voltage violations on a feeder. There are more voltage violations when the solar output is larger. In Figure 4-32, a house is shown where both Volt/Var and Volt/Watt smart inverters eliminate a voltage violation caused by solar.

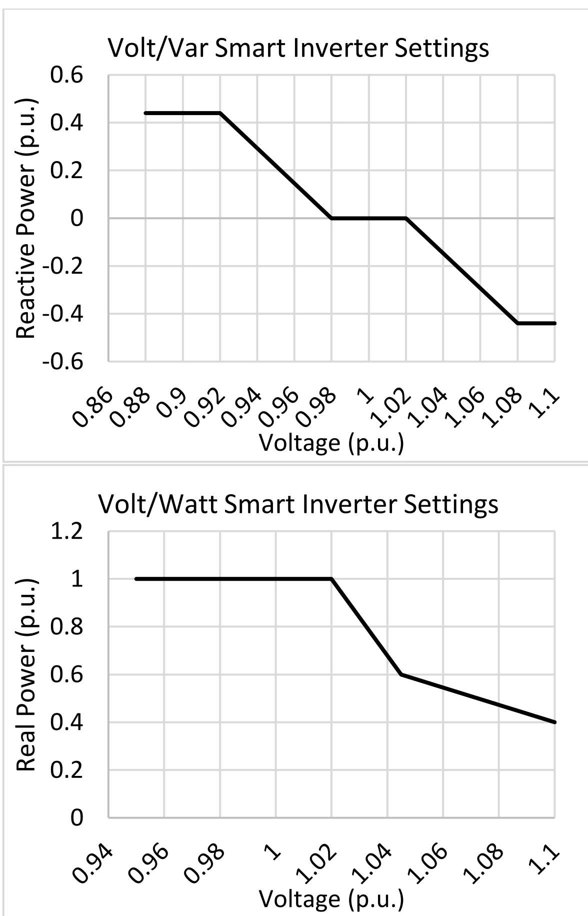


Figure 4-30: Volt/Var and Volt/Watt smart inverter settings.

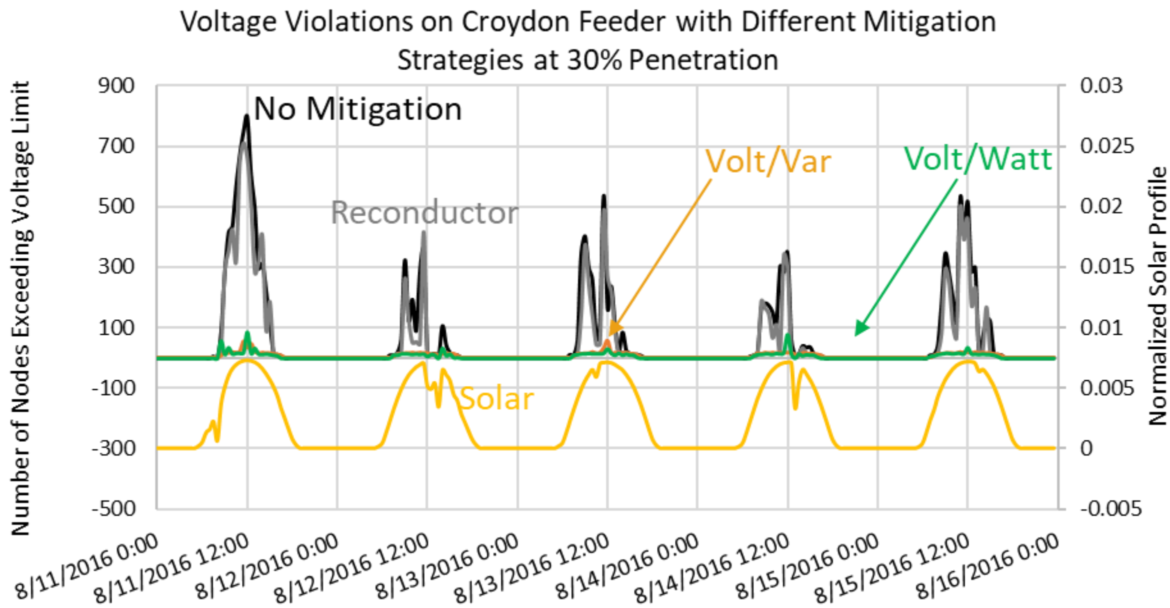


Figure 4-31: Voltage violations on a PECO feeder in the summer. There are more voltage violations when the solar output is greater. Volt/Var and Volt/Watt smart inverters eliminate most of the violations.

