The Dissertation Committee for Arkasama Bandyopadhyay
certifies that this is the approved version of the following dissertation:

Techno-Economic Methods for Analyzing the Energetic and Economic Effects of Solar, Storage, and Demand Response

Committee:

Michael E. Webber, Supervisor

Benjamin D. Leibowicz, Co-Supervisor

Matthew Hall

Ross Baldick

Techno-Economic Methods for Analyzing the Energetic and Economic Effects of Solar, Storage, and Demand Response

by

Arkasama Bandyopadhyay

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Dedicated to my family, without whom I could not have started this journey,

and to my husband, Anirban, without whom I could not have finished this journey.

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Techno-Economic Methods for Analyzing the Energetic and Economic Effects of Solar, Storage, and Demand Response

Arkasama Bandyopadhyay, Ph.D.
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Supervisor: Michael E. Webber
Co-Supervisor: Benjamin D. Leibowicz

Growing population, changing climate, urbanization, and rising economic activities have led to an overall increase in electricity demand. Maintaining the balance between supply and this increasing demand often necessitates the usage of old, inefficient, and environmentally-polluting generators as well as the construction of expensive generation, transmission, and distribution infrastructure. Demand response initiatives (e.g. time-varying electricity prices) and distributed energy resources (DERs), like solar photovoltaic panels and onsite energy storage systems, can help offset a portion of this demand while simultaneously reducing harmful emissions. DERs additionally provide a variety of value streams including peak load reduction, energy arbitrage, real time price dispatch, demand charge reduction, congestion management, voltage support, etc. The impact of price-based demand response and DERs at the electricity distribution level is assessed in this dissertation through the following three studies: (1) quantifying the reduction in 4 coincident peak (4CP) loads and Transmission Cost of Service (TCOS) obligations of electric utilities using local distributed solar and storage, (2) evaluating the peak load reduction/shift potential of time-varying electricity pricing in the residential sector, and (3) investigating the combined energetic and economic potential of DERs and time-varying electricity pricing in the residential sector.

When the Electric Reliability Council of Texas (ERCOT) peaks for a single 15-minute interval during each summer month between June and September, the loads of individual Distribution Service Providers (DSPs) in the same time interval are recorded. The averages of these DSP loads, defined as 4CP loads [1], are used to calculate TCOS obligations that each DSP must pay Transmission Service Providers (TSPs) in the next calendar year as compensation for using their transmission infrastructure. First, a generalized tool is built to forecast the change of 4CP loads and corresponding TCOS obligations for electric utilities within ERCOT based on varying amounts of solar and storage capacity. The tool is illustrated by using empirical electricity demand data from the municipally-owned utility in Austin, TX (Austin Energy) and solar generation data from the PVWatts calculator developed by the National Renewable Energy Laboratory. TCOS obligations can be on the order of tens of millions of dollars. Results indicate that solar and storage capacity can substantially lower these payments. For example, a 20 MW increase in local solar capacity in 2018 would reduce Austin Energy's payment by an estimated $180,000 for each subsequent year. By using the novel approach of incorporating coincident peak demand charge reductions at the distribution level, the economic value of local generation and storage is highlighted.

Next, a convex optimization model is developed to analyze the potential for time-varying electricity rate structures to reduce and/or shift peak demand in the residential sector. In this model, a household with four major appliances minimizes electricity costs, with marginally increasing penalties for deviating from temperature set-points or operating appliances at inconvenient times. The four specific appliances included are: heating, ventilation and air-conditioning (HVAC) systems, electric water heaters (EWHs), electric vehicles (EVs), and pool pumps (PPs). The study incorporates a one-parameter thermal model of the home and the electric water heater, so that the penalties can apply to the room and water temperatures rather than the total appliance loads. Analysis is performed on a community of 100 single-family detached homes in Austin, TX. These homes each host a combination of the four end-use devices while some also have onsite solar panels. Results show that dynamic pricing effectively shifts the residential peak away from the time of overall peak load across the electricity system, but can have the adverse impact of making the residential peak higher. The energy consumption does not differ significantly across the different rate structures. Thus, it can be inferred that the time-varying rates encourage customers to concentrate their electricity demand within low-price hours to the extent possible without incurring significant inconvenience. By incorporating the novel approach of including monetary value of customer behavior in price-based demand response models, this study builds a tool to realistically quantify peak load reduction and shifts in the residential sector.

Finally, the convex optimization model is extended to consider larger sets of distributed technologies that might be deployed in homes and investigate how different combinations of these technologies affect peak grid load, energy consumption from the grid, and emissions in the residential sector under time-varying pricing structures. In the model, households with varied amalgamations of distributed energy technologies minimize electricity costs, amortized capital, and operational costs over a year, with marginally increasing penalties for deviating from room temperature set-points. The four technologies considered are: solar photovoltaic (PV) panels, lithium-ion batteries, ice cold thermal energy storage (CTES), and smart thermostats. Results show that from an economic perspective, it is optimal for residential customers to install solar panels under tiered rates, time-of-use rates, and critical peak prices while it is cheapest to own a combination of solar panels and smart thermostats when real-time prices and demand charges are in effect. The capital and installation costs of both storage systems are still too high to make them economically profitable investments for typical residential customers. Additionally, solar panels are the main instruments to reduce energy purchased from the grid and carbon dioxide emissions under all pricing schemes. Adding smart thermostats can reduce these metrics to a greater extent by making the home energy-efficient. Further, while the energetic effect of the two storage systems can be favorable or detrimental depending upon the load profile of the particular household and the pricing structure, lithium-ion batteries are the main instruments to avoid high demand charges by spreading the demand in the home (and power bought from the grid) evenly to the extent possible without incurring significant customer discomfort. Thus, this study recommends that residential customers invest in solar panels and smart thermostats to minimize overall annual expenditure and make their homes environmentally efficient. Further, as an effective peak load control mechanism, electric utilities should offer significant rebates to encourage residential customer investment in storage systems in addition to subjecting them to demand charges.

Electricity generation from intermittent renewable energy sources has grown rapidly worldwide. DER installation levels continue to rise with the decline in capital costs of energy storage systems and local renewable generation assets, the growth of supportive government policies, and rising concerns about climate change among the masses. Additionally, electric utilities are increasingly employing demand response initiatives to curtail and/or shift peak demand. As a whole, the body of work developed in this dissertation can be used by electric utilities to make optimal decisions about dynamic rate design and policies for increased DER adoption. It can also be used by residential electricity customers to maneuver their own energy consumption patterns and assess the economic viability of investing in DERs.

Table of Contents

List of Tables

List of Figures

Glossary

Acronym	Definition	Units
α_{EV}	Inconvenience parameter for EV	\$
α_{EWH}	Discomfort parameter for EWH	$\$/^0\mathrm{C}^2$
α_{HVAC}	Discomfort parameter for HVAC	$\$/^0\mathrm{C}^2$
α_{PP}	Inconvenience parameter for PP	\$
$\gamma_{bat,\ loss}$	Energy loss coefficient of the lithium-ion battery	%/hour
$\gamma_{ice,\ CTES,\ loss}$	Energy loss coefficient of the ice CTES	%/hour
Δt	Time interval	hour
$\eta_{bat,\ rt}$	Round-trip charging and discharging efficiency of the lithium-ion battery	–
η_{EV}	Efficiency of EV charging	–
η_{EWH}	Efficiency of EWH	–
$\eta_{ice,\ CTES,\ rt}$	Round-trip charging and discharging efficiency of the ice CTES	–
η_{PP}	Efficiency of PP motor	–
ρ	Density of water	$\mathrm{kg/m^3}$
4CP	4 coincident peak	MW
AC	Air-conditioner	–
AE	Austin Energy	–
AMI	Advanced metering infrastructure	–
CAP	Capital cost	\$
CO_2	Carbon dioxide	–
COP	Coefficient of performance	–
COP_{cool}	Coefficient of performance of the H&C engine while cooling	–
COP_{heat}	Coefficient of performance of the H&C engine while heating	–
COP_{ice}	Coefficient of performance of the H&C engine while making ice	–
C_p	Specific heat capacity of the water	J/kg·K
$C_{p,a}$	Specific heat capacity of the air	J/kg·K
CPP	Critical peak prices	\$/kWh
C_t	Cost of electricity at time step t	\$/kWh
CTES	Cold thermal energy storage	–

DER	Distributed energy resources	–
DG	Distributed generation	–
DR	Demand response	–
DSP	Distribution service provider	–
$E_{bat,1}$	Energy capacity of the lithium-ion battery at the first time step	kWh
$E_{bat,initial}$	Initial energy capacity of the lithium-ion battery	kWh
$E_{bat,max}$	Maximum energy capacity of the lithium-ion battery	kWh
$E_{bat,min}$	Minimum energy capacity of the lithium-ion battery	kWh
$E_{bat,t}$	Energy capacity of the lithium-ion battery at time step t	kWh
$E_{EV,\ consumed,\ daily}$	Energy used to charge the EV throughout the day	kWh
$E_{ice,\ CTES,1}$	Thermal energy capacity of the ice CTES at the first time step	kWh_{th}
$E_{ice,\ CTES,\ initial}$	Initial thermal energy capacity of the ice CTES	kWh_{th}
$E_{ice,\ CTES,\ max}$	Maximum thermal energy capacity of the ice CTES	kWh_{th}
$E_{ice,\ CTES,\ min}$	Minimum thermal energy capacity of the ice CTES	kWh_{th}
$E_{ice,\ CTES,\ t}$	Thermal energy capacity of the ice CTES at time step t	kWh_{th}
$E_{PP,\ consumed,\ daily}$	Energy used by the PP throughout the day	kWh
EPRI	Electric Power Research Institute	–
ERCOT	Electric Reliability Council of Texas	–
ESS	Energy storage system	–
EV	Electric vehicle	–
EWH	Electric water heater	–
F	Hot water flow rate	m^3
FPL	Florida Power & Light	–
H&C engine	Heating and cooling engine	–
HVAC	Heating, ventilation, and air-conditioning	–
ISO	Independent system operator	–
ITC	Investment Tax Credit	–
M_a	Mass of indoor air	kg
N	Total number of time steps	–
NREL	National Renewable Energy Laboratory	–
O&M	Operations and maintenance cost	$
OG&E	Oklahoma Gas & Electric	–

$P_{bat,\ charge,\ t}$	Power used to charge the lithium-ion battery at time t	kW
$P_{bat,\ discharge,\ t}$	Power discharged from the lithium-ion battery at time t	kW
$P_{bought,\ grid,\ t}$	Power bought from the grid at time t	kW
$P_{bought,t}$	Power bought from the grid for use in the home at time step t	kW
$P_{electric,\ H\&C,\ t}$	Power consumed by the H&C engine at time t	kW
P_{EV}	Rated power of the EV	kW
P_{EWH}	Rated power of the EWH	kW
$PG\&E$	Pacific Gas & Electric	–
$P_{H\&C,\ home,\ cool,\ t}$	Thermal power flowing from the H&C engine to cool the home at time t	kW_{th}
$P_{H\&C,\ home,\ heat,\ t}$	Thermal power flowing from the H&C engine to heat the home at time t	kW_{th}
$P_{H\&C,\ ice,\ CTES,\ t}$	Thermal power flowing from the H&C engine to charge the ice CTES at time t	kW_{th}
P_{HVAC}	Rated power of the HVAC system	kW
$P_{ice,\ CTES,\ home,\ t}$	Thermal power flowing from the ice CTES to the home at time t	kW_{th}
$P_{max,H\&C}$	Maximum thermal power output of the H&C engine	kW_{th}
PP	Pool pump	–
P_{PP}	Rated power of the PP	kW
$P_{solar,\ gen,\ t}$	Power generation by the solar panels at time step t	kW
$PUCT$	Public Utility Commission of Texas	–
$P_{uncontrollable,t}$	Uncontrollable power at time step t	kW
$P_{use,\ home,\ t}$	Power used in the home at time step t	kW
PV	Photovoltaic	–
R	Thermal resistance of the tank insulation	$m^2{\cdot}K/W$
$R_{charge,\ max}$	Maximum charging rate of the lithium-ion battery	kW
$R_{discharge,\ max}$	Maximum discharging rate of the lithium-ion battery	kW
REC	Renewable energy credit	–
$REopt$	Renewable Energy Optimization	–
REP	Retail electric provider	–
R_{eq}	Equivalent thermal resistance of the building envelope	K/W
$R_{ice,\ CTES,\ charge,\ max}$	Maximum thermal charging rate of the ice CTES	kW_{th}

$R_{ice,\ CTES,\ discharge,\ max}$	Maximum thermal discharging rate of the ice CTES	kW_{th}
RPS	Renewable Portfolio Standard	–
RTP	Real-time prices	\$/kWh
SA	Surface area of the EWH tank	m^2
$SCADA$	Supervisory control and data acquisition	–
SCE	Southern California Edison	–
SDG&E	San Diego Gas & Electric	–
S_{EV}	Operational level of EV	–
S_{EWH}	Operational level of EWH	–
S_{HVAC}	Operational level of HVAC system	–
S_{PP}	Operational level of PP	–
$T_{amb,t}$	Ambient temperature at time step t	K
$TCOS$	Transmission cost of service	\$
$TCRF$	Transmission cost recovery factor	\$/kWh
$TDSP$	Transmission and distribution service provider	–
TOU	Time-of-use rate	\$/kWh
$T_{r,\ max}$	Customer-specified maximum room temperature	K
$T_{r,\ min}$	Customer-specified minimum room temperature	K
$T_{r,sp,t}$	Set-point temperature of the room at time step t	K
$T_{r,t}$	Temperature of the room at time step t	K
TSP	Transmission service provider	–
$T_{water,\ in}$	Incoming cold water temperature	K
$T_{w,\ max}$	Customer-specified maximum water temperature	K
$T_{w,\ min}$	Customer-specified minimum water temperature	K
$T_{w,sp,t}$	Set-point temperature of the water at time step t	K
$T_{w,\ t}$	Temperature of water inside the EWH at time t	K
$T_{w,t}$	Temperature of the water at time step t	K
VOS	Value of Solar	\$/kWh

Chapter 1

Introduction

1.1 Motivation

According to the International Energy Agency, worldwide electricity demand grew by 4% or 900 TWh in 2018 [4] and is projected to continue increasing due to population growth, economic expansion, climate change, and urbanization. To avoid grid instability and multiple rolling blackouts, a balance between supply and this increasing demand must be maintained. In the conventional approach to grid management, this need necessitates the construction of expensive generation, transmission, and distribution infrastructure [5,6] and usage of old, inefficient, and environmentally polluting generators like diesel [7].

Worldwide carbon dioxide (CO_2) emissions from the electricity sector also rose by 2.5% in 2018 [4]. One of the major drivers for increased emissions from the electricity sector is rising peak demand, which is often met by fossil fuel generation [8]. Additionally, electric utilities are forced to invest in expensive network

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Some sections of this chapter were adapted from the peer-reviewed conference publication: A. Bandyopadhyay, J. D. Rhodes, J. P. Conger, and M. E. Webber, How solar and storage can reduce coincident peak loads and payments: A case study in Austin, TX, *Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Pittsburgh, PA*. Volume 6B: Energy ():V06BT08A023. DOI:10.1115/IMECE2018-86482 [2]. The majority of the paper's research, analysis, and writing were completed by the author of this dissertation. The co-authors contributed via cognitive interpretation and editing. Some sections of this chapter were also adapted from the journal article: A. Bandyopadhyay, B. D. Leibowicz, E. A. Beagle, M. E. Webber, As one falls, another rises? Residential peak load reduction through electricity rate structures, *Sustainable Cities and Society*, 2020 [3]. The majority of this paper's research, analysis, and writing were completed by the author of this dissertation. The co-authors contributed to defining the direction of this project and editing the manuscript.

infrastructure every year solely to meet increasing peak demand [5]. About 10% of electric system capacity in the United States is built to meet demand in just 1% of hours during the year [9] and thus the additional infrastructure built to serve peak load sits idle for a majority of the year. According to the Intergovernmental Panel on Climate Change, some of the strategies for reducing emissions from the electricity sector include shifting generation from higher-emitting coal plants to lower-emitting natural gas plants, building new nuclear generating capacity, encouraging usage of energy-efficienct devices and retrofitting efforts in homes and businesses, increasing installation of renewable energy generators, increased carbon capture and sequestration efforts, etc. [10]

Demand response initiatives and Distributed Energy Resources (DERs) like on-site solar panels and energy storage systems can potentially reduce peak power bought from the grid, energy consumption from the grid, and emissions [11, 12]. Demand response refers to the change in electricity consumption patterns of customers as a result of time-varying electricity prices or incentive programs intended to reduce consumption during periods of high wholesale market prices or low generation adequacy [11].

DERs refer to electric power generation resources and storage technologies connected to low-voltage or medium voltage distribution systems rather than bulk power transmission networks [12]. In addition to the benefits mentioned above, DERs also provide other value streams including voltage support, transmission congestion management, coincident and non-coincident peak reduction, electric supply reliability and quality, etc. [13]. The penetration of DERs has increased rapidly over the past few years as a result of supportive government policies, technological development, rising concerns over climate change, and declining capital costs [12, 14, 15].

As the electricity distribution sector changes with the increase of DERs, rise in EV adoption, smart meters, two-way communication between the customer and the utility, dynamic pricing, and utility rebates and incentives, it is important to quantify the economic and energetic impacts of demand response and DERs like solar photovoltaic (PV) and energy storage systems. While these topics have been studied extensively by many researchers, some knowledge gaps exist which are described below.

In the Texas electric market, open access to transmission allows Distribution Service Providers (DSPs) to use the transmission infrastructure of Transmission Service Providers (TSPs) [16]. The usage costs are recovered by TSPs in the form of transmission cost of service (TCOS) obligations. When the Electric Reliability Council of Texas (ERCOT) peaks for a single 15-minute interval during each month between June and September, the peak loads of individual DSPs during the same interval are recorded and averaged to calculate their 4 coincident peak (4CP) loads [1]. These loads, along with a transmission rate pre-approved by the Public Utility Commission of Texas (PUCT) [17], are used to calculate TCOS obligations that each DSP, based on their relative share of the 4CP, must pay the TSPs in the next calendar year. Several utilities like Austin Energy, Centerpoint Energy, Bryan Texas Utilities, and Bluebonnet Electric Cooperative serve as both TSPs and DSPs and are known as Transmission and Distribution Service Providers (TDSPs). TDSPs both deliver and receive TCOS payments and the net payment delivered can be substantial; for example, the greatest net TCOS delivered within ERCOT in 2019 was $544 million [18]. DSPs usually recover these fees by charging large commercial and industrial customers for their contribution to the coincident peak [19] and from other customer classes via mechanisms like transmission cost recovery factors. While many researchers analyze the effects of local generation and demand response on reduction in coincident peak load and payments of large commercial customers [7,20], the impact of local renewable generation and storage on coincident peak load and TCOS obligations from the perspective of the TDSP has not been studied previously in academic literature. As these payments can be on the order of tens of thousands of dollars, it is essential to take a 'bird's eye view' and analyze coincident peak demand charge reductions at the DSP level.

Demand response or load control has several benefits including incentive payments and reduced monthly electricity bills for end-use customers, fewer power outages, and avoidance of building new generation, distribution and transmission infrastructure [11]. Although the load reduction potential in the industrial and commercial sectors is higher, demand response can also have a substantial impact on the residential sector because of the large number of residential customers and the regular usage of a variety of energy-intensive domestic appliances [5]. The residential sector accounts for 27% of global final electricity consumption, 17% of global carbon emissions, and comprises half of the summer peak demand in hot climates like Texas [21–23].

A branch of the demand response literature focuses on analyzing findings from historical dynamic pricing pilot programs launched by electric utilities [24–28]. Another line of research focuses on quantifying peak load reduction and economic savings in the residential sector using optimization models [29–43]. However, most of these economic models neglect the monetary value of the effort, time, and discomfort experienced by customers who reduce and/or shift their loads in response to incentives offered by the local electric utility. Thus, these models are limited in their ability to realistically model peak load shifts and/or reductions in the residential sector.

Several optimization and algorithmic studies exist to analyze the combined effects of DERs and demand response strategies on residential energy consumption patterns and customer expenditure [44–48]. Again, most of these models do not incorporate the economic value of discomfort/inconvenience of customers. Further, there is a lack of a comprehensive analysis accounting for different combinations of distributed energy technologies and dynamic pricing structures for a community of homes. Such an in-depth study is necessary to help utilities make decisions about dynamic rate design and prioritize the penetration of DERs in order to improve system economics and environmental performance. Additionally, while ice cold thermal energy storage (CTES) systems are extensively studied in the commercial sector [49–51], their applicability in the residential sector has barely been explored. The limited number of articles analyzing residential ice CTES have exhibited significant thermal load shifting and emission reduction potential [52,53]. A study combining ice CTES with more commonly adopted DERs like solar panels and lithium-ion batteries under alternative pricing structures could highlight novel energetic and economic benefits of adopting this technology.

This work explores the effectiveness of price-based demand response (dynamic rates) and quantifies various financial and energetic value streams of solar panels and energy storage systems within and beyond the residential sector. In this dissertation, I first build a generalized calculation tool to forecast the change of 4CP loads and TCOS obligations based on varying amounts of distributed local solar and storage capacity over a 10-year period for utilities within ERCOT. This work is novel in its approach of incorporating coincident peak demand charge reductions at the DSP level. Next, I develop a convex optimization tool to model price-based demand response in the residential sector while incorporating the monetary value of customer discomfort of deviation from set-point temperatures and inconvenience of running appliances at certain times of the day. Finally, I extend this optimization framework to model the interactions among four technologies in the residential sector — solar panels, lithium-ion batteries, ice CTES, and smart thermostats — under dynamic prices.

1.2 Scope and Organization of Dissertation

The research detailed in this dissertation will add to the existing knowledge base by presenting new techno-economic methods for evaluating the efficacy of residential price-based demand response and investigating various advantages of increased penetration of DERs. Although the models developed are demonstrated using empirical energy usage and solar generation data from Austin, TX, the methodology can also be used to analyze electric utilities and residential communities.

Reproducibility of academic research is essential for ensuring transparency, transfer of knowledge, and as proof of integrity. In a 2016 survey of researchers published in *Nature*, over 70% of respondents reported that they had tried and failed to reproduce other scientists' experiments, explaining why many academics believe that there is currently a reproducibility crisis [54]. One contributing factor to the inability to reproduce experiments is that the methodology or the code is unavailable or is not provided in sufficient detail [55]. To make this entire dissertation easily replicable for other energy system modelers, I have used the open-source statistical programming language *R* for analysis, open-source optimization solver packages, and have made the detailed codes for each of the chapters available for free on Github[1]. Additionally, I have developed an *Rshiny* application so that individual households can use the model developed in Chapter 4 to optimally control their appliances in response to more complex rate structures that might be in place in the future by

[1]See https://github.com/arkasama/Dissertation for codes from each of the three analytical chapters of this dissertation.

entering the parameter values specific to their own appliances into a smart home system, tuning the model with discomfort/inconvenience parameters, and so on.[2]

1.2.1 Research Objectives

This dissertation has three main research objectives:

1. **Establish a generalized method to quantify the impact of local distributed solar and storage on reducing coincident peak loads and corresponding payments for electric utilities**

   (a) Identify the mathematical approach used to calculate TCOS obligations for electric utilities within ERCOT.

   (b) Forecast future coincident peak loads and payments for a range of scenarios.

   (c) Model the impact of different levels of currently-installed distributed solar PV and lithium-ion batteries on future reduction in 4CP loads and TCOS obligations.

2. **Develop a method to accurately model price-based demand response in the residential sector by incorporating the economic value of customer discomfort/inconvenience**

   (a) Formulate an optimization framework from the perspective of a rational household (using a bottom-up approach) to quantify peak electricity demand reduction and/or shifting in the residential sector using dynamic prices.

[2] See https://emmalaub.shinyapps.io/Peak_Load_Reduction_Tool_ver2/.

(b) Incorporate distinct discomfort functions for each household controllable appliance.

(c) Assess the impact of alternative electricity pricing on power bought from the grid, operational level of the controllable appliances, timing and magnitude of peak electricity demand, energy consumed, and greatest ramp rate.

3. **Develop a method to model the interactions among various DERs in the residential sector under price-based demand response schemes**

(a) Extend the optimization framework developed in Objective 2 to investigate the effect of different combinations of DERs and time-varying prices on annual customer expenditure, peak grid load, energy consumption from the grid, and emissions in the residential sector.

(b) Identify the particular combinations of DERs most beneficial to the customer and the electric utility.

(c) Recommend policy decisions to aid adoption of above-mentioned DERs.

As a whole, this dissertation explores the effectiveness of dynamic rates and quantifies various economic and energetic value streams of solar panels and energy storage systems within and beyond the residential sector. The work aims to aid electric utilities as they make decisions about dynamic rate design and DER rebates to curtail peak demand and/or shift energy usage. It also aims to help residential customers assess the financial viability of DER investments under alternative rate structures.

1.2.2 Dissertation Organization

The motivation, background, research methodology, and analysis to address the three objectives identified in this dissertation as well as key takeaways and future avenues of research are presented and discussed in the following chapters. The current chapter (Chapter 1) provides the motivation and practical need for the original research conducted in this dissertation, outlines each of the individual research objectives, and briefly discusses their applicability. Chapter 2 provides background information needed to understand the analysis covered in Chapters 3 – 5 and discusses relevant literature in detail to identify the knowledge gaps filled by this work.

Chapter 3 describes the development of a generalized tool to forecast the change of 4CP loads and TCOS obligations based on varying amounts of local distributed solar and storage capacity over a 10-year period for utilities within ERCOT. The methodology developed is demonstrated in a case study which uses empirical load data from Austin Energy, the local municipally-owned electric utility in Austin, TX. The basis for this chapter is a peer-reviewed conference paper published as proceedings of the *2018 ASME International Mechanical Engineering Congress and Exposition, Pittsburgh, PA* [2].