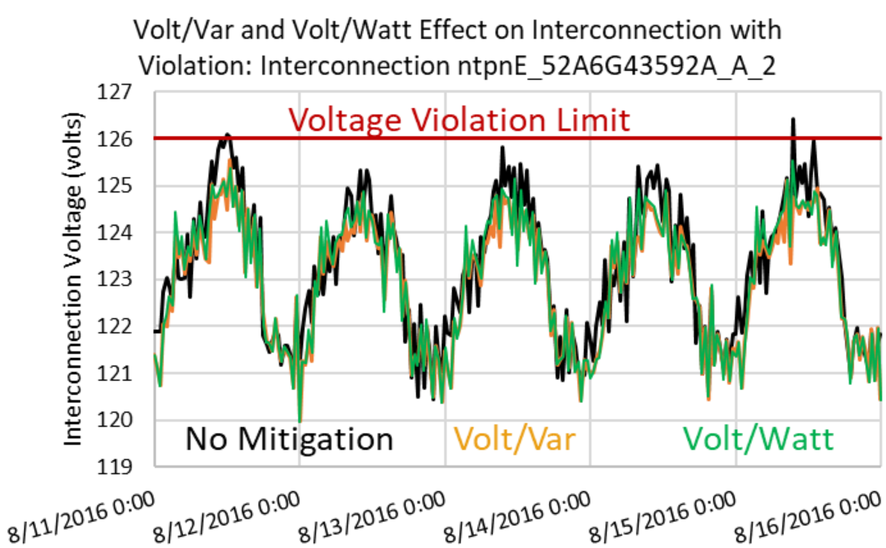


Figure 4-32: A house where a smart inverter eliminates the voltage violation at the interconnection point.

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Chapter 5: Rate impacts of capacity deferral using targeted solar deployment with energy storage in the PECO service territory

Abstract

We assess the ability of rooftop solar and storage to reduce peak loads and defer distribution capacity projects in the PECO service territory. We find that solar may modestly reduce rates and that the value of solar at 5% energy penetration[12] can be increased up to fourfold if solar is targeted at overloaded locations. In Chapter 4, we estimate that a 5% solar energy penetration would increase rates by 0.9% over a 20-year horizon. This estimate assumes untargeted placement of solar, a low effective capacity (i.e. the reduction in peak load relative to solar's nominal capacity), a 1% growth rate, and based on a PECO engineering assessment, 1% of PECO's distribution capex budget that is deferrable. Targeted placement of solar, a higher effective capacity using energy storage, a 30% hosting capacity[13] and 10% growth-related capex could reduce the rate increase to 0.5% and generate $70-100MM of deferral value over the same 20-year time horizon. We conclude that capacity deferral with solar should be included in PECO's planning process but that large administrative efforts to manage deferral projects, such as markets, are probably not warranted.

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[12] In Chapter 5, we use solar energy penetration to describe how much solar energy is produced in Pennsylvania. It is defined as the total solar energy relative to total energy consumption.

[13] Distribution engineers often describe the amount of solar on a feeder using peak penetration, the nominal solar AC capacity relative to peak feeder load. Hosting capacity is defined as the maximum peak penetration possible on a feeder before solar violates system limits, such as high voltages.

5.1 Introduction

More than 30 states have grid modernization plans (Trabish 2017). New York and California are both developing frameworks that incorporate solar and other DER into their utilities' planning processes. The New York Reforming Energy Vision (REV) foresees utilities as "distribution system platform providers" that oversee markets where third parties and DER compete to provide services on distribution networks. California's Distribution Resources Plan (DRP) is also developing a framework to procure DER to provide distribution network services. Both the REV and DRP rely on EPRI's "Integrated Grid Framework" (EPRI 2015). Key features of the "Integrated Grid" are hosting capacity maps and locational value maps that, respectively, show how much DER can be placed on the network without violating system constraints and show developers where DER may have value.

The capacity deferral value of solar (VOS) is one benefit frequently cited in grid modernization plans. Examples include New York's report from the Market Design and Platform Technology Working Group (New York DPS 2015) or the deferral framework developed for California's Distribution Resource Plans (CPUC 2016). Capacity deferral value is the value that solar creates by reducing overloaded equipment and deferring capital investments to later years. Although several studies have estimated the capacity deferral VOS, we are not aware of any study that evaluates how utility policies regarding solar placement affects the VOS and the total deferral value created. It is important to consider solar placement because most statewide solar penetration targets are often low and the solar is deployed over many years. The result is small incremental solar additions to the locations that could benefit from capacity deferral, which may not be enough solar to defer investments by useful amounts of time.

Throughout the literature review and our analysis, we use three planning classifications.

1. *No targeting:* Rooftop solar is placed without regard to locations with overloading and without overloading, and all rooftop solar owners are compensated for the value created by solar.
2. *Targeted Compensation:* Rooftop solar is placed without regard to location, but rooftop solar owners are compensated only if they are in a congested area.
3. *Targeted Placement:* A fraction of rooftop solar is placed only in overloaded locations. The amount of rooftop solar placed in overloaded locations is limited by the hosting capacity.

We define hosting capacity as the maximum nameplate solar AC capacity that can be added to a network relative to the network's peak load. In the *No Targeting* scenario, no effort is made to place solar where it is needed. Deferral value opportunities are missed, which decreases the VOS. The *Targeted Compensation* VOS is sometimes estimated in studies. It does not create any more total deferral value than the no targeting scenario but results in a higher VOS because it distributes capacity deferral value among a smaller number of solar owners. In contrast, *Targeted Placement* puts more solar in locations where it is needed, ensuring that deferral opportunities are not missed and creates longer deferral times. The result is a higher VOS and a higher total deferral value.

5.2 Comparison with Previous Research

The present worth method for estimating the value of capacity deferral is used by academics and consultants (Woo, et al. 1994) (Willis 2000). In this method, solar or other DER causes a load reduction on an overloaded feeder and capital investments in that feeder are deferred to later years. Net Present Value (NPV) calculations are used to estimate the deferral value. That value is divided by the total generated solar energy to find the value of solar. The result is sensitive to the cost of the capacity deferral projects, load growth on the feeder, and how solar's nominal capacity is credited with reducing peak loads.

In New York, Energy and Environmental Economics (E3) estimates the distribution deferral value of solar at ~0.5₵/kWh without targeting and ~2.5₵/kWh with targeted compensation (NYSERDA 2015). Cohen et al. (2016) estimate a distribution deferral value of solar in California ranging from 0.05-0.2₵/kWh without targeting and 0.25-1₵/kWh under targeted compensation. The ranges are based on varying rollout scenarios over 10 years. Faster solar rollouts are able to create more total deferral value by deferring capacity projects with earlier start dates. However, faster solar rollouts generate more solar energy years before some projects need to be deferred, resulting in a lower value of solar. In the Supporting Materials, we discuss further how these rollout scenarios differ from targeted solar placement used in this study.

The capacity deferral value of solar is very sensitive to the cost of replacing or augmenting overloaded equipment, which is often estimated with the marginal cost of service (MCOS). The MCOS is the average cost of growth-related capacity projects. Cohen et al. (2016) use a dataset that includes feeder level capacity expenditures and growth rates but do not disclose these data. E3 has published MCOS values for each of the New York utilities ranging from \$250/kW to \$1000/kW and averaging \$750/kW (NYSERDA 2015). In E3's avoided cost calculator (E3 2018), the MCOS is approximately \$600/kW[14]. As discussed below, we also estimate PECO's MCOS to be \$600/kW, based on four growth related projects planned for the next five years.

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[14] This is the average avoided capacity cost of all zones in PG&E's service territory. E3 provides avoided capacity costs in \$/kW-year, but we use \$/kW in this chapter. We converted to \$/kW assuming a 30 year lifetime and a 7% discount rate.

The capacity deferral value of solar is sensitive to feeder load growth. If the load growth is low, the deferral will be longer. Unfortunately, we are not aware of any value of solar studies that include feeder load growth assumptions.

E3 uses the Peak Capacity Allocation Factor (PCAF) to assign a capacity credit to solar (Horii, et al. 2016). The PCAF method estimates the capacity credit based on solar's contribution to peak load reduction during daily peak load events within one standard deviation of the largest yearly peak (Horii, et al. 2016). An advantage of the PCAF method is that it creates a temporal component to the distribution value of solar. A disadvantage is that it does not describe the declining capacity value of solar with increasing penetrations. Cohen et al. (2016) instead base the capacity credit only on peak loading days and do capture the declining value of solar with increasing penetration. They estimate roughly a 50% reduction in the capacity credit of solar at a 50% penetration. Our method for estimating the capacity credit is most similar to Cohen et al. (2016), but is based on 19 years of loading data. Details are in Chapter 3 and the method section below.

5.3 Method

5.3.1 Utility Financial Model

We have developed a utility financial model that serves as the foundation of our capacity deferral model and generates three key metrics: the all-in-rate, reduced earnings, and value of solar. Details of these metrics are in the Metrics section of Chapter 4. The utility financial model and capacity deferral modeling is done with Analytica®.

The utility financial model estimates how the combination of avoided costs associated with solar and lost revenue associated with NEM ultimately affect rates. First, the model forecasts PECO's revenue requirement (i.e. revenue needed to pay for the cost of service, utility debt, and equity), including pass-through costs and non-pass-through costs. The model begins with PECO's revenue requirement in the year 2016 and forecasts each revenue requirement component based on the relevant escalation factors. The revenue requirement includes depreciation in PECO's rate base. Second, a forecast of volumetric sales, customer charges, and demand charges are used with the revenue requirement to baseline customer rates without solar by performing a rate case every three years. Third, solar is associated with avoided costs (i.e. a lower revenue requirement) and reduced revenue from volumetric sales and demand charges that will affect PECO rates.

The utility financial model was adapted from a spreadsheet model developed by E3 for the National Action Plan for Energy Efficiency (NAPEE 2007) and later work by Satchwell et al. (2014), which focused on solar's effect on a prototypical deregulated northeast utility and southwest vertically integrated utility. When applied to a typical Northeastern utility, Satchwell et al. (2014) estimate that a 5% solar energy penetration will increase rates by 0.7%. This estimate is very close to our own estimate of a 0.9% increase in rates (see Chapter 4). Our estimate for the value of solar is lower than the LBNL's report value because energy costs have declined and because we estimate a lower distribution deferral value of solar.

In Chapter 4, we find that the total deferral value created by solar is small when it is not targeted at overloaded networks. The purpose of this chapter is to determine how much targeted placement of solar on overloaded networks can increase the total deferral value and reduce the rate increase observed under a 5% solar energy penetration with untargeted solar.

5.3.2 Capacity Deferral Model

The capacity deferral model estimates savings caused when solar and energy storage reduce peak demands and defer investments to later years. Key parameters for the entire utility financial model are summarized in Table 4-1. Key parameters for the capacity deferral model are summarized in Table 5-1.