Chapter 4 develops a convex optimization tool to model price-based demand response in the residential sector while incorporating the monetary value of customer discomfort of deviation from set-point temperatures and inconvenience of running household appliances at certain times of the day. Four different electricity pricing structures are evaluated and four types of controllable loads are considered. Sensitivity analysis is performed by varying the discomfort/inconvenience parameters for the different controllable loads to analyze their effect on the peak residential electricity demand. The model is demonstrated using empirical appliance-level energy usage data from Pecan Street Inc. [56, 57] and electricity rates from Austin Energy. The basis for this chapter is a journal article published in *Sustainable Cities and Society* [3].

Chapter 5 extends the optimization framework developed in Chapter 4 to model the interactions among four technologies in the residential sector — solar panels, lithium-ion batteries, ice CTESs, and smart thermostats — under price-based demand response. Five different electricity pricing schemes are evaluated and implications for customer expenditure, peak power consumed from the grid, energy consumption from the grid, and emissions in homes with different combinations of the four technologies are recorded. The model is demonstrated using empirical energy usage and solar generation data from Pecan Street Inc. [56, 57] and electricity rates from Austin Energy.

The key findings of this dissertation are summarized in Chapter 6 along with highlighting directions for future work.

Chapter 2

Background and Literature Review

Traditionally electricity was generated in large central power plants (often, coal) located far away from cities and transported unidirectionally via transmission and distribution lines to consumers. Since then, the electric sector has changed significantly. Many environmentally polluting coal plants have been decommissioned with natural gas and renewables being the new fuels of choice. Customers no longer simply consume electrical energy but also produce and inject electricity back to the grid using DERs like small wind turbines, rooftop solar, and lithium-ion batteries (e.g. Tesla Powerwall) — thereby playing an active role in electricity markets as 'prosumers' [59]. To highlight a few other notable transitions, real time energy consumption data

Some sections of this chapter were adapted from the peer-reviewed conference publication: A. Bandyopadhyay, J. D. Rhodes, J. P. Conger, and M. E. Webber, How solar and storage can reduce coincident peak loads and payments: A case study in Austin, TX, *Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Pittsburgh, PA*. Volume 6B: Energy ():V06BT08A023. DOI:10.1115/IMECE2018-86482 [2]. The majority of the paper's research, analysis, and writing were completed by the author of this dissertation. The co-authors contributed via cognitive interpretation and editing. Some sections of this chapter were also adapted from the journal article: A. Bandyopadhyay, B. D. Leibowicz, E. A. Beagle, M. E. Webber, As one falls, another rises? Residential peak load reduction through electricity rate structures, *Sustainable Cities and Society*, 2020 [3]. The majority of this paper's research, analysis, and writing were completed by the author of this dissertation. The co-authors contributed to defining the direction of this project and editing the manuscript. The descriptions in Sections 2.2.2 – 2.2.3 were adapted from the two peer-reviewed conference publications: A. Bandyopadhyay, J. P. Conger, and M. E. Webber, Energetic Potential for Demand Response in Detached Single Family Homes in Austin, TX, *Proceedings of the 2019 IEEE Texas Power and Energy Conference, College Station, TX.* pp 1-6. DOI: 10.1109/TPEC.2019.8662166 [48] and A. Bandyopadhyay, J. P. Conger, E. A. Beagle, M. E. Webber, and B. D. Leibowicz, Energetic and Economic Potential for Load Control for Residential Customers in Austin, TX, *Proceedings of the 2020 ASME International Mechanical Engineering Congress and Exposition* [58]. The majority of both papers' data curation, research, analysis, and writing were completed by the author of this dissertation. The co-authors contributed via providing insights and editing.

are tracked with advanced metering infrastructure; digital innovation has made two-way communication between the utility and customer possible; energy consumption patterns can be altered using smart technologies like thermostats; the transportation sector is being electrified; customers are increasingly investing in energy efficient technologies and retrofitting efforts for their homes and businesses.

This dissertation develops new techno-economic methods for evaluating the efficacy of residential time varying pricing as a load control strategy and for investigating various benefits of increased penetration of DERs. The background section provides information to help comprehend the methods and analyses presented in Chapters 3 – 5 and identifies the contributions of this dissertation to the existing academic knowledge base. Sections 2.1.1 – 2.1.2 describe how transmission costs are calculated and recovered for utilities within ERCOT. Existing academic literature in this realm and associated knowledge gaps are highlighted in Section 2.1.3 along with the novel contributions made by Chapter 3. Section 2.2 introduces residential incentive-based and price-based demand response, details existing studies, and summarizes the novel contributions made by Chapter 4. Finally, Section 2.3 provides background on DERs and briefly describes government policies promoting their widespread adoption. Relevant academic literature analyzing the effect of DERs and dynamic electricity rates is also summarized along with detailed descriptions of the original contributions which Chapter 5 seeks to make.

2.1 TCOS obligations

2.1.1 Transmission and distribution

Electricity is usually not entirely consumed at the place where it is generated. Transmission lines carry bulk electric power from generation sites to substations closer to areas of demand at high voltages (above 60 kV) [60, 61]. Distribution systems are lower voltage lines which transport electricity from these substations through neighborhoods and deliver it to individual homes, businesses, and other energy users [60]. Transmission (Distribution) Service Providers own and operate the infrastructure needed to transmit (distribute) electricity [62].

2.1.2 Recovery of transmission costs in ERCOT

ERCOT is the independent system operator (ISO) for about 90% of Texas — serving more than 26 million customers [63]. It is a nonprofit corporation subject to oversight by the PUCT and the Texas Legislature [63]. Some of ERCOT's responsibilities include unbiased coordination of market transactions, system-wide transmission planning and implementation, ensuring grid reliability and adequacy, and guaranteeing 'open access to transmission' (allowing DSPs to use the transmission facilities of TSPs) [64].

ERCOT coordinates with TSPs to assess expected future demand, generation patterns, and existing network infrastructure, and also to plan new transmission lines and/or transmission system improvements where needed [64]. TSPs are financially responsible for building, maintaining, and improving transmission infrastructure [64]. They recover the related costs of transmission network upgrades and maintenance through TCOS obligations (defined previously in Chapter 1) from DSPs. Many electric utilities serve as both TSPs and DSPs, thereby both delivering and receiving these payments. The net payment delivered can be substantial — e.g. the greatest net TCOS obligation in 2018 was \$511 million and that in 2019 was \$544 million [18]. Figure 2.1 shows historical TCOS obligations from 2004 – 2018 for two utilities (a large municipal utility serving 0.5 million customers [65] and a small electric co-operative serving 6,705 customers [66]) within ERCOT.

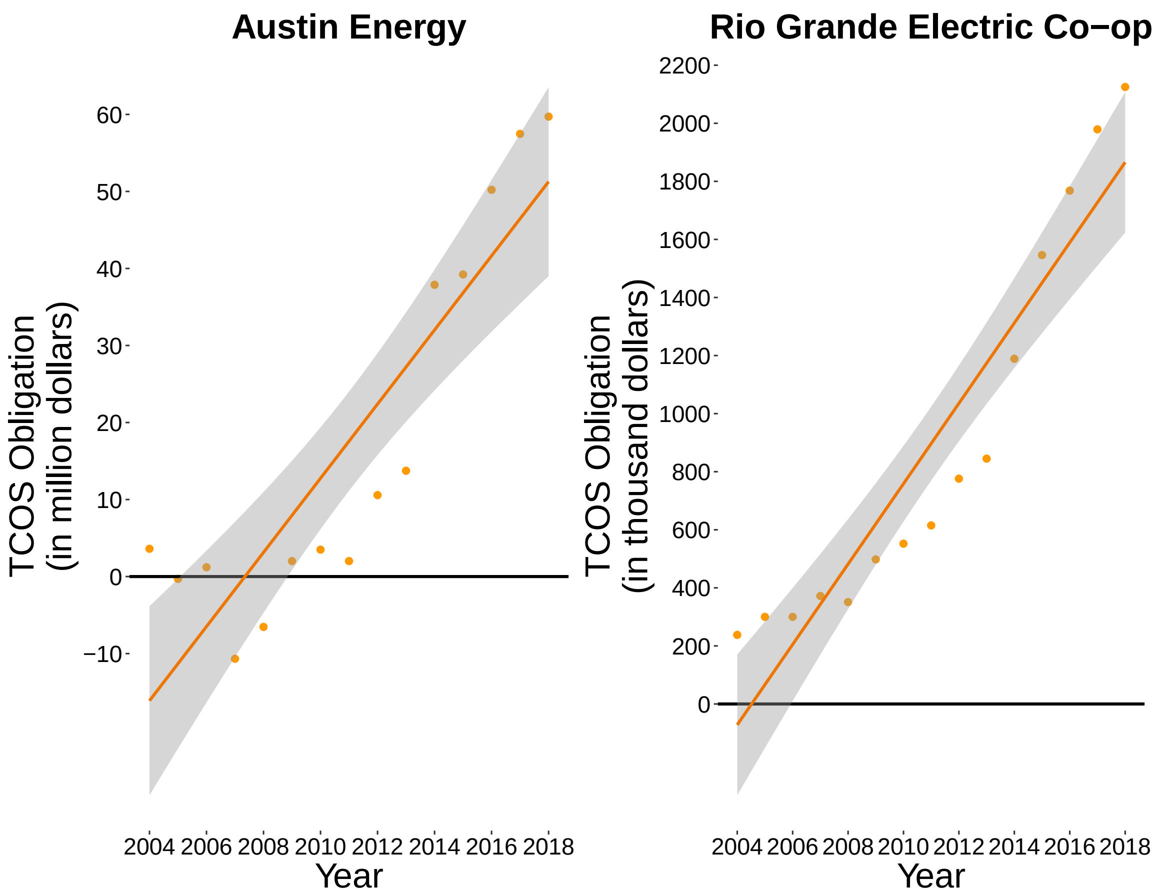

Figure 2.1: Historical net TCOS obligations (represented by the orange dots) show an increasing trend. A positive number indicates that net payment was delivered and a negative number indicates that net payment was received. The gray shaded regions represent the 95% confidence interval band width for the linear fit, which is represented by the solid orange line.

DSPs are allowed by the PUCT to pass these TCOS charges to competitive retail electric providers (REPs) through transmission cost recovery factors (TCRFs). REPs, in turn, recover these fees by incorporating a levelized monthly charge in the electricity bills of large industrial customers over the calendar year following the peak [19]. Large industrial customers within ERCOT are monitored via supervisory control and data acquisition (SCADA), using advanced metering infrastructure (AMI) that keeps track of real-time grid data throughout the ERCOT service area [67]. Each customer is then charged coincident peak prices for their relative contribution to the average of the 4CPs [19]. Municipal utilities often have their own way of recovering these costs, e.g. Austin Energy passes these fees to various customer classes through regulatory charges [68, 69].

2.1.3 Relevant academic literature

Although 4CP events correlate with ambient temperature [20] and generally occur on summer weekdays around 5 pm [70], it can be difficult to predict the actual day and timing of the peak [71]. A branch of relevant literature focuses on developing algorithms to accurately predict the coincident peak. Liu and Brown use classification algorithms like convolutional neural network (CNN), long short-term memory (LSTM), and Stacked Autoencoder to forecast the peaks 24 hours ahead of time [72]. Dowling et al. use a feed-forward neural network to estimate the probability of coincident peak events and find a more effective strategy than conventional forecasting methods using historical demand data [71].

Another branch of literature analyzes the reduction in coincident peak charges of datacenters, which are large centralized loads with the ability of providing significant flexibility to the grid through shift in consumption patterns. Lukawski et al. [20] study the potential for datacenters to reduce coincident peak load through pre-cooling prior to probable peak events. They find that, using this strategy, annual electricity bills can be reduced by 7.8 – 8.6% while only increasing total energy consumption by 0.05% [20]. Liu et al. find that a combination of workload shifting and local generation can significantly reduce coincident peak charges for datacenters, which can account for up to 23% of a datacenter's electricity bill [7].

The total number of studies in this realm is limited. Zarnikau and Thal find that if an electricity consumer could reduce its consumption by 1 MW during each of the four coincident peak events, it could save about $25,000 in transmission charges the following year — a substantial monetary benefit [19]. Baldick [73] investigates the effectiveness of coincident peak pricing on avoiding new transmission investments. To the best of my knowledge, there exists a gap in literature on quantifying the reductions in coincident peak loads and TCOS obligations with local generation and storage from the perspective of DSPs. Chapter 3 aims to fill this gap.

2.2 Demand response

2.2.1 Types of demand response

Demand response (DR) or load control (defined briefly in Section 1) can be divided into two categories based on the mechanism used to motivate customers to shift energy consumption: incentive-based and price-based [74, 75]. In incentive-based DR, customer participation is usually motivated by incentives or rebates offered by the local electric utility and electricity usage reduction is determined *ex ante*. Customers, in some cases, face the risk of financial penalties if they fail to respond or meet the load reduction requirements [74]. In the residential sector, direct load control of air-conditioners (ACs), which involves the utility directly increasing the set-point thermostat temperature or cycling on and off the AC during peak times, is a type of incentive-based DR. Price-based demand response involves manual control of loads by customers or automatic control by appliances, and generally takes place in response to time-varying prices (real-time pricing, critical peak pricing, time-of-use rates, variable peak pricing, etc.) [74]. Customers can voluntarily reduce usage of energy-intensive appliances during periods of high prices or shift usage to a different time – for example, waiting to run the dishwasher until the peak period is over.

2.2.2 Overview of demand response in the residential sector

The residential sector comprises 27% of global final energy consumption [22] and nearly 50% of the summer peak demand in hot climates like Texas [23]. Residential demand is highly correlated with the timing of usage of end-use appliances [76]. Thus, if the timing and frequency of use of these household appliances can be controlled, peak demand can be substantially reduced or shifted to a different time.

Residential loads can be divided into two categories: controllable and critical (uncontrollable) [77]. Controllable loads or appliances are those which can be controlled, like water heaters and clothes dryers, without significant impact on the comfort or lifestyle of end-users. Critical loads include loads, like lights, refrigerators, televisions, and kettles, which can either not be controlled or cannot be shifted to another time of the day [77, 78]. Heating, ventilation and air-conditioning (HVAC) systems, electric water heaters (EWHs), electric vehicles (EVs), and pool pumps (PPs) are some of the greatest energy-consuming (but controllable) devices used by residential customers. HVAC demand comprises 32% of average annual residential consumption in the United States [79] and 50% of summer peak demand in hot climates like Texas [80]. In winter-dominated climates, domestic EWHs can contribute 30% of total electricity consumption [81]. In addition, the load profile for EWHs closely follows average diurnal load profiles, thus making up a significant portion of the peak demand [82]. A single EV battery being charged using a residential Level 2 charger can double the peak demand in an average North American household [83]. Thus, as EV adoption becomes more widespread, EVs could account for a substantial portion of peak demand if their charging is not intelligently managed. Finally, pool pumps can consume 3000–5000 kWh per year [84] which is about half the average annual electricity consumed by residential utility customers [85].

2.2.3 Residential incentive-based demand response

Many electric utilities offer monetary incentives to their residential customers in lieu of being allowed to control certain household appliances during specific peak hours. For example, Austin Energy has an optional Power Partner Thermostat Program for its residential customers. Customers must own qualifying wifi-enabled thermostats to enroll in this program and are eligible to receive a one-time $85 incentive for participating [86]. On certain summer days with high energy demand, the utility has the right to increase the thermostat temperature of participating households by 2°F–4°F from 3 pm–6 pm [86]. During these events, customers can override the temperature increase by adjusting thermostat settings or through the app [86]. Florida Power & Light (FPL) offers an optional Residential On Call Extended program. Customers can enroll voluntarily in this direct load control initiative and receive monthly incentives in exchange for allowing their AC, central heater, EWH, and PP to be shut off for a certain number of hours during summer peak days [87].

There is a vast academic literature regarding residential incentive-based demand response. Newsham et al. find that peak demand can be reduced by 10 – 35% in each household as a result of direct load control of residential air-conditioners in southern Ontario, Canada [88]. Bowen finds that the smart wifi-enabled thermostats employed by Austin Energy for direct load control of air-conditioners since 2013 are able to reduce peak demand more than the free thermostats used before which could reduce air-conditioning usage by one-third when triggered by a radio signal from the utility [89]. However, homes with smart thermostats have a higher cooling load over the course of the summer than homes without, thereby limiting the increase in energy efficiency as a result of adopting these wifi-enabled thermostats [89]. Ericson analyzes data from an experimental direct load control program in Norway where residential water heaters were disconnected during peak hours. The study finds that decrease in energy consumption during the control period is followed by an increase in energy usage right after reconnection due to the payback effect [90]. Kondoh et al. develop a direct load control algorithm for residential EWHs to provide regulation services while maintaining customer comfort [91].

2.2.4 Residential price-based demand response

Traditionally, most retail electricity markets offered flat/constant or block/tiered pricing for customers [92]. But as electricity demand increased over the years, many utilities started offering optional time-varying pricing programs in an effort to encourage customers to reduce demand during peak hours and/or shift loads away from peak times. Although electric utilities in the United States started experimenting with time-varying pricing in the late 1970s, most customers were not aware of the availability of these rates and customer acceptance was low because of the high cost of metering and long duration of peak periods [24]. After the multiple large-scale blackouts during the California Electricity Crisis in 2000–2001, various utilities redesigned time-varying rates and re-launched pilot programs to curtail peak demand [24]. A brief background about various residential dynamic pricing structures and related (current and historical) pilot programs are provided in the next few sections.

2.2.4.1 Real-time pricing

Under real-time pricing (RTP), electricity customers are charged prices that vary over short time intervals, typically hourly, and reflect marginal costs of supplying energy at the time of consumption [93]. The first RTP structure for commercial and industrial customers in the United States was implemented in the mid-1980s

[93]. The Energy Smart Pricing Plan introduced in 2003 by Commonwealth Edison in Illinois was the first residential pilot program in the U.S. which gave customers the opportunity to pay hourly real-time prices for their electricity consumption [94]. It was found that most participants responded to the high price notifications by decreasing energy usage. However, the responsiveness decreased over the duration of the peak period and as the number of successive high price days increased [94]. It is interesting to note that Illinois is currently the only state in the U.S. with two large electric utilities hosting voluntary residential RTP programs (Ameran Illinois and Commonwealth Edison) [95]. However, customer acceptance is not as widespread and most customers still choose flat pricing rates [95].

2.2.4.2 Time-of-use rates

Time-of-use (TOU) rates charge customers less when the cost of generating electricity and demand are typically low and charge more at times when these are usually high [96]. TOU rates can vary based on the time of the day, day of the week, and season [96]. Residential TOU pricing program experiments were first initiated in the 1970s [97]. Carolina Power and Light, Connecticut Light and Power, and Southern California Edison were some of the electric utilities which implemented TOU programs in that decade [97].

As of 2017, 14% of all utilities in the United States offered residential TOU rates [98]. Some of the large electric utilities offering these rates include Jersey Central Power & Light, Baltimore Gas & Electric, Virginia Electric & Power, and Ohio Power Company [98]. Although TOU rates have historically been offered to residential customers on a voluntary basis, there has been a gradual shift toward default or mandatory TOU rates with more electric utilities installing smart meters [98]. In 2015, the California Public Utilities Commission ordered three investor-owned utilities

— San Diego Gas & Electric (SDG&E), Southern California Edison (SCE), and Pacific Gas & Electric (PG&E) — to enroll all customers in TOU by 2019 unless they opt-out [99], potentially impacting about 20 million residential customers.

2.2.4.3 Critical peak pricing

Critical peak pricing (CPP) is a time-varying pricing scheme where customers are charged substantially high prices during peak hours on (pre-declared) days when electric utilities anticipate high wholesale market prices or low generation adequacy. In the 2000s, many electric utilities implemented residential pilot programs with critical peak pricing [100]. The Idaho Energy Watch Residential Pilot Program offered in the summer of 2006 showed significant electricity demand reductions on critical peak days [100]. Another CPP program implemented by Sacramento Municipal Utility District during the summer of 2013 taught electric utilities that participants are not only interested in their own savings but also in the savings experienced by other customers and significant staff resources are needed to send notifications about critical price events to participating customers [101].

Pacific Gas & Electric (PG&E) currently has a (voluntary enrollment) 'SmartRate' program for its residential customers. During the summer months from June to September, participating customers pay an additional \$0.60/kWh on top of their standard rates for all usage between 2 pm and 7 pm on extreme days or 'SmartDays' while saving approximately \$0.024/kWh for electricity usage during other times of the day [102]. In addition, they receive a monetary participation credit [102]. Customers are notified of these critical peak days one day in advance through phone, email, or text and the number of the 'SmartDays' usually range from 9 – 15 each year [102].

2.2.4.4 Variable peak pricing

Oklahoma Gas & Electric (OG&E) currently has an optional variable peak pricing program for its residential customers [103]. Although this pricing structure is similar to critical peak pricing, the main difference is that the on-peak prices on the peak event day can have several values (low price, standard price, high price, and critical price in the case of OG&E) depending upon day ahead prices [103]. Previously, OG&E had launched a 'Smart Study Together' pilot program in 2011 where VPP was demonstrated to reduce peak demand by up to 32% [104].

2.2.5 Residential price-based demand response literature

A branch of the academic demand response literature focuses on analyzing findings from historical dynamic pricing programs. An Electric Power Research Institute (EPRI) study, which analyzes the results from various time-varying electricity pricing pilot programs from the late 1970s and early 1980s, observes that customers reduced energy consumption during peak hours and/or shifted energy usage to low-price hours [24]. Allcott [25] evaluates the Energy-Smart Pricing Program in Chicago — the first program in the U.S. to implement hourly real-time prices — to observe that customers reduced energy during peak hours and did not increase energy usage in off-peak hours. Newsham and Bowker review several dynamic pricing pilot programs in North America from the 2000s and find that critical peak prices are more effective at reducing the peak demand than time-of-use rates since the ratio of the on-peak to off-peak prices is generally higher for CPP than for TOU rates [26]. Additionally, CPP events are limited to only a few each year while TOU rates are in effect every single day [26]. Herter [27] uses data from the California Statewide Pricing Pilot of 2003–2004 to show that high energy consuming residential customers reduce more energy in response to critical peak prices while low usage customers experience higher savings in their electricity bill. Wolak [28] analyzes results from a CPP experiment held in 2005 by the City of Anaheim Public Utilities to find that customers exposed to these prices consume 12% less energy during the peak hours as compared to other customers paying constant rates. A recent empirical study by Burkhardt et al. uses a test-bed of homes in the Mueller neighborhood in Austin to conduct a field experiment where a portion of customers are exposed to critical peak prices [105]. They find that in addition to reducing energy consumption by 74% during the critical peak period, these customers also keep energy consumption low during the two hours before and after the peak event. Further, there is no evidence of load shifting to low-price hours as a result of the high prices [105].

Another line of research focuses on developing optimization and algorithmic models to quantify peak load reduction and economic savings in the residential sector. The following subsections describe some relevant types of optimization models found in existing literature and highlight the knowledge gaps which this dissertation aims to fill.

2.2.5.1 Linear optimization models

A linear program consists of a linear objective function which is minimized or maximized subject to a set of linear constraints. Mohsenian-Rad and Leon-Garcia develop a linear program to minimize both customer electricity bills and waiting time for operation of appliances under the effect of a combination of real-time prices and inclining block electricity rates [29]. The results of the algorithm show significant reductions in peak-to-average ratio. Conejo et al. develop a linear optimization model to maximize utility of the customer under the effect of hourly real-time prices subject to various energy consumption and ramp rate constraints [31]. Arun et al. use a linear optimization-based scheduling algorithm to minimize electricity costs for a residential customer under real-time pricing by shifting controllable and schedulable loads [32]. Adika and Wang develop a linear programming model to minimize costs incurred by residential customers under a day-ahead pricing scheme by scheduling appliances during low-demand hours and by energy arbitrage of energy storage systems [33]. Shakouri and Kazemi [34] propose a multi-objective mixed integer linear programming model to minimize peak load and electricity cost under time-of-use rates for a residential area with multiple households. A mixed-integer linear program is built by Duman et al. to minimize customer expenditure in the presence of time-of-use rates by shifting loads to off-peak hours [35]. Farrokhifar et al. [36] formulate an integer linear program to minimize energy costs in an intelligent building in Iran under real-time pricing and solve for the optimal scheduling of smart appliances. Although some of these studies incorporate customer preferred priority of appliances, operation times, and customer-set bounds on permissible temperature, these economic models often lack the monetary value of the effort, time, and discomfort of the customers responding to the peak load reduction initiative by the local electric utility. Further, the linear structure of these models forces the cost minimizer to essentially concentrate all energy usage within the lowest price hours until the hard constraints are violated. Therefore, the ability of linear models to capture load shifting realistically is limited.

2.2.5.2 Convex optimization models

Convex problems refer to the class of potentially non-linear problems where the objective function is convex/concave (for a minimization/maximization problem, respectively) and the constraint set is a convex set. A convex formulation allows a model to capture nonlinear phenomena and effects that are not constant on the margin.

Zhao et al. develop a convex optimization model to reduce electricity costs to maintain the temperature inside a residential building within a comfortable range and reduce peak to average ratio under a real-time pricing structure [37]. This study again does not include the monetary value of the comfort of the customers. Huang et al. create a convex optimization model for a demand response and energy storage management system which minimizes costs for a residential customer with energy storage systems and renewable power generation and meets customer electricity demand requirements [38]. Although this study incorporates the discomfort of the customer in the objective function using the economic value of deviation of actual load consumption from the target load consumption, it lacks detailed models for controllable appliances, model constraints to maintain customer comfort, and separate customer discomfort/inconvenience functions for each appliance. A convex model is developed by Samadi et al. [39] to find the optimal energy consumption levels for several customers by maximizing the aggregate utility function of all customers while minimizing cost incurred by the energy provider. The study includes a quadratic user welfare function that is a function of the customer's overall power consumption but does not include specific utility functions for each device. Gatsis and Giannakis [40] propose a convex optimization model to minimize net cost incurred by the electric utility to provide energy to customers and the total dissatisfaction of the customers. This study includes disutility functions that depend quadratically on the power consumption of various load types (must-run loads, flexible loads, etc.) of the end-users.