Table 5-1: Input for Capacity Deferral Model

Parameter	Base case	Source
Battery Unit Cost	0.5 Hours: $2600/kWh 0.5-2 Hours: $1400/kWh >2 Hours: $400/kWh	(EIA 2018)
Capex Cost Escalation	2%	(Bureau of Labor Statistics 2018)
Deferrable Capex	1-10% of PECO Distribution Capex Budget ($3-30 MM/year)	(PECO 2018)
Deferral Time Min	1 Year	-
Deferral Time Max	20 Years	-
Discount Rate (for estimating average rate change)	5%	-
Energy Growth Rate	0.6%	(PJM 2016)
Feeder Load Profile for estimating D-ELCC	Based on four feeders with mostly residential customers and weather driven load modeling	(PECO 2018) Chapter 3
Feeder Solar Profile	Average of Peach Bottom, Doylestown, Philadelphia International Airport	(NREL 2018)
Hosting Capacity	5-100%	Chapter 4 Analysis
Marginal Cost of Service	$600/kW	(PECO 2018)
Peak Demand Growth	0.7	(PJM 2016)
Solar Energy Penetration	5% Target, linear rollout from 2020-2030	-
WACC (for discounting future capital expenses)	7.7%	Based on 10% Target ROE and 5% Debt with a 53/47% split.

We worked with PECO engineers to determine which capital investments in their 5 year spending plan could be deferred to later years. Four projects were identified (PECO 2018). This “growth-related capex” is about 1% of PECO’s $300MM distribution capex budget. Based on a $600/kW MCOS, this is about 5MW of installed capacity. Thus, in our model we assume one 5MW capacity project per year that can deferred to later years.

Adding solar to the service territory reduces the loading and defers some growth-related capex to later years. The length of time that the capacity investment is deferred depends on the reduction in load created by solar's effective capacity and the feeder load growth, as described by Equation 5-1.

$$Deferral\ Time = \frac{\ln\left(\frac{capacity\ of\ congested\ area}{capacity\ of\ congested\ area - effective\ solar\ capacity}\right)}{\ln(growth\ rate)} \quad (5\text{-}1)$$

Occasionally, enough solar can accumulate on feeders during a deferral period to allow another deferral after the initial deferral period expires. We set the maximum deferral time to 20 years.

We estimate the feeder load growth from the average growth rate of four PECO growth-related capacity projects over the last 5 years. We find that the growth in these areas is low, averaging 0.3%. This average excludes two large load increases of 100% and 50% that are likely one-time load changes from new customer connections.

The reduction in load depends on the capacity credit assigned to solar, which in turn, depends on the yearly penetration of solar. To be consistent with power systems standards, we call this capacity value the Distribution Effective Load Carrying Capability (D-ELCC), which we define as the net load reduction relative to solar system size. Our estimates of the D-ELCC are shown in Figure 4-10 and are based on 19 years of solar and loading profiles from weather driven simulations. D-ELCC$_{worst}$ describes how much solar can reduce the largest net peak load over 19 years for each penetration. It does not allow any overloading. Most PECO feeders peak in the evening, so the D-ELCC$_{worst}$ is low.

For capacity deferral projects where transformer overloading is the main constraint, relying on the inherent overloading flexibility of transformers rather than on costly energy storage can increase the D-ELCC. D-ELCC$_{age}$ allows occasional overloading but limits the total transformer deterioration (i.e. transformer "aging", estimated using IEEE Standard C57.91™) to the amount incurred during typical weather normalization planning processes. Because solar reduces transformer loading more often than it increases transformer loading, D-ELCC$_{age}$ is higher than D-ELCC$_{worst}$.

To complement D-ELCC$_{worst}$, Figure 4-10 also shows the amount of energy storage required at varying solar energy penetrations to ensure a D-ELCC of 50% and 100%. The energy storage requirement is based on the maximum energy overload (MWH) over 19 years, assuming that solar has a D-ELCC of either 50% or 100%. The energy storage duration is the ratio of the peak and energy overload. Further details can be found in Chapter 3. Based on a recent study by the EIA (2018), we assume that storage with a duration less than 0.5 hours costs $2600/kWh, between 0.5 - 2 hours costs $1400/kWh, and storage greater than 2 hours costs $400/kWh. All estimates of the value of solar and total deferral value include these storage costs.

The capacity deferral value associated with solar depends on how solar is deployed in congested areas. We consider the ‘No Targeting’ and ‘Targeted Placement’ scenarios in our analysis. In the ‘No Targeting’ scenario, solar is placed randomly throughout the service territory. The solar energy penetration on a deferrable project depends only on the target solar energy penetration over the solar rollout and the year of the rollout. In a given year, if the amount of solar in an overloaded location is very small there may not be enough solar to defer capex by at least a year, and the deferral opportunity will be missed. Because the solar accumulates over time, there may be enough solar to defer investments in later years.

In the ‘Targeted Placement’ scenario, solar is added to a capacity deferral project until the hosting capacity limit is reached. The total solar capacity installed on overloaded feeders cannot exceed the total incremental amount of solar capacity that becomes available each year. The relatively low number of capacity deferral projects means that there is enough solar to reach high hosting capacity limits. This is true even in most years beyond 2030 when solar is being added to maintain a constant penetration as load grows. Although we do not include 'Targeted Compensation' in our analysis, we do estimate the value of solar under targeted placement if only solar owners are compensated.

Figure 5-1 shows how yearly capacity investments change under these planning scenarios. Solar is not very effective at deferring capacity investments in the 'No targeting' scenario. There is not enough accumulated solar to defer a capacity project until the year 2025, and then, the deferral time is only one year. Capacity investments in the years following 2025 are also deferred by one year, so 2025 is the only year without any capacity investments.

Targeted placement and energy storage are more effective at deferring capacity investments. Without energy storage, targeted placement is able to defer investments by three years, including at the beginning of the solar rollout. There is enough solar added after 2030 that projects can continue to be deferred after 2030. Energy storage resulting in a 50% D-ELCC leads to 10-year deferral times. Capacity projects deferred beyond 2040 are discounted to the year 2040 using PECO's 7.7% weighted average cost of capital (WACC).

The capacity investments in Figure 5-1 are used with a $600/kW MCOS and 2% escalation rate to generate a yearly cashflow. The cashflow is added to PECO's ratebase and depreciated with straight-line depreciation to determine yearly rates. Because deprecation will continue to take place beyond our study horizon (2016-2040), the net present value of solar and total deferral value-unlike rates-are instead calculated directly from the cashflow. The differing time horizons result in small inconsistencies between the rate impact and total deferral value for some scenarios.

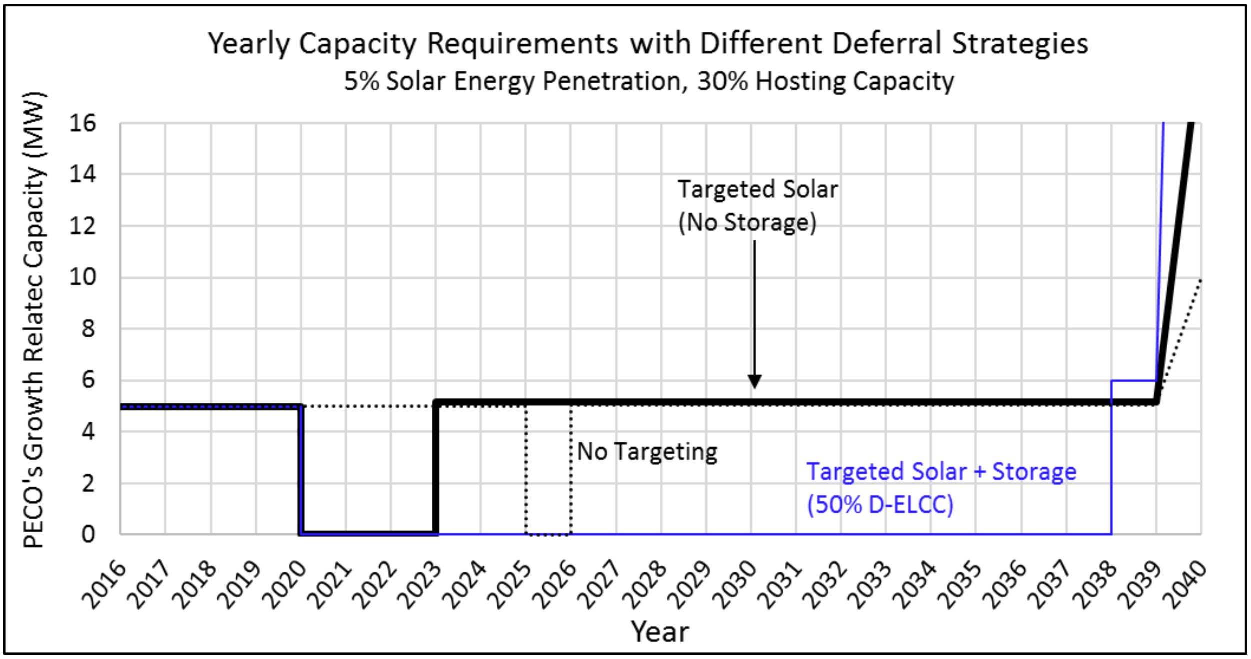

Figure 5-1: Capacity investments are deferred to later years when solar is added to PECO's service territory. Without any solar, PECO installs approximately 5MW of capacity that could be deferred every year. Without targeting, enough solar does not accumulate until the year 2025 to defer capacity projects and the deferral time is only 1 year. Targeted solar without storage and targeted solar with enough storage for a 50% D-ELCC, defer projects by 3 years and 18 years, respectively.

5.4 Results

The ability of solar to create deferral value and reduce rates is strongly influenced by network characteristics and whether solar is targeted at overloaded networks. Hosting capacities below 30% and peak load growths greater than 1% in overloaded networks both reduce the deferral value. A low D-ELCC can also eliminate deferral value and is common on PECO's evening peaking feeders, but options exist: energy storage can be used with solar, or if small amounts of overloading are allowed the D-ELCC increases rapidly. The largest source of uncertainty for capacity deferral value is the number of yearly projects that are deferrable.

Figure 5-2 shows the total deferral value for targeted and untargeted solar placement. Assuming the worst-case D-ELCC and a 30% hosting capacity, targeted placement increases the total deferral value approximately fourfold. The total deferral value increases further when the transformer aging D-ELCC or energy storage is used. This increase applies to both targeted and untargeted scenarios but the increase with targeted placement is larger. Justification for the 30% hosting capacity is found in Figure 4-12, where we observe relatively few voltage violations below 10% energy penetration (approximately the same as a 30% hosting capacity) on four PECO feeders.