2.2.5.3 Bilevel optimization models

Bilevel optimization models include two inter-linked objective functions — an upper-level and a lower-level one with each level having its own set of decision variables [106]. The upper-level objective function includes the leader who has complete knowledge of the decisions of the follower from the lower-level function. The decision variables of the upper-level problem appear as parameters in the lower-level problem. The upper-level decision maker's objective is affected by the lower-level decisions, which the upper-level decision maker is able to anticipate and influence through their own decisions.

Safdarian et al. formulate a bilevel optimization problem to flatten the system-wide residential load profile and minimize costs to individual customers [41]. A bilevel problem between electricity-retailers and consumers is constructed by Carrasqeira et al. and solved using two different methods — an evolutionary algorithm and a particle-swarm optimization algorithm [42]. Erkoc et al. develop a Stackelberg (leader-follower) game problem to shift load by maximizing profits for the energy provider and minimizing costs for the customer [43].

While bilevel optimization highlights strategic interactions between an electric utility and customers, allowing a model to 'optimize' rates leaves open the issue of what the objective should be, and whether the optimal rates it produces are at all feasible or compatible with the types of rate structures utilities could actually implement. Further, bilevel optimization models can be challenging to solve, which limits their complexity and resolution.

2.2.5.4 Additional models

Markov decision processes, stochastic programming, and dynamic programming approaches are also used in the demand response literature. Deng et al. point to several studies that incorporate these models and explain these in greater detail [107].

2.2.5.5 Novel contributions of Chapter 4

Chapter 4 falls within the category of convex optimization models for price-based demand response and aims to fill the knowledge gaps mentioned above. In this chapter, four different electricity pricing structures are evaluated — constant rates, RTP, TOU rates, and CPP — and four types of controllable loads are considered — HVAC systems, EWHs, EVs, and PPs. The chapter also incorporates the monetary value of customer discomfort of deviation from set-point temperatures and inconvenience of running appliances at certain times of the day. The discomfort functions for the HVAC and EWH depend on the room and water temperatures (which the customers care about) respectively instead of the appliance loads. Thus, these thermal models allow the penalties to apply to the temperatures and make the effects of load shifting more realistic by modeling the temperatures dynamically. Further, distinct discomfort/inconvenience functions for each controllable appliance are incorporated. The discomfort functions for the HVAC system and EWH are quadratic to capture the increasing discomfort as temperatures deviate from customer-set temperatures while the inconvenience functions for the EV and PP are step functions which assign different inconvenience penalties to different times. Additionally, minute-interval appliance-level empirical energy consumption data and solar generation profiles from a test-bed of 100 single-family detached homes in Austin, TX are utilized in the chapter [56]. It is extremely rare to have such location-specific, short-interval, disaggregated data available to incorporate into price-based demand response models. Finally, the statistical package 'CVXR' in the open-source R platform is used to find optimal solutions to the model. This package was developed and made available to the public in 2017 and to the best of my knowledge, has never been used in demand response literature.

2.3 Distributed Energy Resources

Distributed Energy Resources (DERs), defined previously in Chapter 1, include generators like fuel cells, microturbines, internal combustion engines, solar panels, diesel engines, small wind turbines, and energy storage technologies like batteries, flywheels and compressed air energy storage [12,108]. With restructuring of electricity markets, increased demand for reliability, concerns about climate change, and increased transmission and distribution network congestion, the penetration of DERs has increased globally [12,14,15,108]. Federal, state, and local governments and electric utilities have been implementing new policies or re-designing old policies in an effort to increase deployment of DERs — particularly renewable energy generators. Further, with technological innovation, the capital costs of DERs have also decreased rapidly. Studies have shown that the capital and installation costs for residential solar panels and lithium-ion battery packs have reduced by 63% and 85% respectively between 2010 and 2018 [109,110]. This trend is likely to continue over the next decade (although the rate of decrease will likely be lesser).

For the purpose of providing information needed to parse through the analysis in Chapter 5, the discussion will be restricted to three types of DERs: solar panels, lithium-ion batteries, and ice cold thermal energy storage (CTES). While solar panels and lithium-ion batteries are widely used terms, 'ice CTES' needs to be defined. Ice CTESs are storage systems used to make ice during off-peak night hours when time-varying electricity prices are typically lower and the coefficient of performance of the chiller is higher [111, 112]. They are discharged (melted) to meet cooling demand in the home during peak evening hours, thereby reducing or negating the need for the energy-guzzling air-conditioner to run. Cold thermal energy storage systems are widely used in commercial buildings like offices, schools, and religious institutions because commercial customers typically face demand charges which serve as incentives to reduce peak load. Further, these buildings are usually unoccupied outside working hours, resulting in negligible thermal load during off-peak hours and allowing the chiller to solely focus on making ice without sacrificing building thermal comfort [49].

It must also be noted that there are battery chemistries other than lithium-ion that are available today and in development for future use e.g. sodium-sulphur, lithium-sulphur, fluoride, etc. However, lithium-ion batteries are sufficiently popular and gaining market share — so they are a useful pick for the analysis in Chapter 5.

2.3.1 Government policies supporting the growth of DERs

The next few subsections provide brief descriptions of some policies which affect the adoption of local renewable generation and onsite storage. These subsections also serve to provide background of the policies used in the analysis of Chapter 5.

2.3.1.1 Investment Tax Credit

The Investment Tax Credit (ITC), which was introduced by the Energy Policy Act of 2005, is a dollar-for-dollar federal tax credit for residential, commercial, and utility investors in solar energy systems [113]. The value of the credit is currently 26% of the capital and installation cost of the system but is scheduled to phase out by 2022 for residential customers while decreasing to a permanent 10% for commercial and utility customers [113]. The 26% ITC also applies to energy storage systems if they solely charge from on-site renewable energy generators like solar panels [114].

Since its introduction, the ITC has greatly impacted the U.S. economy, society, and environment by increasing the deployment of solar, attracting billions of dollars of investments to the solar industry, creating a large number of jobs, and offsetting harmful emissions [113, 115–117].

2.3.1.2 Renewable Portfolio Standard

Renewable Portfolio Standard (RPS) is a policy that specifies that a certain percentage of electricity sold by utilities in participating states must come from renewable energy resources [118]. If the utilities in the state fail to meet the RPS, they typically face some form of penalty [119]. The resources that qualify to meet the RPS include wind, solar, biomass, geothermal, and some hydroelectric plants. Landfill gas, tidal energy, combined heat and power, and energy efficiency initiatives are also included in this list in some states of the U.S. [118]. The benefits of implementation of RPS are diversification of energy produced, reduction in CO_2 emissions and improvement of air quality as a result of increased penetration of renewable energy generators, economic development due to promotion of domestic energy production rather than importing fossil fuels, etc. [118].

Additionally, several states support the inclusion of distributed generation in the RPS while some states like Arizona, Colorado, and Illinois have specific DG carve-outs which require a certain percentage of the RPS requirement must be fulfilled using distributed generation [120]. In lieu of incentives and rebates offered to customers adopting onsite DERs, utilities often take ownership of the renewable energy credits (RECs) associated with distributed generation and use these credits to meet RPS goals [120].

Although the RPS does not directly impact the analysis in Chapter 5, it affects the Value of Solar (VOS) rate (described in detail in Section 2.3.1.3) in Austin, TX which is included in our optimization model. The VOS rate encourages the adoption of distributed solar, which in turn helps meet RPS goals. Some of the impacts of the RPS on the VOS rate and rules in Austin include [121]:

- Application of VOS to third-party leased systems

- Yearly roll over of solar credits in the customer account
- Elimination of size caps for residential systems to avail VOS rate
- Minimum limit for VOS to be equal to Tier 3 of Austin Energy energy charge

The RPS has been a major driver for renewable generation growth since 2000 [119]. However, the role of RPS as the chief propagator of renewable energy has declined in recent years. Diminishing capital costs for renewable energy generators, tax credits, and other state-level policies like net metering and VOS, have risen to the forefront [118].

2.3.1.3 Net metering and Value of Solar

Net metering is a policy or billing mechanism which allows solar customers to get monetary credit for selling excess solar electricity back to the grid [122]. When the cumulative onsite solar generation of a household is greater than its electricity consumption, the household is paid by the electric utility for the net amount of solar electricity at a pre-determined price at the end of the billing period. On the other hand, if the electricity consumption is greater than the solar generation, the household must pay for the net amount of electricity consumed at the standard retail rate [123]. Minnesota was one of the first states to adopt a net metering policy in 1983 [124]. By 1998, utilities in 22 U.S. states had incorporated net metering policies [124].

Although net metering policies have greatly increased the deployment of solar in the U.S., there are several associated challenges. The value of the customer electricity bill savings under net metering depends on the structure of the retail electricity rate and on the characteristics of the customer and solar PV system [125]. Thus, the economic benefits of net metering can vary substantially across individual customers [125]. High energy consuming customers benefit more than average or low energy consuming customers by installing solar under net metering because they are able to reduce the purchase of a greater amount of grid-supplied electricity [126]. Additionally, the utility electricity prices that high energy consuming solar customers forego would have been priced at higher marginal rates under a tiered rate structure. Several fixed costs of the utility are also 'transferred' from solar to non-solar customers because the excess electricity produced onsite is sold to the electric utilities at the retail rate instead of the wholesale rate [126].

Value of Solar (VOS) is the rate ($/kWh) at which customers are credited by their local electric utility for the solar energy produced by their onsite panels [127]. It represents the actual value of distributed solar to the utility [128]. Customers are charged by the utility for their total energy consumption, which includes the energy purchased from the grid and the energy flowing from the solar panels to the home. Then, they receive a monetary credit from the electric utility for the total solar generation based on the VOS rate. The VOS tariff completely decouples the electricity billing (based on energy usage) from the revenue earned for solar generation.

The VOS serves a variety of purposes like creating equity between high and low consuming customers with onsite solar panels, reducing cost shifting between solar and non-solar customers, recovering the utility's fixed costs associated with electricity production and delivery, and encouraging correct sizing for residential solar PV systems [126]. Austin Energy was the first U.S. utility to adopt the VOS mechanism in 2012 [128] while Minnesota was the first state to adopt a VOS policy in 2014 [129].

2.3.2 Relevant literature combining DERs, smart appliances, and residential price-based demand response

Several optimization and algorithmic studies exist to independently analyze the effects of solar panels, lithium-ion batteries, ice CTES, and smart thermostats on residential energy consumption patterns and customer expenditure. I first highlight some key studies involving each of these technologies in the following subsections. In Section 2.3.2.5, I feature some studies that incorporate a combination of the above-mentioned technologies and identify the novel research contributions of Chapter 5.

2.3.2.1 Solar panels

Yang et al. calculate the return on investment and payback period for residential solar photovoltaic (PV) investments [130]. The output performance and payback period of a residential solar PV system in Colorado is analyzed by Johnston [131]. Formica and Pecht evaluate the return on investment of a residential PV system in Maryland using weather conditions and tax credits specific to that area [132].

2.3.2.2 Lithium-ion batteries

Naumann et al. estimate the profitability of investing in lithium-ion batteries for homes with solar PV under various battery ageing behavior, capital cost, and electricity pricing scenarios [133]. Troung et al. analyze the economic benefit of installing Tesla Powerwalls for resdential customers with solar PV under various electricity prices, household demand patterns, battery ageing parameters, topology of battery system coupling, subsidy schemes, and retrofitting of existing PV systems [134]. A linear program is developed by Nottrott et al. to model optimal lithium-ion battery storage dispatch schedules for peak net load and demand charge minimization in a grid-connected combined solar PV and battery storage system under TOU rates [135]. Zhang et al. formulate data-driven dynamic programming algorithms to optimize the real-time charging behavior of batteries in homes with rooftop solar panels under uncertain electricity usage, PV generation, and electricity prices [136].

2.3.2.3 Ice CTES

Sanaye and Shirazi [137] develop a multi-objective optimization model to show that the electricity consumption in an ice thermal energy system coupled with an air-conditioner is 10.9% lower than a conventional A/C system while carbon dioxide emissions are significantly reduced. Campoccia et al. study the effects of ice thermal energy storage systems on diurnal power profile and electricity bills of residential customers in Italy under double-tarriff contracts (similar to TOU rates) [52]. A linear program is developed by Jazaeri et al. and model predictive control is used to show that ice storage systems can effectively shift cooling demand in homes to off-peak periods and improve the voltage profile of the low voltage residential electricity network [53].

2.3.2.4 Smart thermostats

Air-conditioning and space heating comprise 32% of residential energy usage in the U.S. [138]. Smart thermostats are energy management devices that can significantly lower the electricity consumption in residential buildings by improving the operational efficiency of HVAC systems [139]. These devices are able to monitor and 'learn from' occupant behavior, remotely adjust temperature set-points, and in some cases, respond to electricity price signals from the utility to support peak load reductions [139]. Lu et al. analyze the effect of a smart thermostat, which can operate HVAC systems in homes based on user occupancy and sleeping patterns, and observe that 28% of energy is saved on average without affecting customer comfort [140]. The hardware implementation and application of a home energy management system coupled with a smart wifi-enabled thermostat is demonstrated by Saha et al. [141]. Results show that during demand response events, the average power consumption of air-conditioners is lowered, customer comfort levels are maintained, and the equipment lifetime is extended. Keshtkar et al. develop an adaptive learning algorithm to improve the capabilities of programmable communicating thermostats to learn and adapt to occupants' preference changes while saving energy without negatively affecting customer thermal comfort [142].

2.3.2.5 Optimization of combined technologies

O'Shaughnessy et al. use the U.S. National Renewable Energy Laboratory's Renewable Energy Optimization (REopt) model to evaluate the combined effect of solar photovoltaic panels, lithium-ion battery storage, and load control on residential customer expenditure under several electricity pricing structures [44]. The optimal technology combination, sizing, and dispatch in various U.S. locations are observed and it is shown that the integrated approach of solar, storage, and demand response (also referred to as 'solar plus') can improve the value of residential solar [44]. An optimal energy management strategy for a residential energy hub with controllable household loads, solar generation, combined heating, cooling, and power generation, and thermal and electric energy storage systems is developed by Brahman et al. [143]. This study also incorporates the comfort levels of the residential customer. Lorenzi and Silva propose a linear program to compare the potential of storage systems (lithium-ion and lead-acid batteries) versus demand response strategies with the goal of minimizing residential customer electricity bills in homes with small solar PV systems under dynamic prices [46]. A convex optimization model is developed by Babacan et al. for charging and discharging of residential energy storage systems while considering TOU, demand, and supply tariffs, energy arbitrage, and on-site solar PV systems [47]. Bandyopadhyay et al. propose a demand response optimization algorithm to quantify the maximum peak load reduction achievable with residential demand response, solar panels, and lithium-ion batteries [48].

2.3.2.6 Novel contributions of Chapter 5

Chapter 5 falls within the category of literature that analyzes the effect of renewable generation, thermal and electric energy storage systems, and demand response on residential energy demand and yearly expenditure. In addition to solar panels, lithium-ion batteries, and controllable loads, this chapter also incorporates residential ice CTESs and analyzes their combined effect. To the best of my knowledge, such an analysis combining all these distributed energy technologies under the effect of alternative pricing structures has not been conducted. We perform a comprehensive analysis ranging over 80 different scenarios from combinations of the distributed energy technologies and pricing structures. Such an in-depth study unearths interesting features that would otherwise remain hidden. For example, analyzing various combinations of distributed technologies allows us to investigate whether these technologies complement one another's effectiveness or if there are diminishing returns to stacking them. Further, such an extensive analysis helps us evaluate which technology would be most effective if the goal of the optimization problem was to minimize peak net demand or customer electricity bills instead of minimizing overall customer expenditure. Additionally, similar to Chapter 4, this chapter also includes a thermodynamic model for the HVAC system of the home. The discomfort function for the HVAC depends on the room temperature (which affects the customers directly) instead of the appliance load. Thus, the thermal model allows the penalties to apply to the temperatures and makes the effects of load shifting more realistic by modeling the temperatures dynamically.

A descriptive statistics tool called a *functional boxplot* [144] is used to choose a subsample of the 720 hours of each month of the year to include in the model database as representative slices. A classical boxplot graphically represents the center and spread in a univariate dataset based on various summary measures such as the minimum, maximum, median, and interquartile range. While extensions of the boxplot to deal with multivariate data have been considered in the literature, these are not immediately applicable to the current setup since treating a curve merely as a collection of points loses the smoothness information ensuing from the temporal structure. The functional boxplot, however, is the appropriate tool since it enables one to summarize a collection of (discretized) curves while respecting their temporal dependencies. Treating the curve as a whole, it provides a more reliable and reasonable summary compared to multiple usages of the classical boxplot at each time point. This approach makes an important contribution to the growing literature on methods to select representative timeslices for dispatch in energy system optimization models [145–147]. Finally, similar to Chapter 4, the use of a commercially available optimization solver ('CVXR') in the open-source *R* platform and the availability of the model code on Github makes it easy for other energy system modelers to replicate and validate this chapter.

Chapter 3

Developing a method to forecast reductions in 4CP loads and TCOS obligations for utilities within ERCOT as a result of different amounts of distributed solar and storage capacity

3.1 Introduction

Some of the steps taken by electric utilities to reduce 4 coincident peak loads and corresponding payments include demand response [19] initiatives like subjecting large industrial customers to coincident peak pricing and increased penetration of distributed energy resources (DERs) like onsite solar and storage. Many utilities send signals to their customers forecasting potential peak hours in the summer during which customers have the choice to curtail all or part of their energy usage [19]. However, demand response has several challenges associated with it — predicting the actual time of the coincident peak can be difficult, workload shifting risks deadlines not being met, and large industrial customers often do not have the flexibility to respond to the warnings [7,19]. Additionally, turning on less efficient backup generators to avoid buying energy from the grid in the event of a warning can be environmentally costly [7]. Increasing the amount of available local renewable generation, like solar,

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This chapter was adapted from the peer-reviewed conference publication: A. Bandyopadhyay, J. D. Rhodes, J. P. Conger, and M. E. Webber, How solar and storage can reduce coincident peak loads and payments: A case study in Austin, TX, *Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Pittsburgh, PA.* Volume 6B: Energy ():V06BT08A023. DOI:10.1115/IMECE2018-86482 [2]. The majority of the paper's research, analysis, and writing were completed by the author of this dissertation. The co-authors contributed via cognitive interpretation and editing.

can supplement demand side responses as well as keep emissions low [7]. Further, the incorporation of energy storage systems (ESSs) can help mitigate the intermittency and variability of solar production and its non-alignment with peak demand [111].

Previous studies have analyzed the reduction in coincident peak load and corresponding payments of datacenters under demand response [20] or a combination of local generation and demand response [7]. Other studies have attempted to accurately predict the timing of the coincident peak using statistical methods [71, 72] or measure the effectiveness of coincident peak pricing in avoiding new transmission costs [73]. However, there is a gap in the literature in quantifying the impact of local renewable generation and storage on coincident peak load and Transmission Cost of Service (TCOS) obligations from the perspective of the Transmission and Distribution Service Provider (TDSP).

To fill that knowledge gap, this study builds a generalized tool to forecast the change of 4 coincident peak (4CP) loads and payments based on varying amounts of solar and storage capacity over a 10-year period for electric utilities within ERCOT. The tool is illustrated by using empirical data from the municipally-owned utility in Austin, TX (Austin Energy). Employing the novel approach of incorporating coincident peak demand charge reductions at the TDSP level, this study highlights the long-term economic benefits of local generation and storage. Utilities within ERCOT can use the calculation tool to estimate future savings in TCOS obligations by present day DER investments, which could in turn help form policy decisions about offering rebates to customers who want to install onsite DERs. Further, the methodology developed in this chapter can be used by utilities outside ERCOT that might have more than four coincident peaks. For example, PJM has 5 coincident peaks which are calculated using the five highest hours of demand throughout the year [148].

3.2 Methods

The following section describes the structural outline of our approach, relevant equations, underlying assumptions, data sources, and period of analysis. Figure 3.1 breaks down the methodology step-by-step.

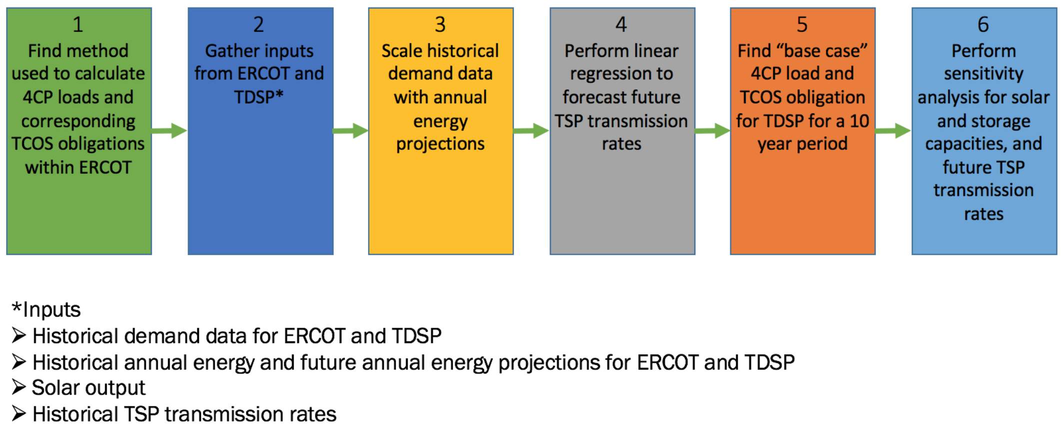

Figure 3.1: Flowchart describing detailed methodology of this chapter.

3.2.1 Relevant equations

The 4CP load of a TDSP is calculated by recording and averaging its load when ERCOT peaks for a single 15-minute interval during each month between June and September [1]. Thus, the 4CP load is not the same as the peak demand of the individual TDSP and the timing of the peak of a TDSP is not necessarily the same as the timing of the coincident peak. The corresponding TCOS obligation is calculated using Equation 3.1 (this equation is discerned from the transmission charge matrix published by PUCT [18]).

$$\begin{aligned}\text{TCOS obligation} = \sum_{i=1}^{N} &(\text{Transmission rate of TSP}_i) \times \text{TDSP 4CP load} \\ &- \text{Transmission rate of TDSP} \times \text{ERCOT 4CP load}\end{aligned} \tag{3.1}$$

where N = number of Transmission Service Providers (TSPs) within ERCOT. The transmission rate of each TSP is calculated using the following equation [17]:

$$\text{Transmission Rate} = \frac{\text{Transmission Cost of Service (TCOS)}}{\text{ERCOT 4CP load}} \tag{3.2}$$

The transmission cost of service reflects the invested capital of the TSP in certain transmission facilities, e.g. power lines and reactive devices operated at 60 kV or above, substation facilities on the high voltage side of the transformer, etc. [17]. Each TSP in the ERCOT region is allowed to approach the PUCT to update its transmission rate a maximum of two times per calendar year [17].

When local solar and storage capacity are available, the 4CP loads of individual TDSPs in each of the summer months are calculated using Equation 3.3. t represents the time interval when ERCOT peaks.

$$\begin{aligned}\text{TDSP 4CP load} = \text{TDSP load}_t &- \text{Local solar output}_t \\ &- \text{Local storage discharge capacity}_t\end{aligned} \tag{3.3}$$

3.2.2 Data sources

The main inputs include historical demand data, historical annual energy consumption and future annual energy projections for ERCOT and our model TDSP (say TDSP AE), solar power availability for a typical meteorological year (generated by determining "typical" meteorological months through a process of weighting various weather parameters over ten or more years [149]), and historical TSP transmission rates. The analysis is performed using the statistical programming language *R*.

3.2.2.1 Future demand forecasts

Linear interpolation is performed on hourly historical ERCOT load data [150] for the months of June to September for years 2011–2017 to get 15-minute interval data. These data are then averaged and forecasted by linearly scaling with annual energy projections [151] for years 2018–2027. The same process is repeated for 15-minute interval historical TDSP AE demand data.

3.2.2.2 Solar resource availability

Solar power data for a typical meteorological year for the location where TDSP AE is located is obtained using the PVWatts calculator developed by the National Renewable Energy Laboratory (NREL) [152]. The assumptions of 14% system losses, fixed array type, crystalline silicon photovoltaic cells and a tilt angle equal to the latitude of location where TDSP AE is located are used.

3.2.2.3 Transmission rates

Historical TSP transmission rates/access fees are obtained from the transmission charge matrices published on the PUCT website [18]. Future projections of transmission rates are obtained from a linear regression analysis. Historical and projected transmission rates can be seen in Figure 3.2. In addition to the 'base case' projected rates (which we obtain from the best linear unbiased prediction), we also consider upper and lower 90% confidence limits of the slope and intercept for sensitivity analysis.

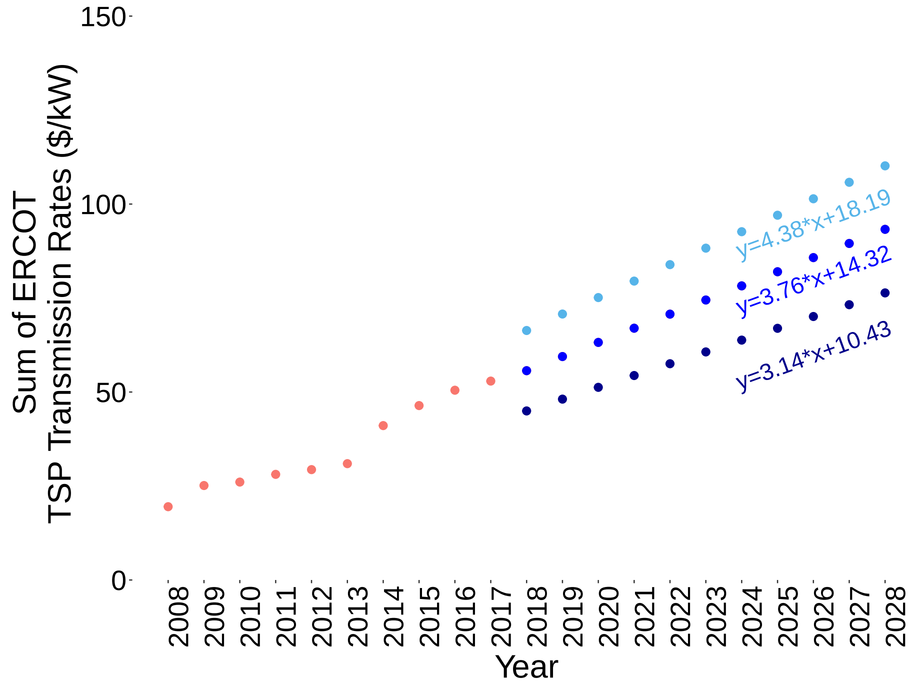

Figure 3.2: Sum of historical TSP transmission rates from 2008–2017 (in red) show an increasing linear trend [18]. Regression analysis is performed (R^2=0.94) to project future sums (in the medium blue shade) for years 2018–2028. The upper and lower 90% confidence limits of future sums are demonstrated by the other two sets of points.