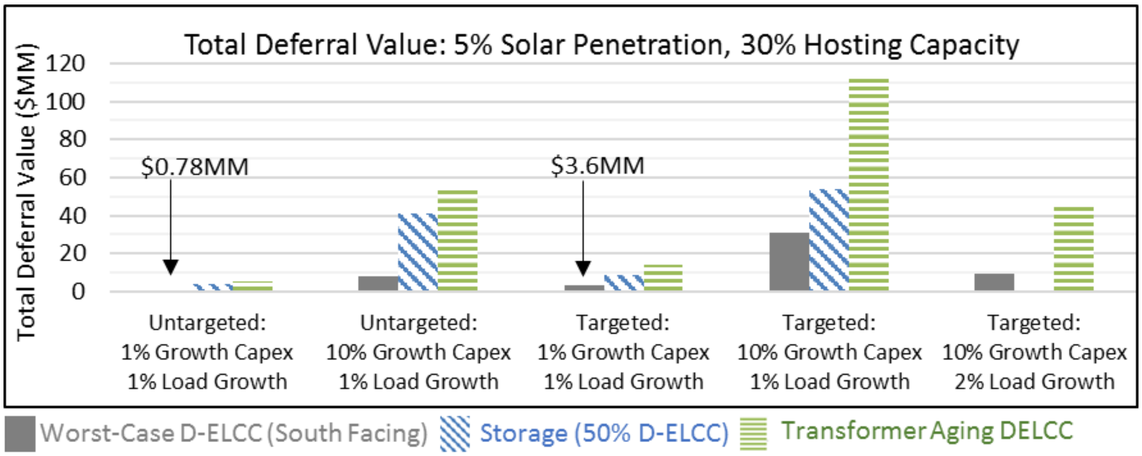

Figure 5-2: Total deferral value generated by untargeted and targeted solar placement. Assuming the Worst-Case D-ELCC, targeted placement increases the total deferral value approximately fourfold. The greatest deferral value is created with the transformer aging D-ELCC, followed by energy storage scenario which includes battery costs. A 2% load growth eliminates most savings because the deferral times are shorter.

Figure 5-3 and Figure 5-4 show the customer rate impact and earnings impact. The rate impact and total deferral value generated is small if only 1% of PECO's distribution capex is growth-related. If 10% of PECO's distribution capex is growth-related and energy storage or the transformer aging D-ELCC is applied to deferral projects, the rate increase from solar drops from 1.1% to 0.6%. However, a higher 2% growth rate would eliminate most of these savings.

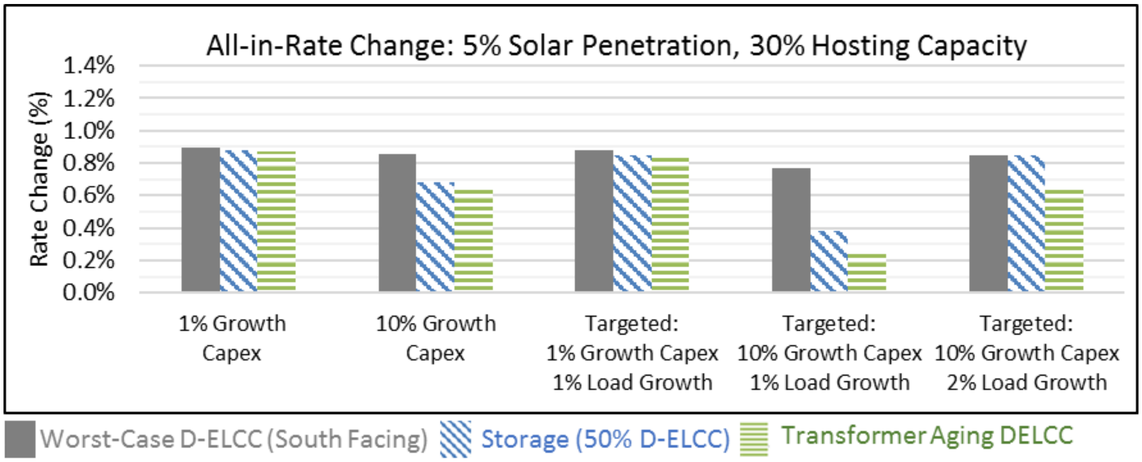

Figure 5-3: All-in-Rate Change with targeted and untargeted solar placement. Based on PECO's estimate that only 1% of their distribution capex is deferrable, both targeted and untargeted solar placement have a small effect on rates. If 10% of capex is deferrable, targeted placement is used, and storage or the transformer aging D-ELCC is applied, then there is a modest reduction in rates.

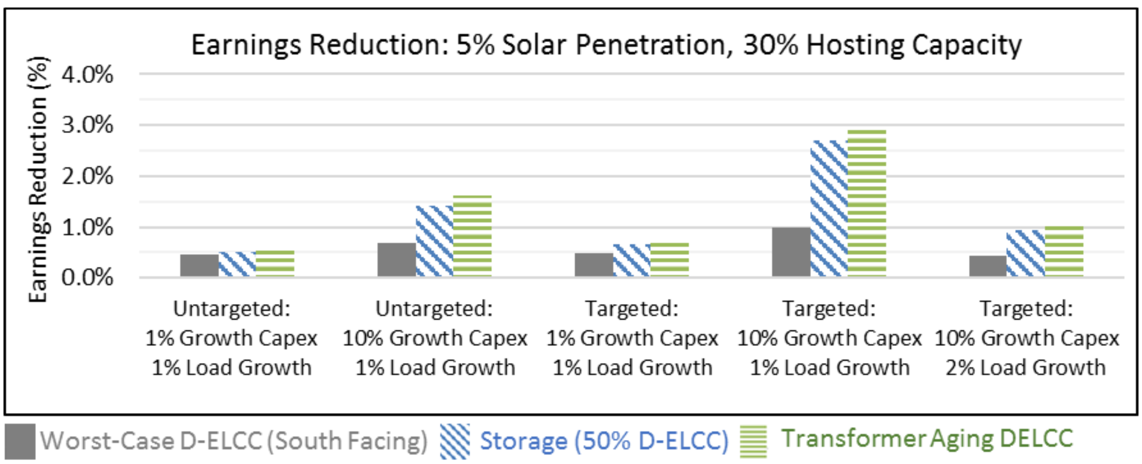

Figure 5-4: PECO earnings decrease as more capital investments are deferred.

While more challenging to monetize, longer deferral times in the targeted placement planning scenario are more manageable in the utility planning process. Without any planning in the 'no targeting' scenario, typical deferral times are just one year. In contrast, assuming the worst-case D-ELCC, targeted placement with only solar typically results in deferral times of 3 years at 30% hosting capacity. The transformer aging D-ELCC can increase the typical deferral time to 13 years. Energy storage targeting a 50% and 100% D-ELCC can increase the deferral time 18 and 20 years, respectively.

Figure 5-5 shows how the value of solar and total deferral value change for different hosting capacities. There is a rapid increase from 0-40% hosting capacity. The sawtooth pattern in the energy storage scenarios is caused by step-function decreases in storage costs as the storage duration increases. The deferral value created by storage decreases rapidly with high hosting capacities because storage size requirements increase rapidly with penetration (see Figure 4-10 or Figure 3-6).

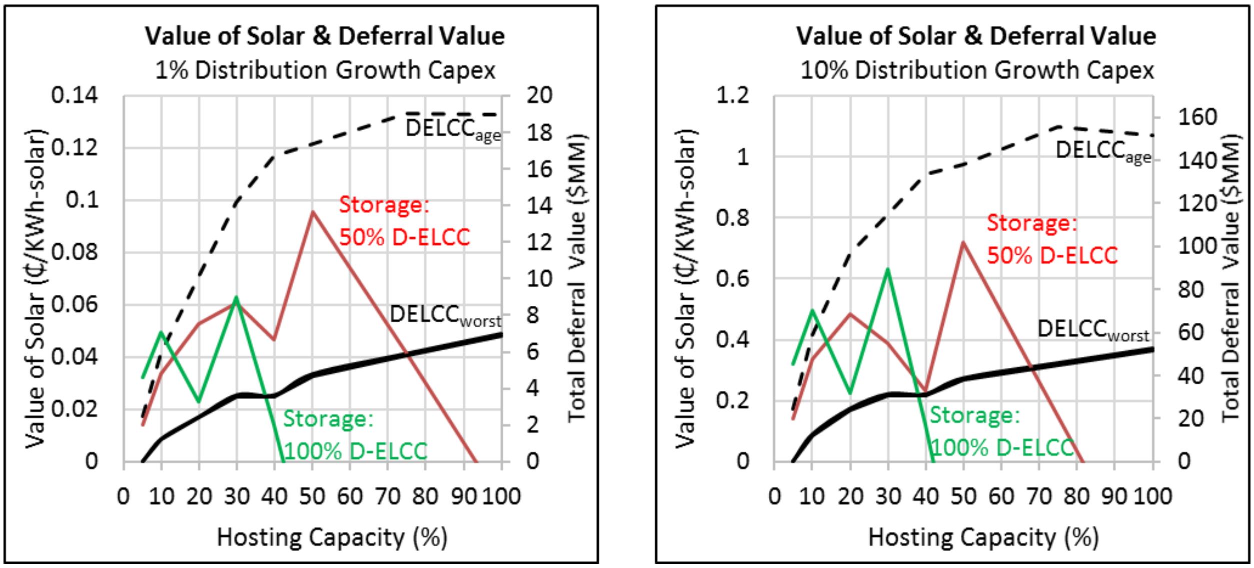

Figure 5-5: The value of solar and total deferral value increases rapidly from 0-40% hosting capacity. Energy storage does not generate additional value beyond 30-50% hosting capacity because of rising costs associated larger storage requirements.

The penetration of solar on most Pennsylvania feeders is very low. A challenge of targeted solar placement is finding enough customers interested in solar to meet the capacity deferral requirements. Utilities may be able to leverage their customer knowledge and work with third parties to achieve target solar penetrations. It is possible that financial incentives to encourage more solar installations will also be needed. Figure 5-6 shows the distribution deferral value of solar when only solar owners are compensated. The high VOS shows that there is enough value concentrated on individual feeders to encourage solar installations where they are needed. However, any incentives used to incentivize solar installations will reduce the ratepayer benefits of non-solar owners.

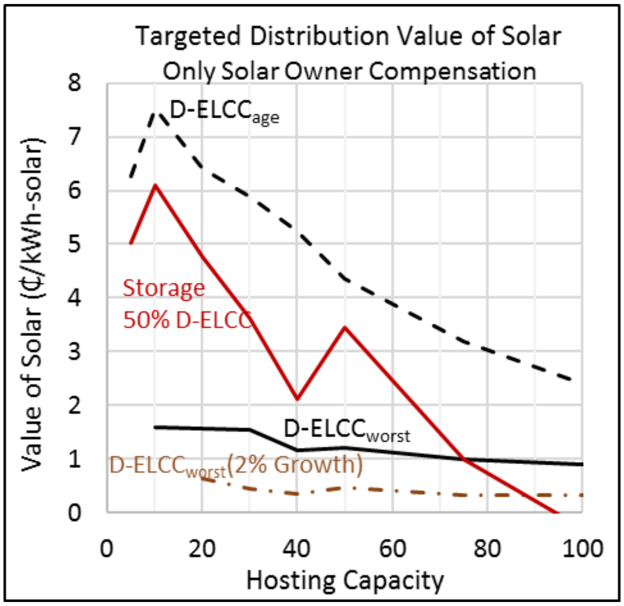

Figure 5-6: Targeted Distribution Deferral Value of Solar when allocated only to solar owners on overloaded networks. The value of solar is high enough to encourage new customers to install solar. High (2%) growth causes a steep reduction in the value of solar.