3.2.3 Assumptions

Some key assumptions are made for simplification purposes and are listed below:

- The solar and storage capacity are viewed in aggregate terms i.e. they are not segregated into commercial, residential, etc.
- The ESSs comprise of lithium-ion batteries.
- The TDSP has perfect foresight.
- As '4CP chasing' is one of the main goals of this analysis, the maximum ESS

capacity is available to offset the demand during the 4CP events.

3.2.4 Period of analysis

4CP loads and TCOS obligations are forecasted for years 2018–2027 and 2019–2028 respectively since loads from a particular year are used to calculate the TCOS obligation for the next calendar year. We use empirical demand data and transmission rates from Austin Energy to demonstrate our tool.

3.3 Results and discussion

The following section describes Austin Energy's projected 4CP loads and TCOS obligations for the base case and sensitivity analyses with solar capacity, storage capacity, and future TSP transmission rates.

3.3.1 Base case

For the base case analysis, a solar capacity of 80 MW and 5 MW (10 MWh) of energy storage is assumed. Although the assumed values are hypothetical and are simply used to illustrate the calculation tool developed in this study, these values are inspired by the ∼78.5 MW of local solar that Austin Energy had as of April 2020 [153]. Additionally, the validation for the storage capacity assumption is the Austin Energy Resource, Generation and Climate Protection Plan to 2025, which aims to install 4 MW of local distribution-connected storage by 2020 and 10 MW by 2025 [154]. It should also be noted that to count towards reducing 4CP load, the 80 MW of solar must be aggregations of smaller systems, each less than 1 MW (greater than that would require it to be registered with ERCOT [155]). Thus, they are likely to be conglomerations of small residential rooftop or commercial systems. The base case 4CP loads for the ten-year period are shown in Figure 3.3. A general increasing trend is observed from the graph (note that the y-axis does not start from zero). The projected load dips in 2021 because of Austin Energy's projection that the annual energy consumption in 2021 (one of the inputs to this model) will be slightly lower than the previous year [156]. Corresponding TCOS obligations range from $68 million in 2019 to $132 million in 2028. Austin Energy's actual 4CP load in 2018 was 2546 MW (higher than our forecast) and the corresponding TCOS obligation was $56.6 million (lower than our forecast) [18].

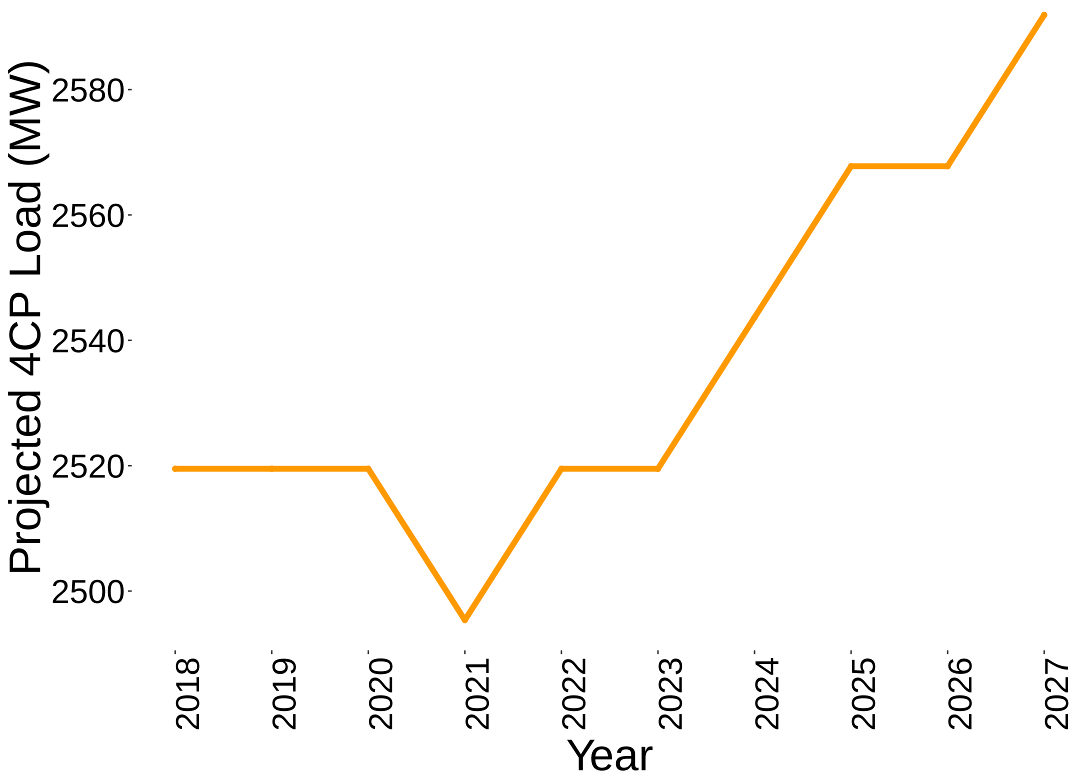

Figure 3.3: Projected Austin Energy 4CP loads for a ten-year period from 2018-2027 for the base case scenario exhibit an increasing trend with a solar capacity of 80 MW and energy storage of 5 MW (10 MWh). The projected 4CP load dips in 2021 because of Austin Energy's forecast that the annual energy consumption in 2021 (one of the inputs to this analysis) will be slightly lower than the previous years [156].

3.3.2 Transmission rate/access fee sensitivity

Future TCOS obligations are calculated using the three future projections of ERCOT TSP transmission rates mentioned in Section 3.2.2.3 and can be observed from Figure 3.4. For context, Austin Energy's current transmission rate is \$1.19/kW [18] and the previous update made in 2014 was \$1.16/kW. TCOS obligations in 2020 range from a best case scenario (from Austin Energy's perspective) of \$45 million to \$106 million. The projected 4CP loads are understandably not affected by variations in transmission rates.

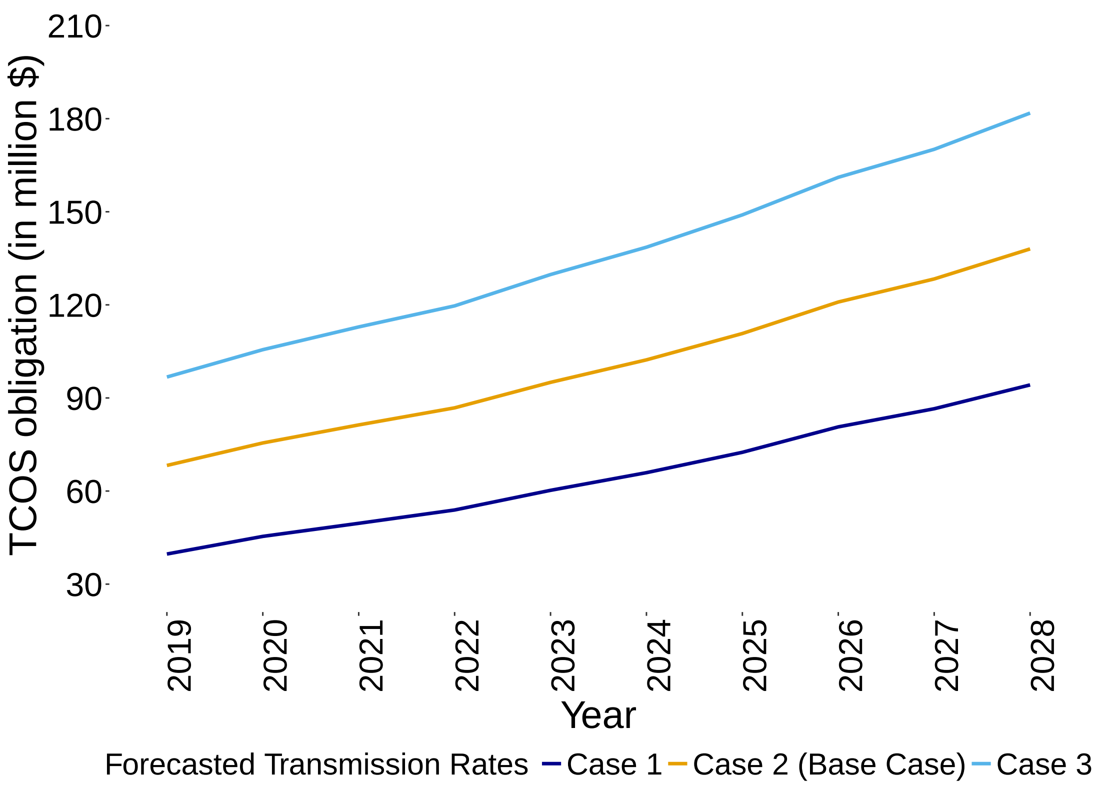

Figure 3.4: TCOS obligations are calculated for different projected transmission rates. A 'best case' scenario (in dark blue) predicts payments of \$40 million in 2019 and \$94 million in 2028. A 'worst case' scenario (in light blue) predicts payments of \$97 million in 2019 and \$182 million in 2028.

3.3.3 Solar sensitivity

4CP loads and corresponding TCOS obligations are calculated for six different solar capacities — 80 MW, 100 MW, 120 MW, 140 MW, 160 MW, and 180 MW. The storage value is kept constant at 5 MW (10 MWh). It can be observed from Figure 3.5 that even with a 100 MW increase in solar from the base case (comparing the 180 MW results with the 80 MW results), the 4CP load is only reduced by 12 MW each year.

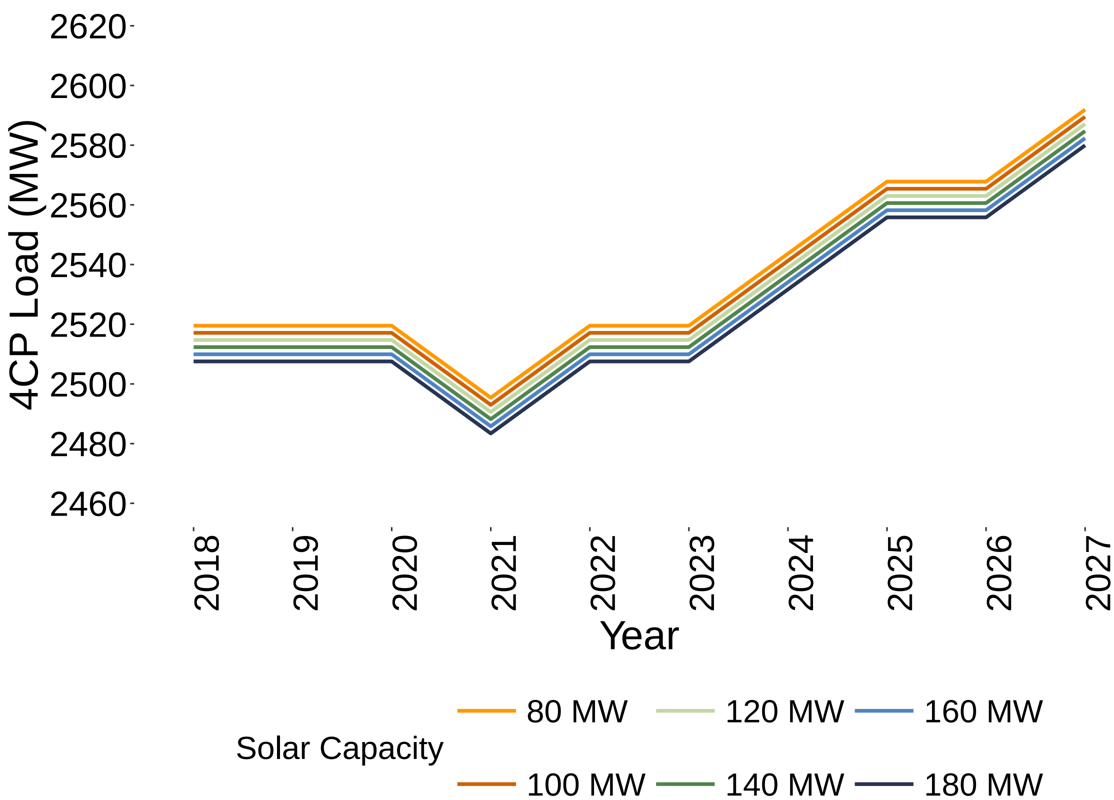

Figure 3.5: Projected Austin Energy 4CP loads for varying amounts of local solar capacity exhibit an increasing trend (note that the y-axis does not start from zero). The reduction in 4CP load is not commensurate with the increase in installed solar capacity because the peak event occurs in the late evening hours and does not align well with solar generation patterns.

The two reasons for these results are:

1. The solar capacities mentioned above are DC ratings and their AC outputs are much less than the maximum nameplate capacity.
2. The peak event occurs in the late evening hours (around 5 pm) when solar generation has already tapered off for the day and thus is not able to reduce the 4CP load significantly.

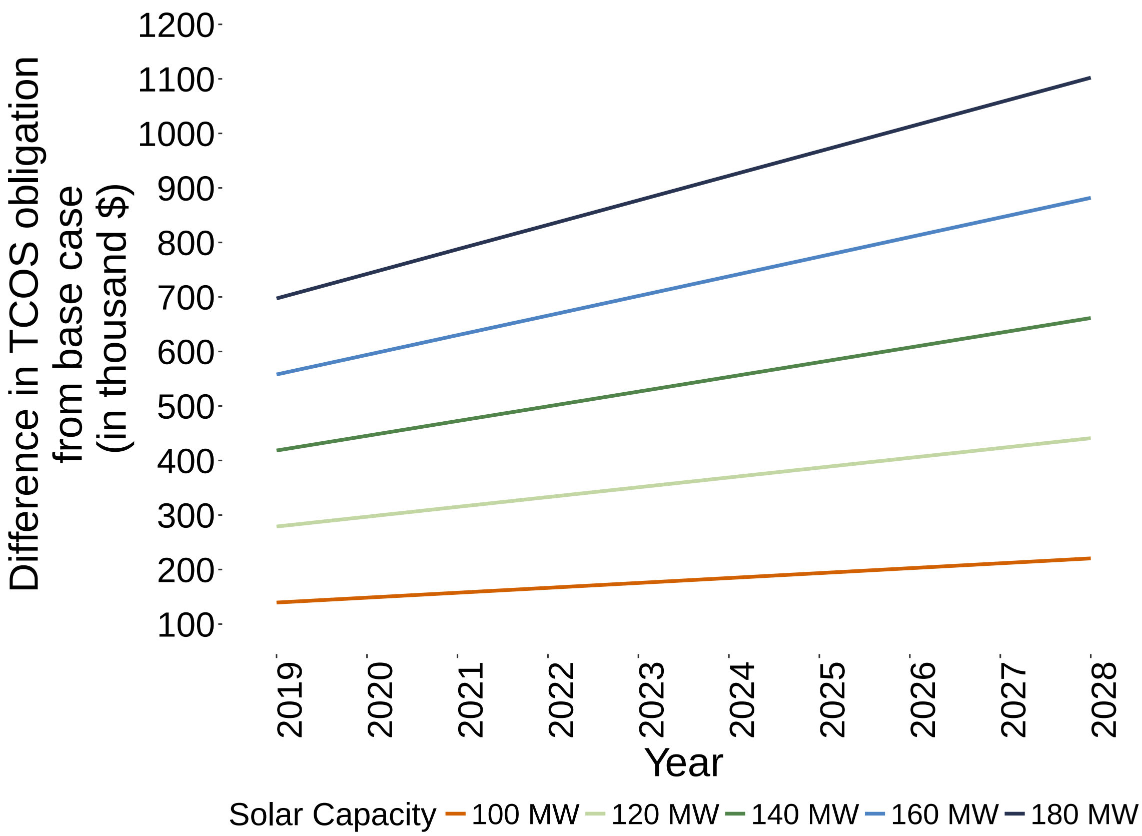

Figure 3.6: Projected deviation in Austin Energy's TCOS obligation from the base case (80 MW of solar) for varying amounts of local solar capacity can be observed. An increase of 20 MW of distributed solar lowers the corresponding TCOS obligation by an average of $180,000 each year. Further, 0.4% of the capital and installation cost is recovered within the first year.

Even though the reduction in 4CP load might seem negligible, Figure 3.6 shows that with 100 MW of solar (increase of 20 MW from the base case), Austin Energy's TCOS obligation is reduced by an average of $180,000 in each subsequent year. When the amount of installed solar is increased to 120 MW (increase of 40 MW from the base case), the average difference is $360,000 each year for the period of 2019–2028 and so on. The deviation from the base case is higher in each subsequent year because the sum of the projected transmission rates of the TSPs within ERCOT increases, thereby increasing the monetary value of unit reduction in Austin Energy's 4CP loads.

3.3.4 Storage sensitivity

Six illustrative energy storage capacities are chosen — 5 MW (10 MWh), 10 MW (20 MWh), 15 MW (30 MWh), 20 MW (40 MWh), 25 MW (50 MWh), and 30 MW (60 MWh). 4CP loads and corresponding TCOS obligations are calculated while keeping the amount of solar constant at the base case value of 80 MW. Similar results are observed as with the solar sensitivity observations, although the differences among the cases are visibly greater (because of the assumption that the entire storage capacity is available to discharge during the peak event). The results are shown in Figures 3.7 and 3.8.

Deviation in TCOS obligation from the base case is on the order of hundreds of thousands of dollars for each subsequent year over the 10-year projection period. The difference is higher in each subsequent year because the sum of the projected transmission rates of the TSPs within ERCOT increases, thereby increasing the monetary value of unit reduction in Austin Energy's 4CP loads.

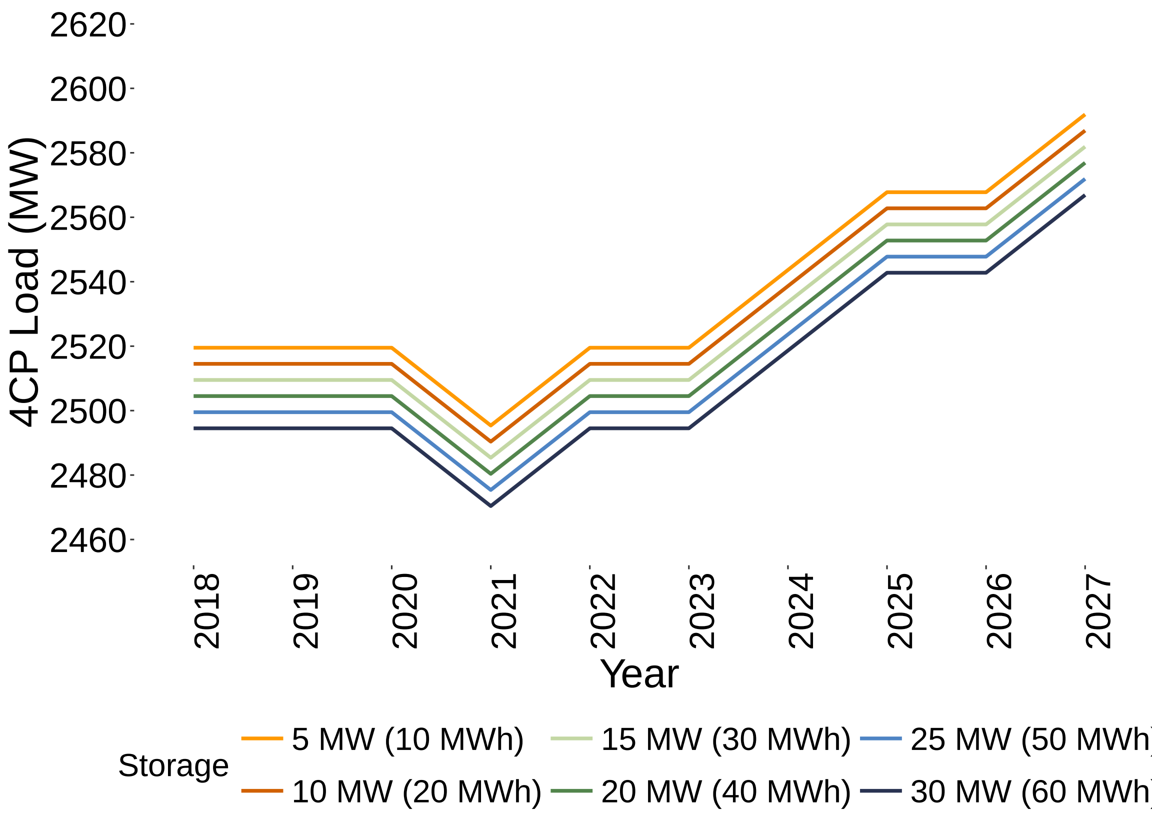

Figure 3.7: Projected Austin Energy 4CP loads for varying amounts of local distributed storage capacity exhibit an increasing trend (note that the y-axis does not start from zero). If the storage systems are fully charged before the peak event, the reduction in 4CP loads as a result of increase in local storage capacity is significant.

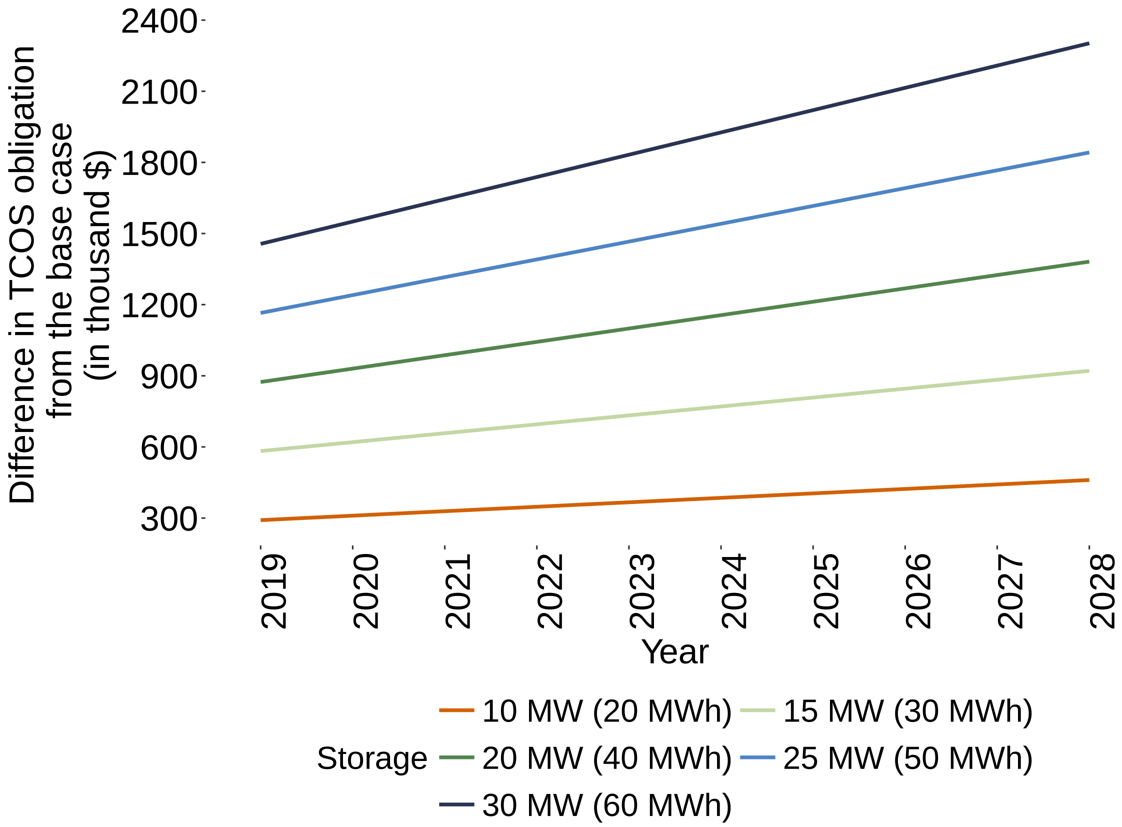

Figure 3.8: Projected difference in Austin Energy's TCOS obligation for varying amounts of local distributed storage capacity. An increase of 5 MW (10 MWh) of distributed storage lowers the corresponding TCOS obligation by an average of \$400,000 each year. Further, 3.4% of the capital and installation cost is recovered within the first year.

3.4 Limitations

Like any other modeling analysis, this study has some limitations. The storage systems are assumed to be fully charged before the peak event. However, this assumption might not always hold true if the ESSs are partially discharged while arbitraging the ERCOT energy market or offsetting customer non-coincident peak demand. Further, the social welfare (the difference between benefits and costs) gained by reducing the 4CP loads and corresponding TCOS obligations using local distributed solar and storage is not measured. TCOS obligations are used to recover invested capital in transmission network infrastructure. If the TCOS obligations for a particular TDSP are reduced, another TDSP must make additional payments that year to cover the transmission system investments already made. Thus, there is transfer of payments from one TDSP to another within ERCOT. Quantifying the overall social welfare to the transmission grid or investigating the potential of local renewable generation and storage for avoiding additional transmission system investments in the future could add an interesting dimension to this analysis. We leave this as an avenue for future work.

3.5 Summary

This chapter develops a calculation tool to help utilities quantify one of the many financial value streams of distributed solar and storage[1]. TCOS obligations of electric utilities can be on the order of tens of millions of dollars. We find that solar and storage capacity can substantially lower these payments. An increase of 20 MW of distributed solar can reduce the corresponding TCOS obligations by an average of $180,000 every year over a ten year period. Further, an increase in 5 MW (10 MWh) of distributed storage can lower TCOS obligations by an average of $400,000 every year over the ten years. To provide some context to interpreting these numbers, Austin Energy's annual operating budget (as of 2018) is $1.4 billion [157].

Future work will include performing similar case studies for other utilities within ERCOT, e.g. large utilities like CenterPoint Energy or electric cooperatives

[1] See https://github.com/arkasama/4CP_Loads_Payments for a detailed reproducible methodology.

likes Bandera Electric Cooperative, which might produce opportunities for comparison of the value of local solar and storage based on the location of the utility or the size of the population served.

Chapter 4

Developing an optimization tool to model residential peak load reduction through electricity rate structures

4.1 Introduction

One of the major drivers for increased emissions from the electricity sector is rising peak demand, which is often met by fossil fuel generation [8]. Meeting this increasing peak demand also necessitates the construction of expensive generation, transmission, and distribution infrastructure [5, 6] (which might not be used for a majority of the year when demand is lower). The residential sector accounts for 27% of global final energy consumption and 17% of global carbon emissions [22]. In hot climates like Texas, residential demand, which is highly correlated with the timing of usage of end-use appliances [76], comprises about half of the summer peak demand [23]. One of the many ways that utilities reduce residential peak demand include demand response initiatives to encourage load shifting to off-peak hours by subjecting customers to demand charges [158] or time-varying electricity rates [159].

A branch of the demand response literature focuses on analyzing findings from historical dynamic pricing pilot programs launched by electric utilities [24–28]. Another line of research focuses on quantifying peak load reduction and economic

This chapter was adapted from the journal article: A. Bandyopadhyay, B. D. Leibowicz, E. A. Beagle, M. E. Webber, As one falls, another rises? Residential peak load reduction through electricity rate structures, *Sustainable Cities and Society*, 2020 [3]. The majority of this paper's research, analysis, and writing were completed by the author of this dissertation. The co-authors contributed to defining the direction of this project and editing the manuscript.

savings in the residential sector using optimization models. Several authors use linear, convex, and bilevel programs to minimize customer electricity costs or maximize utility of the customer under dynamic prices and solve for the optimal scheduling of smart appliances [29–43]. Although some of these studies incorporate customer-preferred priority of appliances, operation times, and customer-set bounds on permissible temperature, many economic models often neglect the monetary value of the effort, time, and discomfort experienced by customers who reduce and/or shift their loads in response to incentives offered by the local electric utility. The limited number of studies that include customer discomfort in their models do not include detailed models for controllable appliances and separate customer discomfort/inconvenience functions for each appliance.

To fill this knowledge gap, this study develops a convex optimization tool to model price-based demand response in the residential sector while incorporating the monetary value of customer discomfort of deviation from set-point temperatures and inconvenience of running appliances at certain times of the day. Four different electricity pricing structures are evaluated — constant rates, real-time pricing (RTP), time-of-use (TOU) rates and critical peak pricing (CPP) — and four types of controllable loads are considered — heating, ventilation, and air-conditioning (HVAC) systems, electric water heaters (EWHs), electric vehicles (EVs), and pool pumps (PPs). Sensitivity analysis is performed by varying the discomfort/inconvenience parameters for the different controllable loads to analyze their effect on the peak residential electricity demand. The model is demonstrated using empirical appliance-level energy usage data from Pecan Street Inc. [56] and electricity rates from Austin Energy, the local municipally-owned electric utility in Austin, TX.

Utilities can use our modeling approach as a tool to anticipate the effects of alternative electricity rate structures on the timing and magnitude of peak load in the residential sector. In an even more direct sense, individual households can use our model to optimally control their appliances in response to more complex rate structures that might be in place in the future by entering the parameter values specific to their own appliances into a smart home system, tuning the model with discomfort/inconvenience parameters, and so on.[1]

4.2 Methods

This section describes our methodology based on developing a convex optimization tool for peak electricity demand reduction and/or shifting in the residential sector using price-based demand response. We provide detailed descriptions of the objective function, constraints, empirical electricity demand profiles, time-varying electricity prices, analysis period, and scenarios — in this order. The model code corresponding to this chapter is available open-source on GitHub.[2]

4.2.1 Objective function

The objective function consists of cost of power bought from the grid, the monetary value of the discomfort of deviation of room and water temperatures from the respective customer-set temperature points, and the monetary value of the inconvenience of charging the EV and running the PP during different times of the day. The function is shown in Equation 4.1.

[1] See https://emmalaub.shinyapps.io/Peak_Load_Reduction_Tool_ver2/ for a user-friendly RShiny application developed in conjunction with this study.

[2] See https://github.com/arkasama/Peak_Load_Reduction_Residential_Sector for sample code.

$$
\begin{aligned}
Obj = &\sum_{t=1}^{N} P_{bought,t} \times C_t \times \Delta t + \sum_{t=1}^{N} \alpha_{EV,t} \times S_{EV,t} + \sum_{t=1}^{N} \alpha_{PP,t} \times S_{PP,t} \\
&+ \sum_{t=1}^{N} \alpha_{HVAC,t} \times (T_{r,t} - T_{r,sp,t})^2 + \sum_{t=1}^{N} \alpha_{EWH,t} \times (T_{w,t} - T_{w,sp,t})^2
\end{aligned} \tag{4.1}
$$

The decision variables in the model at each time step t are as follows (See the glossary for definitions and units of other variables and parameters):

1. Power bought from the grid for use in the home ($\mathrm{P_{bought,t}}$) [kW]

2. Temperature of the room ($\mathrm{T_{r,t}}$) [K]

3. Temperature of the water ($\mathrm{T_{w,t}}$) [K]

4. Operational level of EV[3] ($\mathrm{S_{EV,t}}$)

5. Operational level of PP ($\mathrm{S_{PP,t}}$)

4.2.2 Constraints

The objective function is minimized subject to constraints involving energy conservation around the home. The optimization model also includes a one-parameter thermal model for the HVAC and EWH, charging model for the EV, and operational model for the PP. The customer is able to maintain comfortable conditions in the home by specifying bounds for the room and water temperature. The marginally increasing discomfort penalty for deviating would naturally prevent customers from going too far from the set-point, but we still include hard constraints for upper and lower bounds to keep the solution realistic.

[3] We refer to the operational level of the EV charger as the operational level of the EV in this study

The first constraint, shown in Equation 4.2, specifies that at each time step t, the sum of power flowing from the grid to the home and the power generated by the solar panels must be greater than power usage in the home by the residential customer. The S terms represent the operational level of the respective appliances (as fractions of their maximum operational power). The uncontrollable power ($P_{uncontrollable,t}$) refers to all other power usage in the home other than the four end-use appliances considered in this study.

$$\begin{aligned} P_{uncontrollable,t} + P_{HVAC} \times S_{HVAC,t} + P_{EWH} \times S_{EWH,t} + P_{EV} \times S_{EV,t} \\ + P_{PP} \times S_{PP,t} \leq P_{solar,gen,t} + P_{bought,t} \end{aligned} \tag{4.2}$$

A one-parameter thermal model [160, 161] is used for modeling the HVAC system, as shown in Equation 4.3. Customer comfort is maintained by keeping the room temperature between customer-specified limits (Equation 4.4).

$$\begin{aligned} T_{r,t} = (1 - \frac{\Delta t}{M_a \times C_{p,a} \times R_{eq}}) \times T_{r,t-1} + \frac{T_{ambient,t-1} \times \Delta t}{M_a \times C_{p,a} \times R_{eq}} \\ - S_{HVAC,t-1} \times \frac{COP \times P_{HVAC} \times \Delta \mathrm{t}}{M_a \times C_{p,a}} \end{aligned} \tag{4.3}$$

$$T_{r,min} \leq T_{r,t} \leq T_{r,max} \tag{4.4}$$

A one-element thermal model is developed for the electric water heater (Equations 4.5 – 4.9), which also maintains the water temperature within customer-specified thresholds (Equation 4.10) [81, 82]. The variables C, B, G, and $R^{'}$ in Equation (4.5) are defined in Equations 4.6 – 4.9.

$$\begin{aligned} T_{w,t} = T_{w,t-1} \times e^{\frac{-\Delta t}{R^{'} \times \mathrm{C}}} + (G \times R^{'} \times T_{amb,t-1} + B \times R^{'} \times T_{water,in} \\ + S_{EWH,t-1} \times \eta_{EWH} \times P_{EWH} \times R^{'}) \times (1 - e^{\frac{-\Delta t}{R^{'} \times C}}) \end{aligned} \tag{4.5}$$

$$C = C_p \times \rho \times V \tag{4.6}$$

$$B = C_p \times \rho \times F \tag{4.7}$$

$$G = \frac{SA}{R} \tag{4.8}$$

$$R^{'} = \frac{1}{G + B} \tag{4.9}$$

$$T_{w,min} \leq T_{w,t} \leq T_{w,max} \tag{4.10}$$

The EV is modeled to charge using a 240V Level 2 charger and meets the desired energy capacity with a 10% tolerance interval, as shown in Equation 4.11.

$$\sum_{t=1}^{N} P_{EV} \times \eta_{EV} \times S_{EV} \times \Delta t = E_{EV,consumed,daily} \pm 0.1 \times E_{EV,consumed,daily} \tag{4.11}$$

The PP runs during the day and the operational model is similar to the charging schedule of the EV, as demonstrated in Equation 4.12. PPs are generally operated about 6 hours a day [162] to circulate the water in an average sized swimming pool once every day and maintain national health standards.

$$\sum_{t=1}^{N} P_{PP} \times \eta_{PP} \times S_{PP} \times \Delta t = E_{PP,consumed,daily} \pm 0.1 \times E_{PP,consumed,daily} \tag{4.12}$$

The energy consumed by the electric vehicle and the PP for each home having those appliances are obtained from empirical data by adding the power (kW) at each minute time step throughout the day and multiplying by 60 to get the energy consumed (kWh).

4.2.3 'CVXR' package in R

The objective function of our optimization model mentioned in Section 4.2.1 is a convex function with three linear terms and two quadratic terms. We solve the model using the 'CVXR' — an object-oriented mathematical package in R which allows users to formulate and solve disciplined convex optimization problems [163]. Disciplined convex programs are a subset of convex programs that have a set of conventions imposed upon them which in turn allow the solution to be automated and enhanced [164].

4.2.4 Pecan Street empirical data

Pecan Street is a non-profit organization that collects temporally-resolved disaggregated electricity consumption data from over 1000 homes in Austin, TX. About 250 of these homes have onsite solar panels and 65 are EV owners [56]. While most of these homes that volunteer to provide data to Pecan Street are located in one neighborhood in East Austin, there are several homes in other areas of Austin as well as in California and Colorado [56]. The energy usage data is provided to university researchers worldwide through Pecan Street's online dataport [56]. Such temporally-resolved, location-specific, and appliance-level electricity consumption data are extremely rare. Since the organization's inception in 2009, it has provided data for various modeling and analysis studies [45, 48, 57, 165–169].

We obtain minute-interval data for overall electricity usage, solar generation, and appliance-level data for HVACs, EWHs, EVs, and PPs for 100 homes in Austin. The homes fall within 12 different categories based on ownership of appliances which are listed in Table 4.1. The majority of homes fall within the following three categories: homes with 1) HVAC and solar, 2) HVAC, EV, and solar, and 3) HVAC and EWH. The uncontrollable power of each home at every time step t ($P_{uncontrollable,t}$)

is calculated from the Pecan Street dataset by subtracting the power of each of the energy-intensive appliances from the overall power profile. The amount of energy consumed by the EV ($E_{EV,consumed,daily}$) and PP ($E_{PP,consumed,daily}$) throughout the day, and solar power generation ($P_{solar,gen,t}$) at each time step t for each home are also obtained from this dataset.

Table 4.1: Types of homes analyzed from the Pecan Street dataset [56], broken down by their sets of appliances. 35% of homes have HVAC and solar, 29% have HVAC, EV, and solar, while 10% have HVAC and EWH — thus, the majority of homes fall within these three categories.

Category	**HVAC**	**EWH**	**EV**	**PP**	**Solar**	**Number of homes**
1	✓	✓	✓	✓	✓	2
2	✓	✓	✓	✗	✓	3
3	✓	✗	✓	✓	✓	1
4	✓	✓	✓	✗	✗	2
5	✓	✓	✗	✗	✓	2
6	✓	✗	✗	✓	✓	2
7	✓	✗	✓	✗	✓	29
8	✓	✓	✗	✗	✗	10
9	✓	✗	✓	✗	✗	5
10	✓	✗	✗	✓	✗	6
11	✓	✗	✗	✗	✓	35
12	✓	✗	✗	✗	✗	3

4.2.5 Properties of controllable appliances

The power ratings of the four controllable end-use devices considered in this study — HVAC, EWH, EV, and PP — are obtained from existing literature and are reported in Table 4.2. The customer-specified minimum and maximum room and water temperature, set-point temperatures, and efficiencies of the EV and PP are also included.

Table 4.2: Properties of controllable appliances used in the analysis.

	HVAC	**EWH**	**EV**	**PP**
Power† (kW)	3.5	4.5	6.6	1.1
Minimum Temperature	21°C (69.8°F)	40°C (104°F)	–	–
Maximum Temperature	24°C (75.2°F)	45°C (113°F)	–	–
Set-point Temperature	22.2°C (72°F)	42°C (107.6°F)	–	–
Efficiency‡ (%)	–	90	86.4	70
Coefficient of Performance‡	2.5	–	–	–

† Data sources for rated power: HVAC [160], EWH [91], EV [170], PP [162].

‡ Data sources for efficiency: EWH [171], EV [172], PP [84]. COP: [173].

4.2.6 Period of analysis

We choose the summer peak day (June 23) of 2017 and use 15 minute time steps to demonstrate the results of the model. Selected results for the winter minimum peak day (February 21) can be found in Appendix A.3. The winter minimum peak day refers to that day of the chosen year when the peak electricity demand within the Austin Energy service territory is the maximum across the winter months from November to February.

4.2.7 Electricity pricing

We solve the optimization problem under the following four alternative electricity rate structures to assess the effects of these pricing schemes on the residential load profile, including the magnitude and timing of peak load:

1. Constant rates

2. Real-time prices

3. Time-of-use rates

4. Critical peak prices

We use the Tier 3 (out of five tiers) value (7.81 cents/kWh) of the current Austin tiered residential rate structure for the constant energy charge [68]. The purpose of this simplification is that the tiers are based on customer energy (kWh) usage over a full monthly billing cycle, but the period of analysis of this study is only the summer peak day. Further, we choose the Tier 3 value to best estimate the energy charge for customers at both ends of the energy usage spectrum since this tier (1001–1500 kWh) acts as 'a bridge' between customers with low/average and high energy consumption. Additional charges including monthly fixed customer charge, power supply adjustment, customer benefit charges, and regulatory charges are added to this energy charge to calculate total electricity costs to the customer. These additional charges are listed in Table 4.3 [68]. The following paragraphs describe how the time-varying pricing structures are parameterized.

Table 4.3: Additional electricity charges to the residential customer [68]. These charges are added to the energy cost in the electricity bill that customers within the Austin Energy service territory receive at the end of each billing cycle.

Component	**Unit**	**Value**
Customer Charge	$/month	10
Power Supply Adjustment	cents/kWh	2.895
Community Benefit Charges:		
Customer Assistance Program	cents/kWh	0.154
Service Area Street Lighting	cents/kWh	0.124
Energy Efficiency Program	cents/kWh	0.334
Regulatory Charge	cents/kWh	1.342

Historical 5-minute interval real-time prices from 2017 for ERCOT (Electric Reliability Council of Texas) load zone AEN (Austin) are first converted to 15-minute interval prices and then scaled using a multiplicative scaling factor. This factor is chosen such that the scaled real-time prices yield the same electricity cost to the customer as the case with constant rates when these prices are applied to the load profile for the constant case. The purpose of this scaling is to allow an 'apples-to-apples' comparison, such that the four rate structures start out with the same total electricity cost prior to any load shifting or reduction.

Tier 3 time-of-use rates from Austin Energy's (now suspended) residential pilot program are scaled using a similar methodology as with the real-time prices [174]. TOU prices include on-peak prices (from 2 pm to 8 pm), mid-peak prices (from 6 am to 2 pm and 8 pm to 10 pm), and off-peak prices (from 10 pm to 6 am). Additional charges mentioned in Table 4.3 are added to these historical time-varying prices.

Austin Energy does not have a critical peak pricing program for its residential customers. Thus, we use critical peak prices from the 'SmartRate' program administered by Pacific Gas & Electric (PG&E) in California. PG&E residential customers can enroll in this program on a voluntary basis. During the summer months from June to September, they pay an additional \$0.60/kWh on top of their regular rates for all usage between 2 pm and 7 pm on extreme days or 'SmartDays' while saving approximately \$0.024/kWh for electricity usage during other times of the day [102]. In addition, these customers receive a monetary participation credit [102]. Thus, residential customers participating in this program can experience savings in their monthly electricity bills by either reducing usage of high-energy consuming appliances or shifting time of usage of these appliances to non-peak hours. We linearly scale these critical peak prices from PG&E using Equation 4.13 to apply to our analysis in the Austin Energy service territory [175]. The four pricing schemes for the summer peak day can be observed in Figure 4.1. Critical peak prices are applicable during the peak period in ERCOT from 3 pm to 7 pm [176].

$$\frac{\text{Austin Energy CPP}}{\text{PG\&E CPP}} = \frac{\text{Austin Energy Tier 3 rate}}{\text{PG\&E constant rate } (101\% - 400\% \text{ of baseline})} \tag{4.13}$$

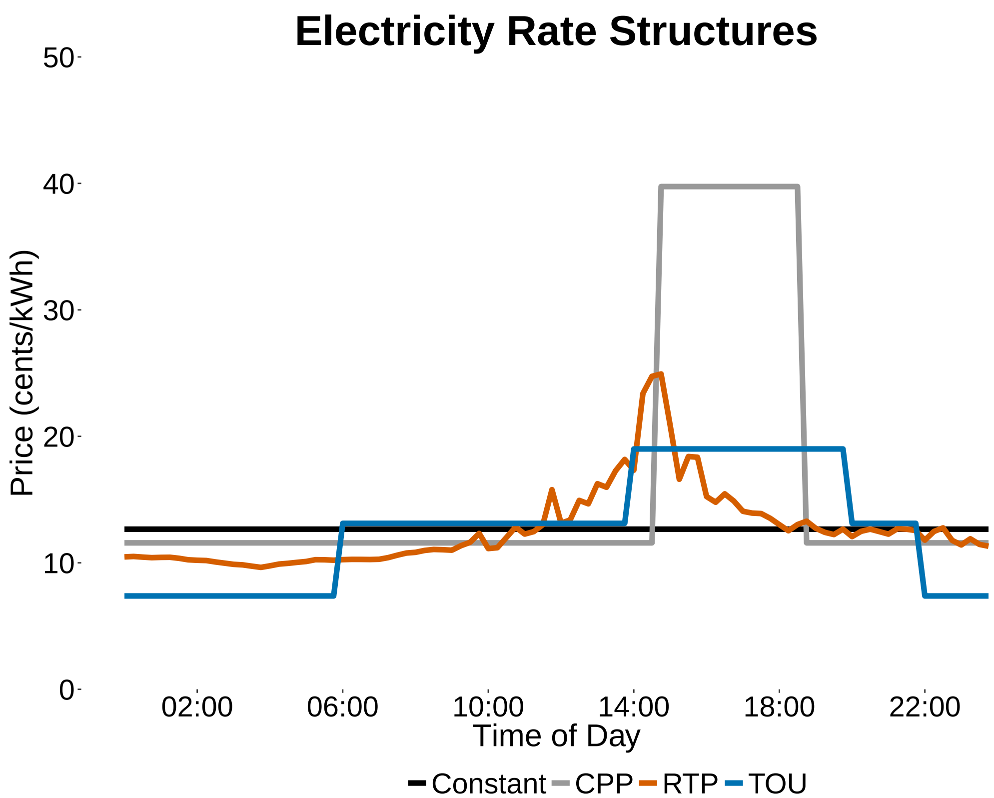

Figure 4.1: Four different pricing schemes considered in this study for the summer peak day. Real-time prices peak at 3 pm; on-peak TOU rates are in effect from 2 pm to 8 pm; CPP are applicable from 3 pm to 7 pm.

Further, instead of a net metering policy, Austin Energy has a Value of Solar (VOS) rate of \$0.097/kWh for its residential customers [127]. The VOS is the rate at which Austin Energy credits its solar customers for the energy produced by their on-site solar energy systems [127]. Customers pay charges to the utility for the total energy usage of their home (both energy bought from the grid and energy flowing from the solar panels to the home) and get a credit from the utility for the solar energy produced by their solar panels based on the current VOS rate [127].

4.2.8 Scenarios analyzed

4.2.8.1 Single-home analysis

We first run the optimization model for a single home in the Austin Energy service territory. The home has all four end-use appliances — HVAC, EWH, EV, and PP — in addition to rooftop solar panels. The purpose of first looking at a single home in isolation is to demonstrate the application of the model and look in detail at how the load profiles of the individual appliances react to the different rate structures. This particular home is chosen because it is one of the two homes in the Pecan Street dataset owning all four end-use appliances and solar panels and having high energy usage ($\sim$ 124 kWh/day). We solve for the power bought from the grid, operational level of the four appliances, timing and quantity of peak electricity demand, energy consumed, and greatest ramp rate under the different pricing structures. An additional scenario is run to highlight key results if the home did not have solar panels.

4.2.8.2 Community-level analysis

The optimization model is then run in succession for 100 homes in Austin, TX. The types of appliances in these homes are listed in Table 4.1. All homes have HVACs, 19% have EWHs (many of the others might have natural gas water heaters), 42% have EVs, 11% have PPs, and 74% have rooftop solar panels[4]. The uncontrollable power

[4]Since the percentage of households owning EVs and rooftop solar panels used in this community-level analysis is not typical of residential neighborhoods at the present time (but could be in the near future), we perform sensitivity analysis with different fractions of homes having EVs and solar panels [177–179].

profile, solar generation, and energy consumed by the EV and the PP for all 100 homes are obtained from the Pecan Street dataset. The metrics mentioned in Section 4.2.8.1 are also measured for this community-level analysis.

4.2.8.3 Sensitivity analysis with discomfort/inconvenience parameters

Discomfort parameters for the HVAC (α_{HVAC}) and inconvenience parameters for the EV (α_{EV}) are inspired from relevant literature [180, 181]. We arbitrarily set α_{EWH} to be equal to α_{HVAC} and α_{PP} to be one-third of the maximum value of α_{EV}. The parameters for the 'base case' analysis are shown in Figure 4.2. For the HVAC and EWH, these parameters represent the monetary value of the first degree of deviation of room and water temperatures respectively from the corresponding set-point temperatures. The monetary value of inconvenience caused to the customer by charging the EV or running the PP at each time step t is represented by α_{EV} and α_{PP} at that time respectively. The discomfort parameters for the HVAC and EWH are lower from 9 am – 4 pm because the customers are modeled to be at work during those hours. The inconvenience parameter for the EV is maximum during 7 am – 6 pm since many customers require their vehicles to commute to work[5] and is set lower (but not equal to zero) from 6 pm – 9 pm to model customers possibly needing their vehicles for evening activities. The inconvenience parameter for the PP is positive from 10 pm to 8 am to account for the noise of the PP motor potentially causing disturbances at night.

It is difficult to accurately estimate the values of the discomfort/inconvenience parameters. Therefore, we conduct sensitivity analysis by halving and doubling the parameters for all four end-use appliances.

[5] We later conduct sensitivity analysis on the times available for EV charging

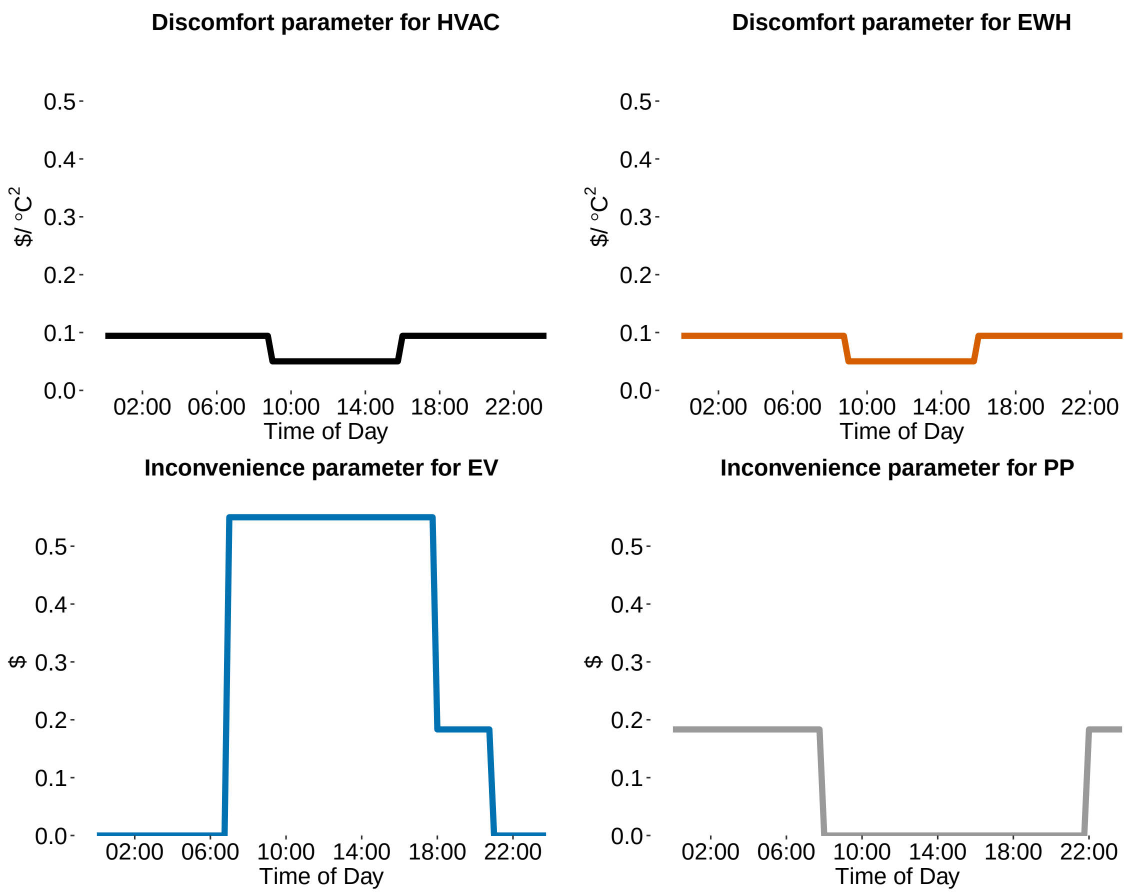

Figure 4.2: Reference values for discomfort/inconvenience parameters for the four end-use appliances are shown. These values vary throughout the day based on customers' schedules and comfort preferences.