5.5 Policy Recommendations

Deferral opportunities created by rooftop solar may serve as a modest opportunity for reducing rates, but several obstacles exist. In the PECO service territory, PECO engineers have identified few deferral opportunities. We recommend that the Pennsylvania PUC and utilities include an analysis of growth-related deferral opportunities in the standard least-cost planning process, and we offer the same recommendation to other states investigating the value of solar for their utilities.

In states with more deferrable growth-related projects, it is important to estimate the deferral value. States experiencing more deferrable opportunities may have higher load growth on their feeders, which can reduce the deferral time and the deferral value.

Using solar as a capacity resource for overloaded networks is often met with skepticism among utility managers, but we find this challenge can be managed with either energy storage or a D-ELCC metric that allows occasional overloading. In the short term, due to its cost effectiveness and low risk, we recommend that utilities do capacity deferral pilots with solar and storage. In the long term, utilities should consider deploying solar without storage as a capacity deferral solution. In Chapter 3, we show that the D-ELCC is high in regions with a strong solar resource. On evening peaking feeders, like in the PECO service territory or in regions with weaker solar, allowing occasional overloading on transformers can increase the effective capacity of solar and generate more deferral value. Transformers are designed to withstand loading beyond their nameplate capacity, and the effective capacity of solar can be set so that transforming aging does not increase with solar.

Finally, we recommend targeted placement of solar. Compared to untargeted placement, targeted placement can increase the total deferral value as much as fourfold. It also increases the total deferral time and will be more manageable within the utility planning process. In the PECO service territory, however, we did not observe enough total deferral value to warrant managing deferral opportunities with overly complicated market or administrative processes.

5.6 Discussion and Future Research

To summarize, we find that solar may modestly increase rates and that the value of solar at 5% energy penetration can be increased up to fourfold if solar is targeted at overloaded locations. Based on Chapter 4, we estimate that a 5% solar energy penetration of solar would increase rates by 0.9% over a 20-year horizon. This estimate assumes untargeted placement of solar, a low effective capacity (i.e. the reduction in peak load relative to solar's nominal capacity), a 1% growth rate, and based on a PECO engineering assessment, 1% of PECO's distribution capex budget that is deferrable. Targeted placement of solar, a higher effective capacity using energy storage, a 30% hosting capacity and 10% growth-related capex could reduce the rate increase to 0.4% and generate $50MM of deferral value over the same 20-year time horizon. We conclude that capacity deferral with solar should be included in PECO's planning process but that large administrative efforts to manage deferral projects, such as markets, are probably not warranted.

In our work, we were surprised at the low number of PECO capacity deferral opportunities. As stated above, PECO engineers identified only $3MM per year of deferrable projects. In contrast, PECO plans to spend approximately $50MM per year on projects related to aging infrastructure and resiliency. This spending is partially related to Pennsylvania's Long-Term Infrastructure Investment Plan (LTIIP) that encourages utility investment in aging infrastructure by bypassing the rate case process and allowing quarterly rate increases to cover capital investments.

The high amount of LTIIP spending may be indirectly related to PECO's low growth-related spending. PECO, like many utilities, makes capacity investments assuming worst-case loading scenarios. Consequently, it is more likely for distribution equipment to reach its age limit before it becomes overloaded, and the capacity deferral paradigm may not be the best way to value solar and other Distributed Energy Resources (DER).

Utilities could make smaller capacity investments and deploy DER so that infrastructure reaches its age limit and loading limit at similar times. Further research is needed to determine whether this more complicated planning process would create savings. Utility engineers often justify making larger capital investments by citing the low marginal cost of equipment with more capacity. The low marginal cost of more capacity would need to be included in any assessment of using more DER. Research would also be needed to value the optionality of DER, which creates immediate savings through smaller capacity investments, but may never be deployed on a feeder.

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5.8 Supporting Materials

5.8.1 Planning with solar compared with rollout scenario analysis

Cohen et al. (2016), do a sensitivity analysis on the VOS by varying the rollout speed of solar in the entire PG&E service territory. This sensitivity analysis does not model the same effect as targeted placement. If utilities are planning with solar, then the VOS increases when solar is deployed as near as possible to the anticipated overload year. Otherwise, the utility must begin paying solar customers before they are producing any deferral value. The rollout scenarios used by Cohen et al. (2016) miss this opportunity because each scenario is applied to all feeders regardless of when each feeder likely to be overloaded. A fast rollout scenario applied to all feeders will create more deferral value because fewer deferral opportunities will be missed. It will also have to pay solar owners for solar generation years before a deferral occurs. Additionally, under targeted placement, the total amount of solar capacity placed on the feeder is only limited by the hosting capacity, so deferral times can be longer.

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