4.2.8.4 Additional scenarios

We run two additional scenarios to relax two of the constraints in the original model that might not be relevant for all homes. We first perform a case study by setting the inconvenience parameter for EV (α_{EV}) to zero throughout the day for each home in the community of 100 single-family detached homes that owns EVs. This means that the customers owning EVs have their cars parked at home during the day (e.g., work from home, retired, do not use their EVs to commute to work).

Another case study is performed by hard-coding the inconvenience parameter for PPs (α_{PP}) to be zero throughout the day for each home in the community of 100 single-family detached homes that owns PPs. This refers to the case where the PPs are are quiet enough to prevent any potential noise issues that might stem from nighttime operation.

4.3 Results and discussion

The following subsections describe the results to our convex optimization model. We start by looking at the single home to illustrate the behavior of the model in detail and then move on to the community of 100 homes. We finally highlight key results from the sensitivity analysis with discomfort/inconvenience parameters and the cases where constraints on EVs and PPs are relaxed. The time taken for the CVXR solver to set up the optimization problem for each individual house is about 10^{-3} s and the computation time is on the order of 10^{-2} s.

4.3.1 Single home with solar panels

Table 4.4 shows that time-varying pricing structures shift the timing of the residential peak away from the time of overall electricity system peak load (6 pm on this particular summer peak day), but lead to a higher peak in the residential sector. The most significant shift is seen for the RTP case in which the peak is at 3:45 am when the EV is charged and the PP is run. The energy consumption for all four cases is similar while the ramp rates for the time-varying rates are higher than for the constant rate.

Table 4.4: Differences in peak load timing and characteristics for a sample home with solar panels on the summer peak day of 2017 for four electricity pricing structures. Dynamic prices shift the timing of the residential peak, but can increase its magnitude. Real-time prices cause the most significant shift.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	9:15 pm	3:45 am	10 pm	7 pm
Peak Load (kW)	6.09	10.61	7.73	6.85
Energy Consumption (kWh)	57.1	57.45	56.1	56.59
Greatest Ramp Rate (kW/min)	0.15	0.49	0.27	0.32

Figure 4.3 shows the power bought from the grid for a home with four high energy consuming end-use appliances - HVAC, EWH, EV, and PP - and solar panels for the summer peak day. For the constant rate, the power profile (in black) peaks at 9:15 pm. The power bought for the real-time pricing structure (in orange) peaks at 3:45 am since the prices are lowest at that time of the day. The critical peak prices are in effect from 3 pm – 7 pm. As a result the power flow into the home (in gray) peaks during the time interval from 7 – 7:15 pm right after the prices decrease. For the case with TOU rates, we observe an interesting insight. The power bought (in blue) rises right before the prices change from off-peak rates to mid-peak rates at 6 am, right after prices decrease from on-peak to mid-peak rates at 8 pm, and finally after prices decrease from mid-peak to off-peak rates at 10 pm. No power flows into the home from 10 am – 6 pm for all four pricing structures because the solar panels generate electricity and meet the household demand. Key results for the case where the home has all four appliances but no solar panels are shown in Appendix A.1.

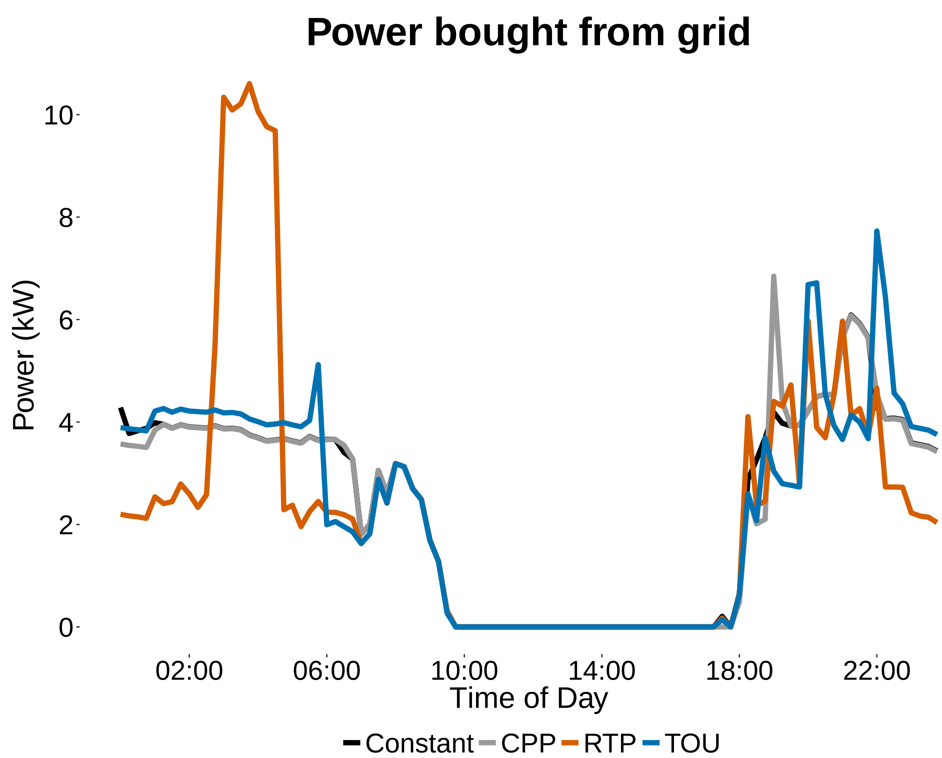

Figure 4.3: Power bought from the grid on the summer peak day of 2017 for a sample home with solar panels under four different pricing structures. Dynamic prices shift the timing of peak demand, but can cause a second higher peak.

Figures 4.4 to 4.7 describe the operational level (normalized power) of the four end-use appliances considered in this study — HVACs, EWHs, EVs, and PPs. The operational level of the HVAC (S_{HVAC}) for each of the four pricing structures is modeled using Equation 4.3 from Section 4.2.2 while the rated power and permissible room temperature limits are mentioned in Table 4.2. It can be observed from Figure 4.4 that S_{HVAC} follows the pattern of the ambient temperature which rises throughout the day and peaks at 4 pm. For the constant rates, S_{HVAC} is high from 10 am – 6 pm and reaches maximum capacity at 4:15 pm. The rapid oscillations observed for S_{HVAC} for the case with real-time prices mimic the varying nature of these prices.

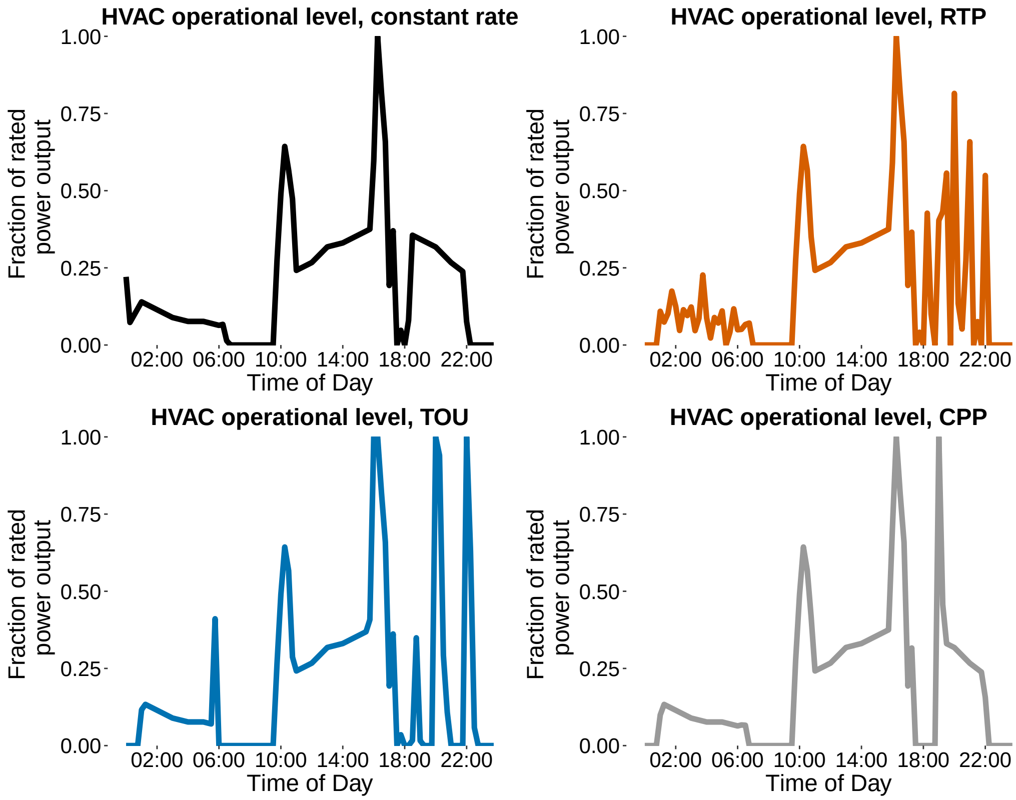

Figure 4.4: Operational level of the HVAC under different pricing structures for a sample home with solar panels on the summer peak day of 2017. The operational levels in all cases mimic the ambient temperature curve but differ across pricing structures based on duration of on-peak periods and diurnal variability of prices.

For the case with TOU rates, the HVAC reaches its maximum output at four different time-points — 4 pm, 4:15 pm, 8 pm, and 10 pm. The rise and fall of S_{HVAC} during the late evening hours is likely to take advantage of the decrease in prices from on-peak to mid-peak rates at 8 pm and from mid-peak to off-peak rates at 10 pm. The operational level is zero from 5:30 pm – 7 pm for the CPP case since the high prices are in effect from 3 pm – 7 pm (the ambient temperature is likely too high before 5:30 pm for the HVAC to be turned off and still keep the room within the customer-set minimum and maximum room temperatures). It rises to 1 right after the prices decrease at 7 pm. This intuitive operating schedule for the HVAC system only emerges in our optimization model because we have a dynamic thermal model of the temperature in the home.

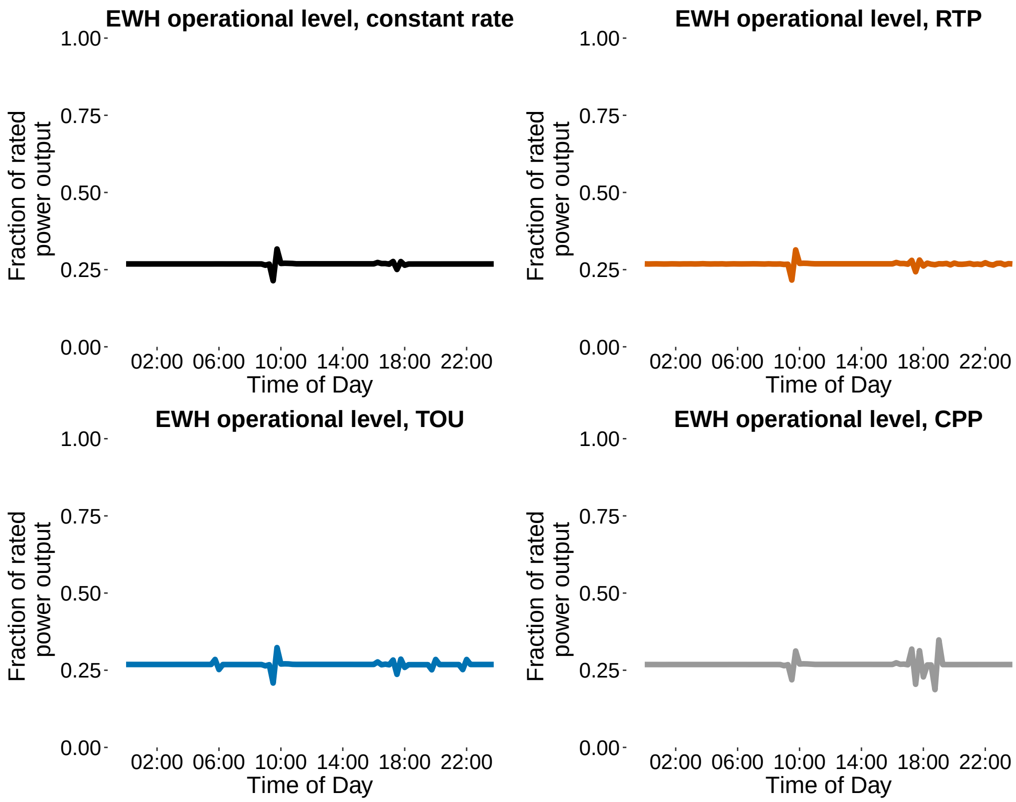

Figure 4.5: Operational level of the EWH under different pricing structures for a sample home with solar panels on the summer peak day of 2017. The operation of the EWH is less dependent on the ambient temperature (when compared to the HVAC system) and remains constant across pricing structures. The slight fluctuations represent time points corresponding to sharp changes in the price levels and/or discomfort parameters.

The operational level of the EWH (S_{EWH}) is modeled using Equations 4.5 – 4.10 while the rated power of the EWH and permissible water temperature limits are mentioned in Table 4.2. It can be observed from Figure 4.5 that S_{EWH} is less dependent on the ambient temperature. It almost remains at a constant value of 0.27

throughout the day for all four pricing structures. For the TOU rates, the operational level (in blue) wavers a little from the constant value as the prices change among the on-peak, mid-peak, and off-peak rates.

The operational level of the EV (S_{EV}) is modeled using Equation 4.11 from Section 4.2.2 and is shown in Figure 4.6. For the constant and CPP rates, the EV charges from 12 am – 7 am and again from 9 pm – 12 pm. This is due to α_{EV} being zero during those time periods.

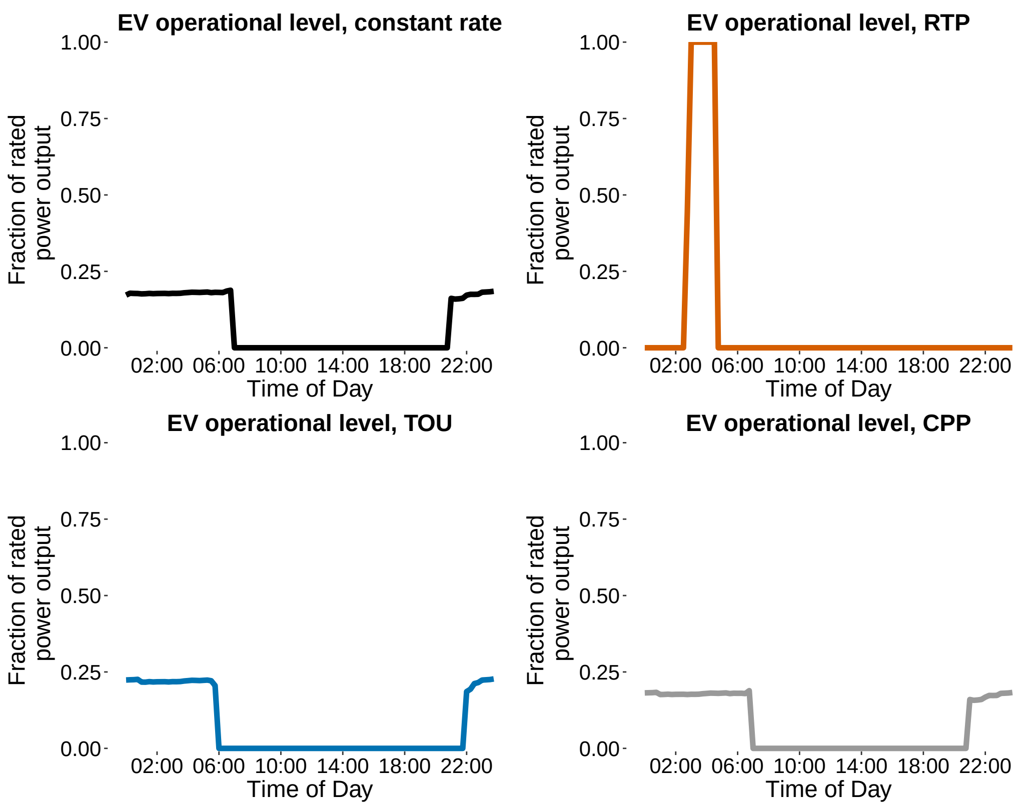

Figure 4.6: Operational level of the EV under different pricing structures for a sample home with solar panels on the summer peak day of 2017. The most contrasting result is observed for the RTP case where the entire charging occurs between 3 am and 4:30 am when prices are lowest.

S_{EV} for the RTP case reaches its maximum value between 3 am and 4:30 am when prices are lowest. For the case with TOU rates, the EV is charged before 6 am and after 10 pm when off-peak prices are in effect and α_{EV} is zero. It should be noted that for each of the pricing structures, the EV is charged to the same energy level (specified by the value of $E_{\text{EV, consumed}}$ obtained from the Pecan Street dataset) and the maximum energy charged to the EV during each time interval is restricted to 6.6 kW, as mentioned in Table 4.2.

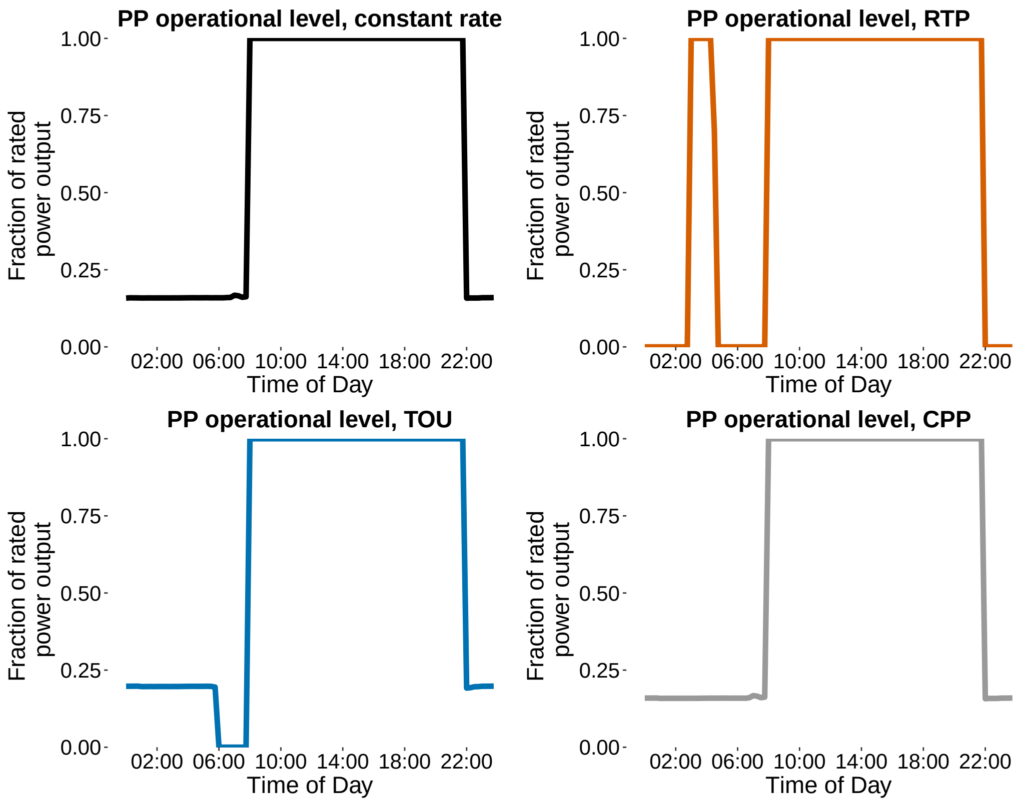

Figure 4.7: Operational level of the PP under different pricing structures for a sample home with solar panels on the summer peak day of 2017. Both the inconvenience parameter (with a value of zero from 8 am - 10 pm) and diurnal variations in prices play significant roles in determining the optimal operating schedule for the PP.

The PP is modeled using Equation 4.12 from Section 4.2.2. For the constant rate and CPP cases, the PP runs at full capacity from 8 am – 10 pm and at 16%

capacity at other times, as shown in Figure 4.7. This trend occurs because α_{PP} is zero from 8 am to 10 pm. $\mathrm{S_{PP}}$ for the RTP case is 1 from 3 am – 4:30 am to take advantage of the low prices and again from 8 am – 10 pm as α_{PP} is zero during that time interval. The PP runs at 20% capacity from 12 am – 6 am for the TOU rates and then decreases to zero during the mid-peak period from 6 am – 8 am. It then ramps up to full capacity from 8 am – 10 pm and back to 20% capacity after 10 pm.

4.3.2 Community-level analysis

Table 4.5 shows that time-varying pricing structures increase the magnitude of the residential peak load but shift the timing of the peak. The total energy consumption over the course of the day is similar in all four cases while the ramp rates for the time-varying rates are higher than for the constant rate. The maximum ramp rate is for the TOU case although the jump from the non-peak rate to the critical peak rate for the CPP case is the highest.

Table 4.5: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes on the summer peak day of 2017 for four electricity pricing structures. Dynamic prices increase the magnitude of the residential peak but shift the timing. The total energy consumption over the course of the day remains relatively constant across the four cases.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	9:15 pm	8 pm	10 pm	7 pm
Residential Peak Load (kW)	301	452	553	461
Energy Consumption (kWh)	3752	3776	3783	3757
Greatest Ramp Rate (kW/min)	4.3	19.6	24.6	23.1

Figure 4.8 shows the total power purchased from the grid by the community of 100 single-family detached homes under the four different pricing structures over the course of the summer peak day. The four pricing structures analyzed in this study

are shown in Figure 4.1 in Section 4.2.7. Unlike the results from the single home analysis, the power flow from the grid to the home is not zero in the middle of the day because 26% of homes do not own solar panels (as listed in Table 4.1) and many of the homes with solar do not produce enough solar electricity to completely meet their needs during the period of generation.

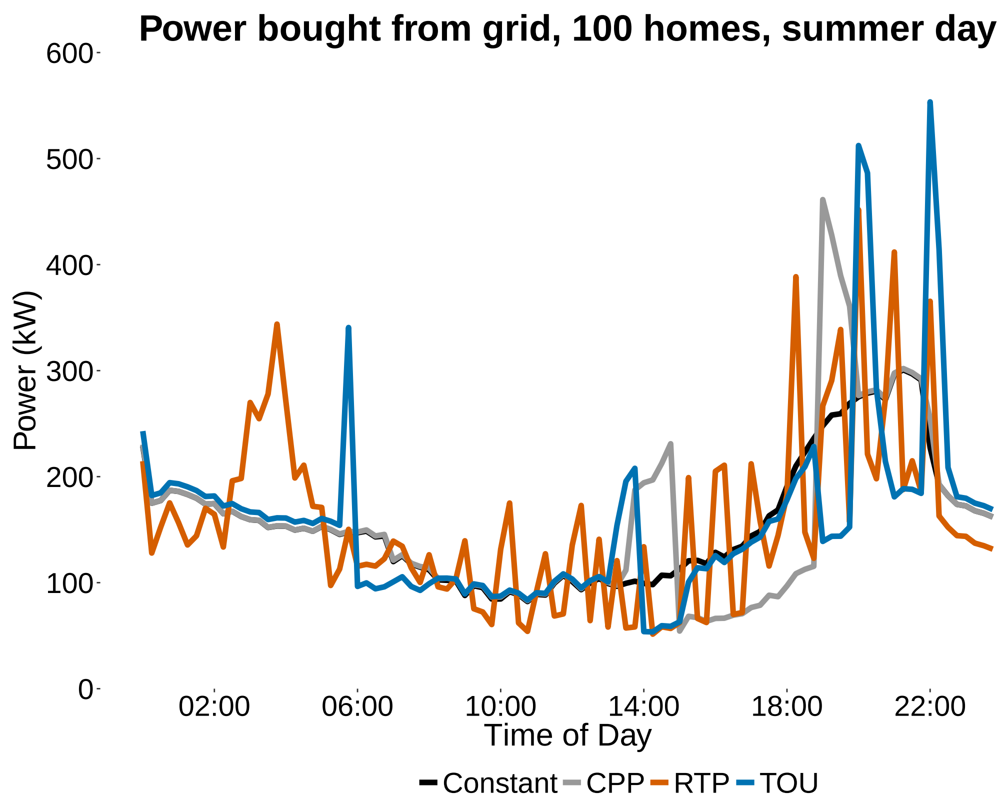

Figure 4.8: Power bought from the grid on the summer peak day of 2017 for the community of 100 single-family detached homes under four different pricing structures. Dynamic prices shift the timing of the residential peak but increase its magnitude.

For the case with constant electricity rates (in black), the peak demand occurs at 9:15 pm. With the real-time pricing structure, power consumed (in orange) spikes between 2:30 am and 5 am when prices are low but the peak demand occurs at 8 pm. The TOU case (in blue) exhibits similar characteristics as observed before with the power bought spiking right before prices increase and right after prices decrease. The peak for this case is at 10 pm. The CPP analysis (in gray) closely mirrors the constant case (as expected since the prices for all times of the day except 3 pm to 7 pm are almost equal to the constant value). However, the power bought spikes right before 3 pm in anticipation of the price increase and decreases between 3 pm and 7 pm. The demand then peaks during the time interval from 7 pm to 7:15 pm. The operational levels of the four individual end-use appliances can be found in Appendix A.2. Results from the sensitivity analyses involving different fractions of homes owning EVs and solar panels are listed in Appendix A.4 and A.5. Tables A3 – A11 demonstrate that the overall findings of this chapter remain valid across the variety of scenarios considered.

Empirical studies by [25] and [105] found more of a pure load reduction effect rather than load shifting to other hours as our model suggests. However, those studies are based mainly on human behavior and decision-making while our computational study foresees a future where an optimization device automatically controls the operation of multiple devices — like HVAC systems, EWHs, EVs, and PPs — in response to dynamic prices. In contrast to the findings from [25] and [105], an EPRI study found that customers reduced energy consumption during peak hours and/or shifted energy usage to low-price hours [24]. Thus, it can be concluded that results from empirical price-based demand response studies can vary across time, control group, availability of automated technology, etc. To fully comprehend the similarities and differences between the results from the two methodologies, it is imperative to conduct the empirical analysis and computational modeling of load control on the exact same test-bed of homes under the same dynamic pricing structures. We leave this as an avenue for future work.

4.3.3 Sensitivity analysis

The following subsections describe the results of the sensitivity analyses conducted by varying the α values and the two additional scenarios involving setting α_{EV} and α_{PP} to zero throughout the day.

4.3.3.1 Discomfort/Inconvenience parameters

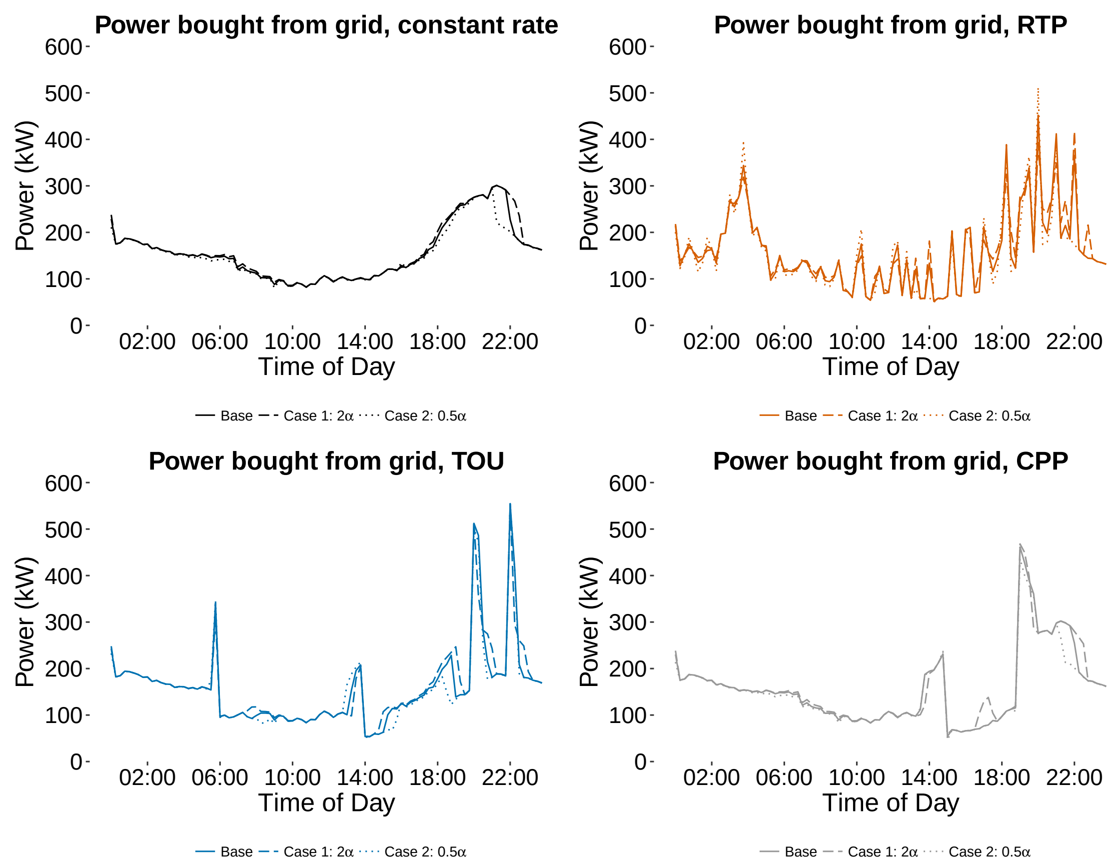

Figure 4.9: Power bought from the grid on the summer peak day of 2017 for the community of 100 single-family detached homes under four different pricing structures and different scalings of the inconvenience parameters.

Figure 4.9 demonstrates how power bought from the grid changes from the base case (solid lines) as the discomfort/inconvenience parameters for all four end-use appliances are halved (dotted lines) and doubled (dashed lines). The main takeaway from this sensitivity analysis is that the findings of our optimization model are relatively robust to changes in the inconvenience parameters.

4.3.3.2 Scenario with daytime EV charging tolerated

The power utilized by the EVs during charging in the base case (solid lines) and in the case when α_{EV} is zero (dotted lines) throughout the day for the community of 100 homes under four electricity pricing structures is shown in Figure 4.10.

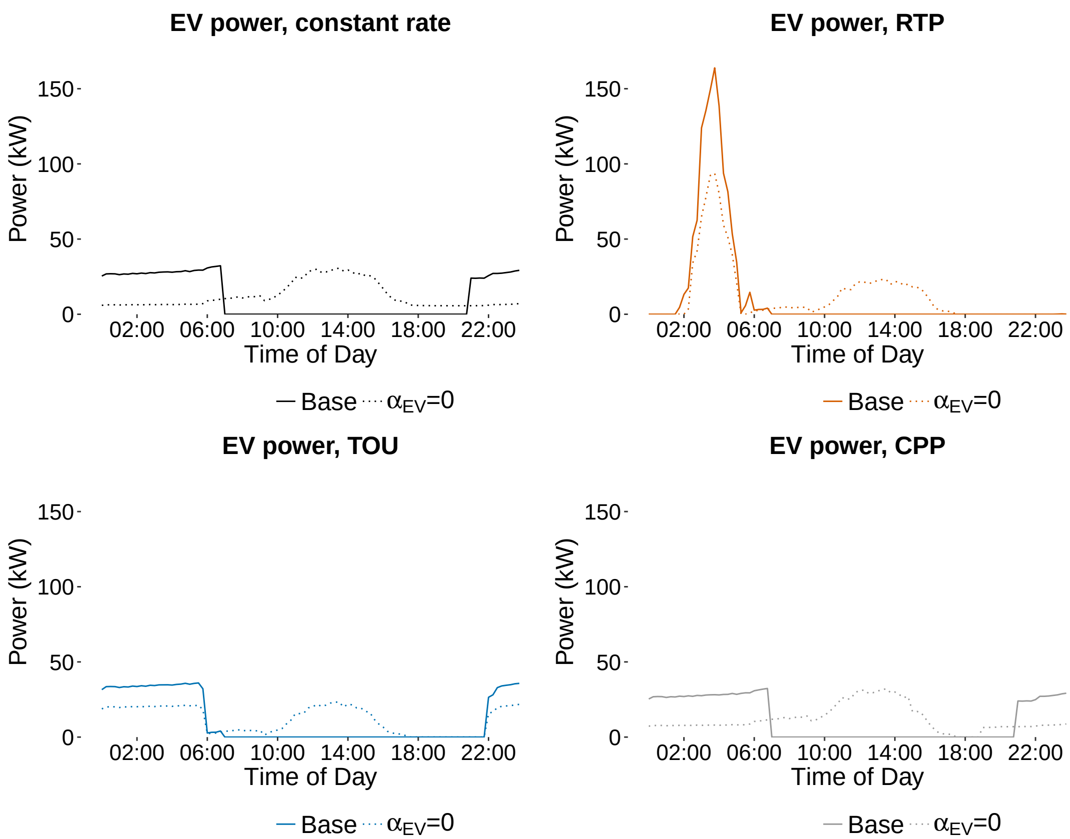

Figure 4.10: Power consumption of the EVs on the summer peak day of 2017 for the community of 100 single-family detached homes under four different pricing structures when α_{EV} is zero. Part of the charging schedule during the early morning and late evening hours is shifted to the middle of the day when the solar power generation can be utilized.

A portion of the power consumption during the early morning and late evening hours is shifted to the middle of the day when the solar power generation can be utilized for charging the EVs.

4.3.3.3 Scenario with nighttime PP operation tolerated

Figure 4.11 shows the power utilized by the PPs for the base case (solid lines) and the case when α_{PP} is zero (dotted lines) for all 24 hours for the community of 100 homes under four electricity pricing structures.

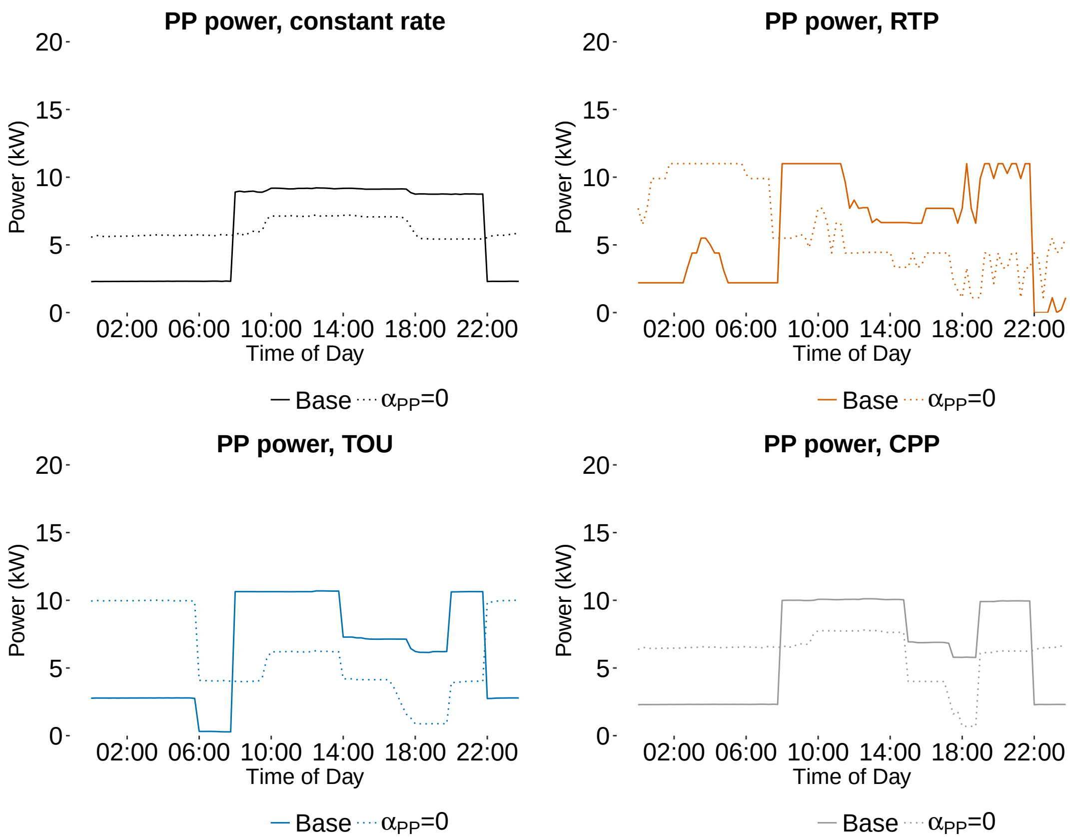

Figure 4.11: Power consumption of the PPs on the summer peak day of 2017 for the community of 100 single-family detached homes under four different pricing structures when α_{PP} is zero. A portion of the energy consumption during the middle of the day is shifted to the early morning and late night hours.

When α_{PP} is zero, a portion of the energy consumption during the middle of the day is shifted to the early morning and late night hours. For the RTP case, the power consumption is greatest during the early morning hours when prices are the lowest while for the TOU rates, power utilized is maximum during the off-peak period from 10 pm – 6 am. When critical peak prices are applied simultaneously with α_{PP} being zero, energy use by the PP decreases further from the base case during the peak period from 3 pm to 7 pm.

The inconvenience parameter being zero is not able to completely negate PP usage during the on-peak or critical peak period or when real-time prices are highest (around 3 pm). This occurrence is likely due to the assumption made about the PP rated power which in turn puts an upper bound on the power utilization in a specific time interval as well as the $E_{PP,consumed,daily}$ value from the homes that have PPs.

4.4 Limitations

Like any other modeling study, this analysis is subject to a number of limitations. Although the uncontrollable power profile, solar generation, and energy consumed throughout the day by the EV and PP are obtained from the Pecan Street dataset, other inputs to the model like the rated power of the four end-use appliances, thermal properties of the homes, and inconvenience parameters are obtained from the literature. Our lack of knowledge about the individual appliances and thermal properties of each home in the Pecan Street dataset necessitates the combination of the empirical load data with parameterizations of appliance properties and the thermal model inspired by the literature.

Another important limitation is that households might not be rational cost minimizers, or they might lack the automated control technology required to implement the solutions presented in this study. Further, the discomfort/inconvenience parameters for each appliance will likely differ across homes based on personal preferences. In addition, on a day to day basis, whether an EV can charge at certain times depends on the particular trips that the household members take.

Additionally, the historical real-time prices which are used in our study are exogenous inputs to the model, instead of being determined endogenously based on supply-demand balance during the course of a model run. As a result, once our model allows the electricity demand profile to deviate from the base case in response to the dynamic prices, it does not allow the real-time prices to adjust accordingly and cuts off the cycle of feedbacks between demand and price that would be likely to occur in reality.

Additionally, the optimization model presented in this paper is a deterministic, convex problem. Our model does not include battery storage with charging and discharging schedules or controllable appliances which function as batch processes with fairly long durations (which would make the inter-temporal dynamics more complex and our perfect foresight assumption more limiting). However, we are aware that certain features might have been lost due to the deterministic nature of the problem.

Finally, the period of analysis is restricted to two days of 2017 - summer peak day and winter minimum peak day. Although we believe that these days provide contrasting weather patterns to yield results at both ends of the spectrum, we acknowledge that the variability in electricity demand patterns, solar generation, ambient temperature, and electricity prices throughout the year can potentially yield different conclusions. The focus of this study is on peaks rather than the load profile over the entire year and thus, while this work cannot make any claims about the broader effects and desirability of the dynamic rate structures, it sheds light on their residential peak shifting and reduction potential.

4.5 Summary

This chapter establishes a tool to model price-based demand response or load control initiatives in the residential sector while accounting for the monetary value of customer comfort levels and convenience. The peak load reductions and shifts arise endogenously via the household's cost-minimizing control of four end-use appliances under the effect of four time-varying electricity rate structures.

Results show that dynamic pricing programs can effectively shift the residential peak away from the time of overall electricity system peak load. However, they can actually increase the magnitude of the residential peak load by incentivizing customers to concentrate appliance usage within the low-price hours. These time-varying prices do not appear to reduce overall energy consumption, even as loads are reallocated through time. Thus, our analysis challenges the frequently expressed notion that dynamic prices would be "cure-all" solutions to high peak demand issues in the electricity sector [182–184]. Our results indicate that implementing these rate structures could lead to other problems.

The ramp rate of power delivered from the distribution grid to the home is greater for the time-varying rates than for the constant rate case. Sensitivity analysis performed by varying the discomfort/inconvenience parameters of the four end-use appliances shows that the results of our optimization study are relatively robust to changes in these parameters. Additional scenarios are run by neglecting the inconvenience parameters for EVs and PPs in the objective function of the optimization model which shift corresponding appliance loads to the middle of the day to utilize solar generation and to off-peak hours respectively.

Several avenues for expanding the scope of this study exist. The period of analysis can be extended to one representative day from each month of the year to get the full spectrum of peak load reductions and shifts throughout the year. In addition, since the Pecan Street dataset also contains minute-interval appliance-level data for homes outside of Texas, similar community-level analysis can be performed for other locations like Colorado or California to see if the corresponding weather patterns, demand profiles, and electricity pricing structures result in significantly different peak load reductions and shifts.

Residential tankless EWHs have been recently gaining popularity since these water heaters take up less space, have longer lifespans, and can be 24 – 34% more efficient than tank EWHs by eliminating standby thermal energy losses from a large storage tank [185, 186]. However, tankless EWHs generally cost more than their traditional counterparts, do not have energy storage potential, and have limited flow rates, thereby restricting the simultaneous usage of hot water by multiple household appliances [186]. The optimization framework developed in this chapter can be used to perform a community level case study in which a fraction of households is modelled to have on-demand tankless EWHs instead of the storage tank variety. As more households choose to install tankless EWHs, this analysis can potentially lead to interesting insights about the magnitude of peak load reduction feasible in residential communities in the future.

Moreover, a recent study has shown that many first-time installers of rooftop solar panels are also interested in home energy storage although currently only 20% of those people end up purchasing the combination of solar and storage [187]. As the capital and installation costs for residential storage decrease and utility and federal incentives become available, more residential customers are likely to invest in battery storage. Energy storage systems can be added to the optimization model to calculate the additional peak load reduction/shift that can be achieved by energy arbitrage.

Although Austin Energy currently does not have demand charges for its residential customers, various utilities across the nation, like Westar Energy in central Kansas [158], have started to propose mandatory or voluntary residential demand charges. The purposes of these charges are to encourage customers to reduce electricity usage during peak hours, shift consumption of energy-intensive appliances to non-peak hours, and for the utility to recover some of the generation, transmission, and distribution costs related to meeting peak electricity demand. Future work can include adding demand charges to our analysis on top of time-of-use rates to highlight additional peak load reduction/shift achieved.

Chapter 5

Establishing a techno-economic method to analyze the combined effect of distributed energy resources and price-based demand response to reduce residential peak loads

5.1 Introduction

About 33% of energy-related CO_2 emissions in the United States are produced by the electric power sector [188]. One of the causes for high emissions from the electricity sector is rising peak demand, which is often met with less efficient and higher emitting fossil fuel generation [8]. According to the Intergovernmental Panel on Climate Change, some of the strategies for reduction of emissions from the electricity sector include shifting generation from higher-emitting coal plants to lower-emitting natural gas plants, expanding nuclear generating capacity, encouraging usage of energy-efficiency devices and retrofitting efforts in homes and businesses, increasing installation of renewable energy generators, and increasing carbon capture and sequestration efforts [10].

The residential sector accounts for 37% of U.S. electricity-based CO_2 emissions [189] and half of the summer peak demand in hot climates like Texas [23]. Demand response initiatives [11] and increased penetration of DERs like on-site solar panels and energy storage systems can potentially reduce residential peak electricity demand, energy consumption from the grid, and emissions.

Several existing studies have analyzed the effects of DERs [53, 130–135, 137] and price-based demand response [34, 36, 37] separately as well as their combined effect [44,46,47,143]. However, the interactions of residential ice cold thermal energy storage (ice CTES) with other commonly installed DERs (like solar PV and lithium-ion batteries) and dynamic prices have not been explored before. As residential air-conditioning load can comprise about 50% of overall system summer peak demand and the limited number of studies on residential ice CTESs have exhibited significant thermal load shifting and emissions reduction potential [23,52,53,137], it is important to perform this analysis.

To fill this knowledge gap, this chapter develops an optimization framework to model the interactions among four technologies in the residential sector — solar panels, lithium-ion batteries, ice CTES, and smart thermostats — under price-based demand response. Five different electricity pricing schemes are evaluated — tiered rates, real-time pricing (RTP), time-of-use (TOU) rates, critical peak pricing (CPP), and demand charges coupled with TOU rates — and implications for customer expenditure, peak grid demand, energy consumption from the grid, and emissions in homes with different combinations of the four technologies are recorded. The model is demonstrated using empirical energy usage and solar generation data from Pecan Street Inc. [56] and electricity and VOS rates from Austin Energy. The results of this analysis can potentially aid utilities to design residential rates and prioritize the penetration of distributed energy technologies to improve system economics and environmental performance. Further, as the capital costs for DERs decline [109, 110] and electric utilities incentivize customer ownership of these technologies by offering rebates [190], a growing number of residential customers will face the decision of whether to invest in these technologies. This chapter aims to be a key tool in aiding that decision-making process.

5.2 Methods

This section describes our methodology based on developing an optimization framework to analyze the interactions among solar panels, lithium-ion batteries, ice CTES, and controllable HVAC load in the residential sector under time-varying electricity pricing structures. Figure 5.1 shows the thermal and electric power flows among the grid, solar panels, lithium-ion battery, heating and cooling (H&C) engine (this engine also makes ice), ice CTES, and the home for a residential customer with all technologies considered in this study.

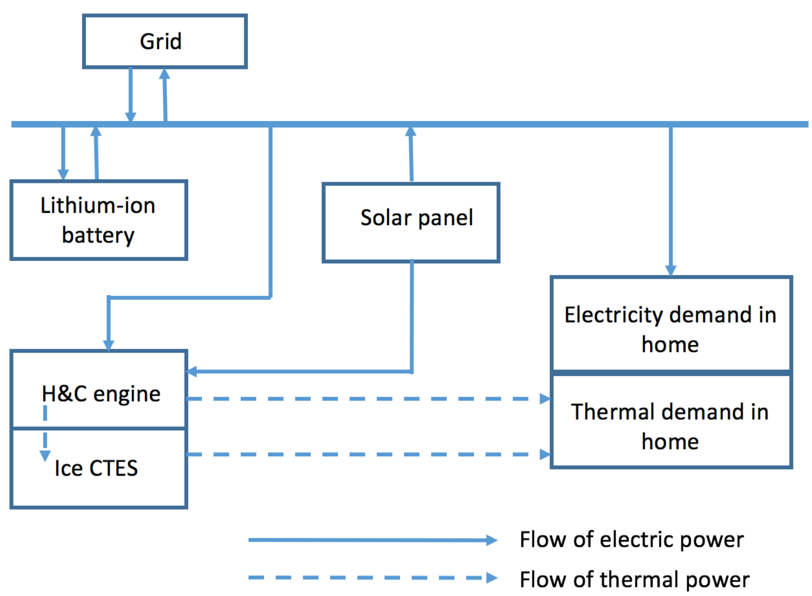

Figure 5.1: Electric and thermal power flows among the technologies and the home.

The configuration of the ice CTES and H&C engine is inspired by Ice Energy's Ice Cub system [191, 192], which completely replaces the conventional HVAC unit in the home by combining the HVAC unit and storage unit. In the following subsections, we sequentially provide detailed descriptions of the objective function, constraints, empirical electricity demand profile, properties of the distributed energy technologies, analysis period, time-varying electricity prices, rebates, hourly emission factors, discomfort parameters, and scenarios. The model code corresponding to this chapter is available open-source on GitHub.[1]

5.2.1 Objective function

The objective function consists of cost of energy used in the home, capital and operations and maintenance (O&M) cost for each of the technologies, investment tax credit for solar panels, utility rebates for solar panels, revenue earned by the customer for solar generation through the value of solar program, and the monetary value of the discomfort of deviation of room temperature from the customer-set temperature points. The function is shown in Equation 5.1 and is minimized subject to several constraints mentioned in Section 5.2.2.

$$\begin{aligned} Obj = \sum_{t=1}^{N} P_{use,home,t} \times C_t \times \Delta t + (CAP + O\&M)_{solar} + (CAP + O\&M)_{ice,CTES} \\ +(CAP + O\&M)_{bat} + CAP_{thermostat} - ITC_{solar} - Rebate_{solar} \\ -VOS \times \sum_{t=1}^{N} P_{solar,gen,t} \times \Delta t + \sum_{t=1}^{N} \alpha_{HVAC,t} \times (T_{r,t} - T_{r,sp,t})^2 \end{aligned} \tag{5.1}$$

The terms in Equation 5.1 are described in Table 5.1. Please refer to the glossary for definitions and units of other variables and parameters. The technology capacities (i.e. size of solar panels, size of lithium-ion batteries, etc.) are fixed for each scenario and are chosen based on commercially-available distributed energy technologies [56, 193,194]. The decision variables of the optimization framework relate to dispatch and

[1] See https://github.com/arkasama/Analysis_distributed_technologies_residential_sector for sample code.

operation. Instead of using commercially-available technology capacities, if we chose to use optimal technology capacities in this chapter, a separate optimization problem would need to be formulated and solved for the least-cost optimal size of technologies based on electricity rates and the demand profile of each household. We leave this as an avenue for future work.

Table 5.1: Descriptions of acronyms used in the objective function.

Variable	**Explanation**	**Unit**
α_{HVAC}	Inconvenience parameter for HVAC	$\$/^0C^2$
CAP	Capital cost	\$
C_t	Cost of electricity at time step t	\$/kWh
Δt	Time interval	hour
ITC	Investment Tax Credit	-
N	Total number of time steps	-
O&M	Operations and maintenance cost	\$
$P_{use,\ home,\ t}$	Power used in the home at time step t	kW
$T_{r,t}$	Temperature of the room at time step t	K
$T_{r,sp,t}$	Set-point temperature of the room at time step t	K
VOS	Value of Solar	\$/kWh

5.2.2 Constraints

The objective function is minimized subject to several constraints including energy conservation around the home, charging and discharging limits for the storage systems, limits on energy capacities of the storage systems, energy conservation around the H&C engine, and power limits of the H&C engine. The optimization model also includes a one-parameter thermal model for the HVAC system. The customer is able to maintain comfortable conditions in the home by specifying bounds for the room temperature. The marginally increasing monetary discomfort penalty for deviating would naturally prevent the room temperature from going too far from the set-point, but we still include hard constraints for upper and lower bounds to keep the solution realistic.

The first constraint, shown in Equation 5.2, specifies that at each time step t, the total power consumed in the home is less than the sum of the power bought from the grid and the solar electricity generated by the onsite solar panels.

$$0 \leq P_{use,home,t} \leq P_{bought,grid,t} + P_{solar,gen,t} \tag{5.2}$$

The second constraint stipulates that at each time step t, the sum of the uncontrollable demand, electricity consumed by the H&C engine (to heat/cool the home and/or make ice), and the power lost due to efficiency losses in the lithium-ion battery must be equal to the power used in the home (home envelope). This study assumes that all power usage in the home except the thermal demand (for maintaining room temperature) cannot be controlled.

$$P_{use,home,t} = P_{uncontrollable,t} + P_{electric,H\&C,t} + P_{bat,charge,t} - P_{bat,discharge,t} \tag{5.3}$$

The next set of constraints is related to the lithium-ion battery. Equation 5.4 refers to the initial energy state of the lithium-ion battery. Equations 5.5 and 5.6 state that the energy stored in the lithium-ion battery at any time step is dependent on the power flowing in and out and must lie between the minimum and maximum energy capacity of the lithium-ion battery. Equations 5.7 and 5.8 place bounds on the maximum and minimum charging and discharging rates of the lithium-ion battery.

$$E_{bat,1} = E_{bat,initial} \tag{5.4}$$

$$E_{bat,t} = (1 - \gamma_{bat,loss}) \times E_{bat,t-1} + (P_{bat,charge,t} \times \eta_{bat,rt} - \frac{P_{bat,discharge,t}}{\eta_{bat,rt}}) \times \Delta t \tag{5.5}$$

$$E_{bat,min} \leq E_{bat,t} \leq E_{bat,max} \tag{5.6}$$

$$0 \leq P_{bat,charge,t} \leq R_{charge,max} \tag{5.7}$$

$$0 \leq P_{bat,discharge,t} \leq R_{discharge,max} \tag{5.8}$$

The fourth set of constraints is related to the ice storage system. Equation 5.9 refers to the initial thermal energy state of the ice CTES. Equations 5.10 – 5.11 state that the thermal energy stored in the ice CTES at any time step is dependent on the thermal power flowing in and out and must lie between the minimum and maximum thermal energy capacity of the ice CTES. Equations 5.12 – 5.13 place bounds on the maximum and minimum charging and discharging rates of the ice CTES.

$$E_{ice,CTES,1} = E_{ice,CTES,initial} \tag{5.9}$$

$$\begin{aligned} E_{ice,CTES,t} = (1 - \gamma_{ice,CTES,loss}) \times E_{ice,CTES,t-1} + (P_{H\&C,ice,CTES,t} \times \eta_{ice,CTES,rt} \\ - \frac{P_{ice,CTES,home,t}}{\eta_{ice,CTES,rt}}) \times \Delta t \end{aligned} \tag{5.10}$$

$$E_{ice,CTES,min} \leq E_{ice,CTES,t} \leq E_{ice,CTES,max} \tag{5.11}$$

$$0 \leq P_{H\&C,ice,CTES,t} \leq R_{ice,CTES,charge,max} \tag{5.12}$$

$$0 \leq P_{ice,CTES,home,t} \leq R_{ice,CTES,discharge,max} \tag{5.13}$$

Equations 5.14 and 5.15 conserve the H&C engine's energy at each time step and place bounds on its power capacity respectively. Equation 5.14 states that, for every time interval, the electricity consumed by the H&C engine must be used to provide heating or cooling energy to the home and/or make ice for the ice CTES. We assume an 80% de-rating factor for making ice [111], which means that the engine's coefficient of performance (COP) in ice-making mode is 80% of its COP in cooling mode. This assumption is made since ice-making significantly lowers the COP of a cooling engine [50]. $COP_{cool,t}$ and $COP_{heat,t}$ are functions of the ambient temperature [195].

$$P_{electric,H\&C,t} = \frac{P_{H\&C,home,cool,t}}{COP_{cool,t}} + \frac{P_{H\&C,home,heat,t}}{COP_{heat,t}} + \frac{P_{H\&C,ice,CTES,t}}{COP_{ice,t}} \tag{5.14}$$

$$0 \leq P_{H\&C,home,cool,t} + P_{H\&C,home,heat,t} + P_{H\&C,ice,CTES,t} \leq P_{max,H\&C} \tag{5.15}$$

A one-parameter thermal model [160], [161] is used for modeling the HVAC system, as shown in Equation 5.16. Customer comfort is maintained by keeping the room temperature between customer-specified limits (Equation 5.17).

$$\begin{aligned} T_{r,t} = (1 - \frac{\Delta t}{M_a \times C_{p,a} \times R_{eq}}) \times T_{r,t-1} + \frac{T_{ambient,t} \times \Delta t}{M_a \times C_{p,a} \times R_{eq}} \\ - \frac{(P_{H\&C,home,cool,t} - P_{H\&C,home,heat,t} + P_{ice,CTES,home,t}) \times \Delta t}{M_a \times C_{p,a}} \end{aligned} \tag{5.16}$$

$$T_{r,min} \leq T_{r,t} \leq T_{r,max} \tag{5.17}$$

5.2.3 Pecan Street empirical data

To demonstrate our optimization framework, we obtain 15 minute-interval data for overall electricity usage, solar generation, and appliance-level data for the HVAC system for 25 homes in Austin from Pecan Street. Pecan Street is an Austin-based non-profit organization that collects temporally-resolved electricity consumption data disaggregated by appliances from over 1000 homes and businesses [56]. While several of the homes in this dataset are located in one neighborhood in east Austin, electricity usage data are also available from homes in other Texas cities as well as from cities in California and Colorado [56]. Such temporally-resolved, location-specific, and appliance-level electricity consumption data are extremely rare and have fueled various modeling studies in recent years [45, 48, 165–168]. We first use the 15-minute interval data to calculate hourly averages and then obtain the uncontrollable power at every time step t ($P_{uncontrollable,t}$) by subtracting the power of the HVAC system from the overall demand profile.

5.2.4 Properties of distributed energy technologies

Table 5.2: Properties of distributed energy technologies†.

	Solar	**Lithium-ion battery**	**Ice CTES**	**Smart thermostat**
Capital Cost	\$2350/kW$_{dc}$	\$933/kWh	\$15,000	\$250
O&M Cost	\$20/kW$_{dc}$-yr	\$10/kWh-yr	\$225/yr	-
Size	6 kW	13.5 kWh	35.16 kWh$_{th}$	-
Lifetime (years)	25	15	20	10
Initial Energy	-	6.75 kWh	0 kWh$_{th}$	-
Maximum Energy Capacity	-	13.5 kWh	35.16 kWh$_{th}$	-
Minimum Energy Capacity	-	1.35 kWh	0 kWh$_{th}$	-
Maximum Charging Rate	-	5 kW	10.55 kWh$_{th}$	-
Maximum Discharging Rate	-	5 kW	10.55 kWh$_{th}$	-
Efficiency (%)	-	90	95	-
Minimum Temperature	-	-	-	19.44°C (67°F)
Maximum Temperature	-	-	-	27.78°C (82°F)
Set-point Temperature	-	-	-	22.2°C (72°F)

† Data sources for capital cost: Solar [196], Lithium-ion battery [197], Ice CTES [198], Thermostat [199].

O&M: Solar [200], Lithium-ion battery [201], Ice CTES [202]. Size: Solar [56], Li-ion battery [193], Ice CTES: [194].

Lifetimes: Solar [203], Lithium-ion battery [204], Ice CTES [205]. Initial Energy: Lithium-ion battery [166].

Energy Capacity: Lithium-ion battery [206, 207], Ice CTES [194, 208].

Charging & discharging rates: Lithium-ion battery [206], Ice CTES [194].

Efficiency: Lithium-ion battery [206], Ice CTES: [205]. Maximum and minimum temperatures: [209].

The capital cost, O&M cost, size, and lifetime of the four distributed energy technologies considered in this study — solar panels, lithium-ion batteries, ice batteries and controllable HVAC — are obtained from existing literature and are reported in Table 5.2. The customer-specified minimum and maximum room temperature, set-point temperature as well as initial energy, charging and discharging rates, energy capacity bounds, and efficiencies of the storage systems are also included.

5.2.5 Period of analysis

The period of analysis for this study is one year. We use functional boxplots [144] and hourly ambient temperature data for an entire year from Pecan Street [56] to find the most representative day for each month. Figure 5.2 shows the functional boxplot of the ambient temperature curves for the month of August, developed using the function 'fbplot' from the R package 'fda'. One hour time intervals for each of the representative days from the twelve months are used to demonstrate the results of our model. Since the analysis period is one year, the capital and O&M cost of the distributed energy technologies, mentioned in Section 5.2.4, as well as associated rebates and tax credits are amortized with Equation 5.18, using a 7% interest rate (i) [208] and considering the lifetimes (n) of the individual assets.

$$\text{Amortized cost} = \text{Total cost} \times \frac{i \times (1+i)^n}{(1+i)^n - 1} \tag{5.18}$$

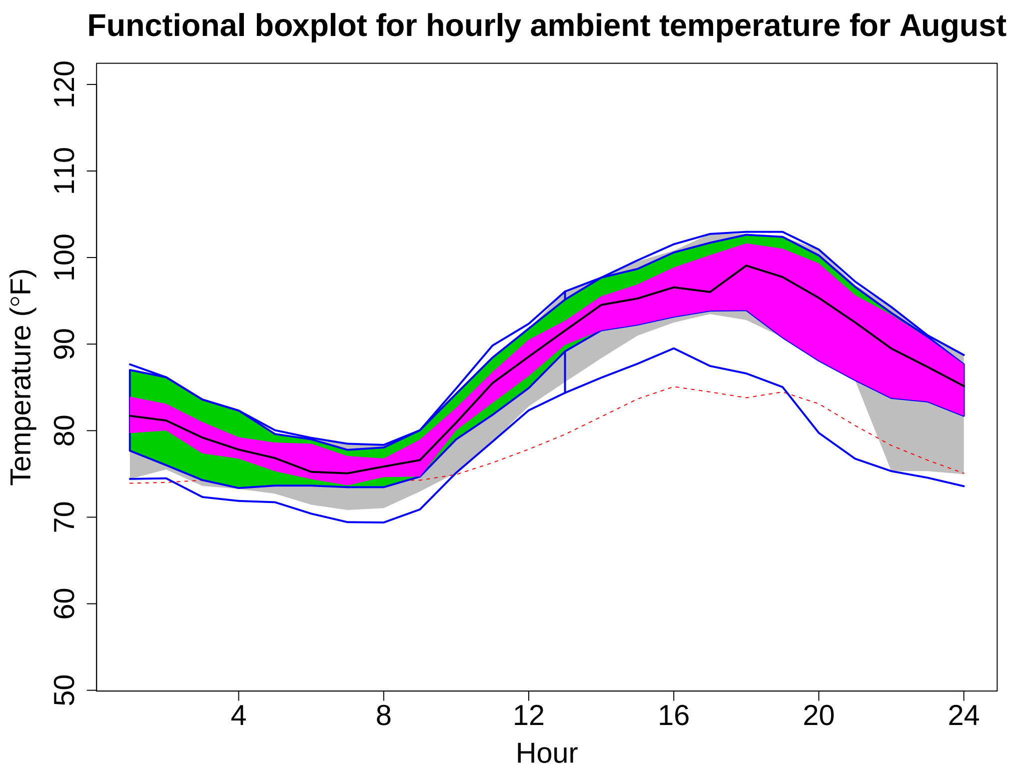

Figure 5.2: Functional boxplot for ambient temperature curves for August. The blue curves denote the maximum envelope of the dataset excluding the outliers and the black curve represents the median curve (with the greatest band depth) [144]. The median temperature curve belongs to the most representative day for August and constitutes data from an actual single day. The magenta indicates the 25% central region, green represents the 50% central region, and gray denotes the 75% central region. The red dashed line is the outlier temperature curve, detected by the '1.5 times the 50% central region' rule [144].

5.2.6 Electricity pricing

We solve the optimization problem under the following five residential electricity rate structures to assess the effects of these pricing schemes and different combinations of smart technologies on yearly emissions, peak power flowing from the grid to the home, energy bought from the grid, and financial burden of a residential customer:

1. Tiered rates
2. Real-time prices (RTP)
3. Time-of-use (TOU) rates
4. Critical peak prices (CPP)
5. Demand charge on top of time-of-use (TOU) rates

For the first pricing structure, we use the current Austin Energy tiered residential energy charge [68]. Additional charges — including monthly fixed customer charge, power supply adjustment, customer benefit charges, and regulatory charges — are added to this energy charge to calculate total electricity cost to the customer [68]. The following paragraphs describe how the dynamic pricing structures are parameterized.

Historical 15-minute interval RTP from 2013 for ERCOT (Electric Reliability Council of Texas) load zone AEN (Austin) are obtained [210] and scaled using a multiplicative scaling factor. This factor is chosen such that the scaled RTP yield the same yearly electricity cost to a customer as the case with tiered rates when these prices are applied to the load profile for the tiered case in a home without any of the four technologies. The purpose of this scaling is to allow a fair comparison by having each of the five rate structures start out with the same total electricity cost prior to any demand shifting or reduction. Additionally, the real-time prices obtained from ERCOT [210] are at the wholesale market level and not actually faced by residential customers. Thus, it is reasonable to subject these prices to a scaling process before applying them to the residential sector.

TOU rates from Austin Energy's residential pilot program are scaled using a similar methodology as with the real-time prices [211]. The power supply charge portion of this rate structure, which depends on amount of energy consumed, is its only dynamic component. This charge varies depending on the time of the day, day of the week (weekdays or weekend), and season (summer or winter). On weekdays, on-peak prices are in effect from 3 pm to 6 pm, mid-peak prices from 7 am to 3 pm and 6 pm to 10 pm, and off-peak prices from 10 pm to 6 am [211]. Weekends have off-peak hours for the entire day. The time-varying power supply charge is added on top of the tiered constant rates along with additional charges like regulatory charges, community benefit charges, etc.

Austin Energy does not have a critical peak pricing or demand charge program for its residential customers. Thus, we base the CPP rate structure on the optional 'SmartRate' program administered by Pacific Gas & Electric (PG&E) in California. During the summer months from June to September, participating residential customers pay an additional \$0.60/kWh on top of their regular rates for all usage between 2 pm and 7 pm on extreme days or 'SmartDays' while saving approximately \$0.024/kWh for electricity usage during other times of the day [102]. This pricing scheme motivates participating customers to reduce usage of high-energy consuming appliances like dishwashers and electric vehicle chargers and/or shift time of usage of these appliances to non-peak hours.

There are usually 9-15 'SmartDays' in a year [102]. We assume that our year of analysis has 12 critical peak days - three in each of the summer months. Since we analyze one representative day from each month, it would be incorrect to consider that day as a critical peak one (and then annualize the results). This erroneous assumption would lead to the unrealistic modeling of all 120 days of the summer as critical peak days. Thus, we create a price vector where each summer month has three critical peak days and 27 days with tiered pricing while the other months have the usual tiered pricing structure. This vector is demonstrated by Equation 5.19. Finally, this price vector is further scaled using the same method as with the RTP and TOU rates to apply to our analysis in the Austin Energy service territory. We assume that the CPP are in effect during the peak period in ERCOT from 3 pm to 7 pm [176]. The five pricing schemes which we analyze in this study can be observed in Figures 5.3 and 5.4. The RTP are plotted in a separate figure to highlight the very high peak in the month of August.

$$\text{New CPP} = 0.9 \times \text{Tiered pricing} + 0.1 \times \text{CPP} \tag{5.19}$$

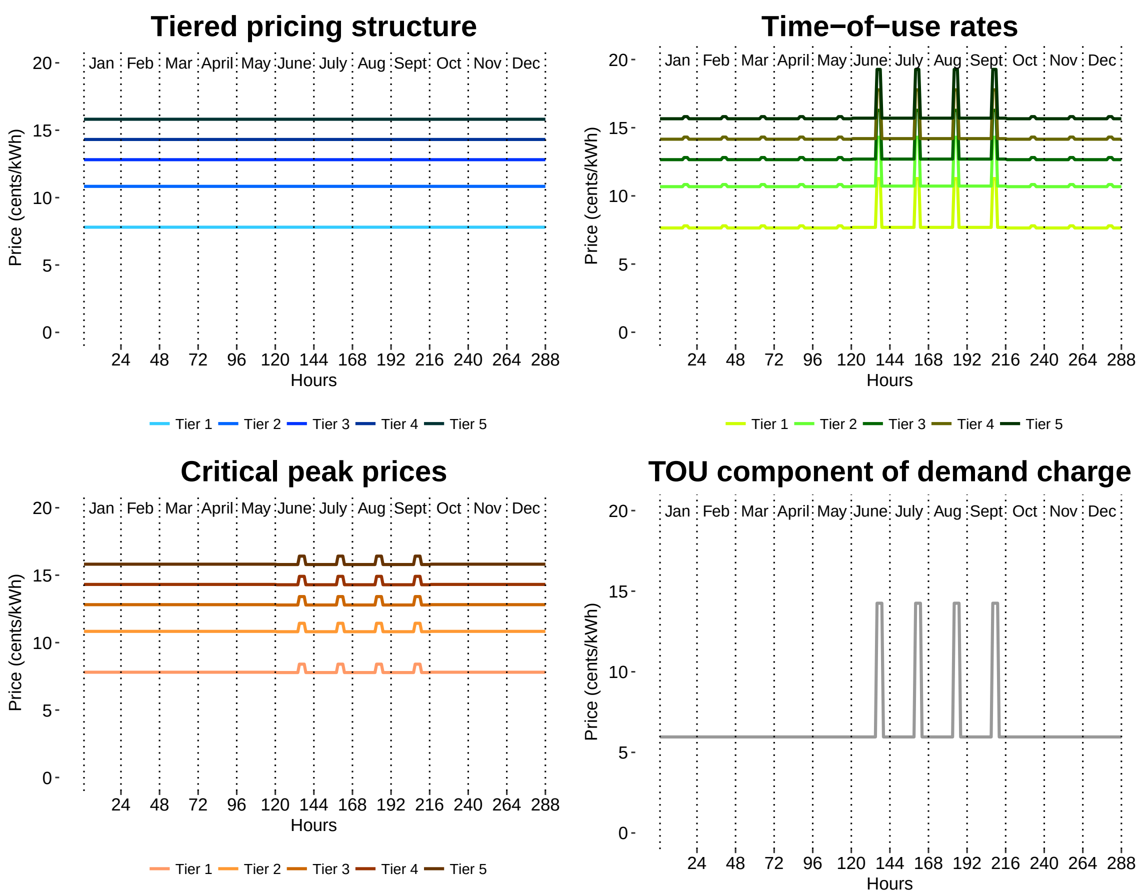

Figure 5.3: Four different pricing schemes considered in this study (all rates except tiered prices are scaled versions of original rates). The demand charge also includes a demand component ($/kW) for each month (not shown here). One representative day from each month of the year is modeled and the results are annualized at the end. So the total number of hours modeled is (12 × 24) or 288.

For the final pricing scheme, we use residential demand charges from Georgia Power's optional 'Smart Usage' program [212]. Participating residential customers pay time-of-use rates for energy usage throughout the year (which further varies based on time of day and season). These rates are usually lower than standard rates. However, they are additionally charged a \$7.90/kW demand charge each month for the greatest usage of power in their home during any 60-minute period [212]. This pricing structure encourages customers to shift energy usage away from the peak periods, by 'flattening' the energy consumption pattern. Similar to the other time-varying pricing structures, we scale these prices from Georgia Power to apply to the Austin Energy case study.

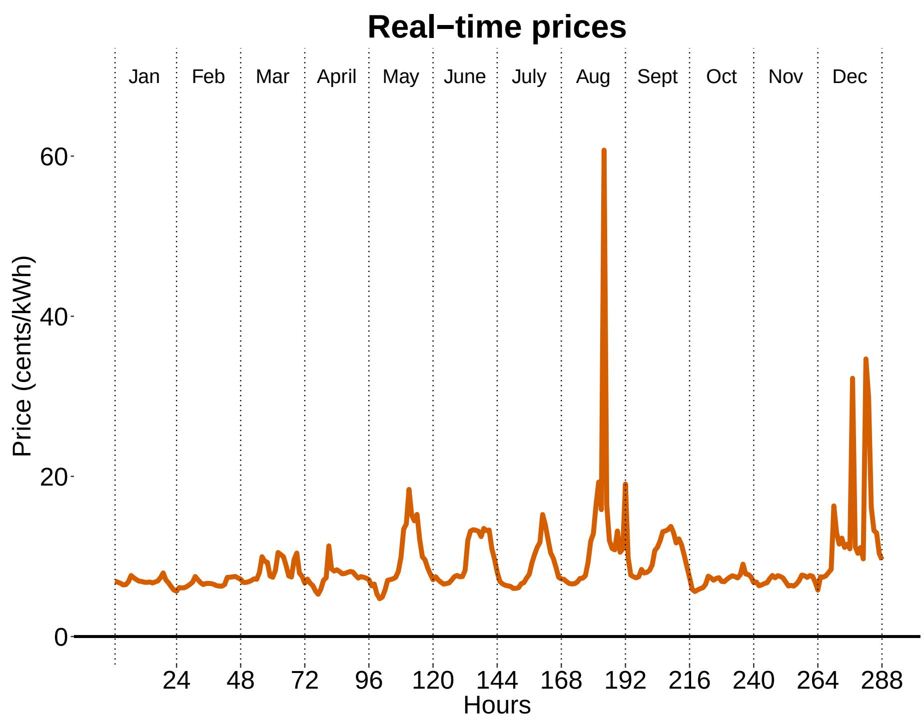

Figure 5.4: Scaled RTP inputs used in this study. The total number of hours modeled is 288 (one representative day from each month of the year). These prices can vary siginifcantly over the course of the day and the year — as exhibited by the large spike in August.

Further, instead of a net metering policy, Austin Energy has a Value of Solar (VOS) rate of 9.7 cents/kWh for its residential customers [127]. The VOS, which represents the actual value of distributed solar to the utility [128], is the rate at which Austin Energy credits its solar customers for the energy produced by their on-site solar energy systems [127]. Customers pay the electric utility for the total energy usage of their home using the applicable pricing structure. This total usage includes both energy bought from the grid and energy flowing from the solar panels to the home. Then, they are issued a credit from the utility for the solar energy produced by their solar panels based on the current VOS rate [127].

5.2.7 Rebates and tax credits

Austin Energy residential solar customers are eligible to receive a flat $2500 rebate for installing on-site solar photovoltaic panels [190]. Customers can also avail an investment tax credit (ITC) of 26% of the capital and installation cost of the solar panels. The ITC is a dollar-for-dollar federal tax credit for residential, commercial, and utility investors in solar energy systems [113]. The ITC also applies to energy storage systems if they solely charge from on-site renewable energy generators like solar panels [114]. However, we do not include tax credits for the lithium-ion battery or the ice CTES in this analysis.

5.2.8 Hourly emission factors

We use average hourly CO_2 emission factors (lb/MWh) for each month in ERCOT to calculate yearly emissions. This dataset was published by the National Renewable Energy Laboratory [213] in 2011. These factors are temporally scaled forward using annual CO_2 total output emission rates [214] to account for the decline of coal and growth of natural gas and wind in Texas over the past decade. We acknowledge that although this scaling process provides a better estimate of the emission factors than simply using the historical dataset, our method is not as accurate as using the most updated set of factors (since the diurnal and monthly energy generation patterns of renewable generators are different from coal or natural gas plants). We leave this modification in modeling as future work.

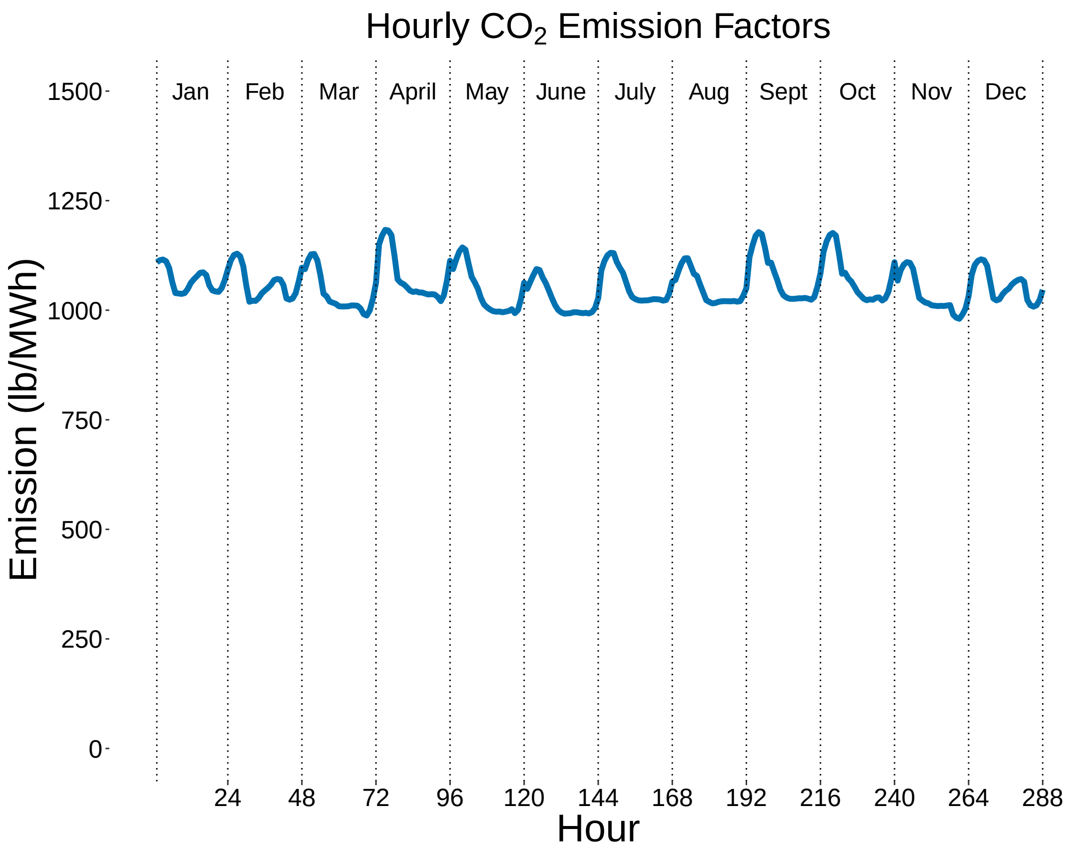

Figure 5.5: Hourly emission factors for ERCOT.

5.2.9 Discomfort parameters

Discomfort parameters for the HVAC (α_{HVAC}) system are inspired from relevant literature [181] and are shown in Figure 5.6. These parameters represent the monetary value of the first degree of deviation of room temperature from the set-point temperature. These parameters are lower from 9 am – 4 pm because the customers are modeled to be at work during those hours so that the home is generally less occupied.

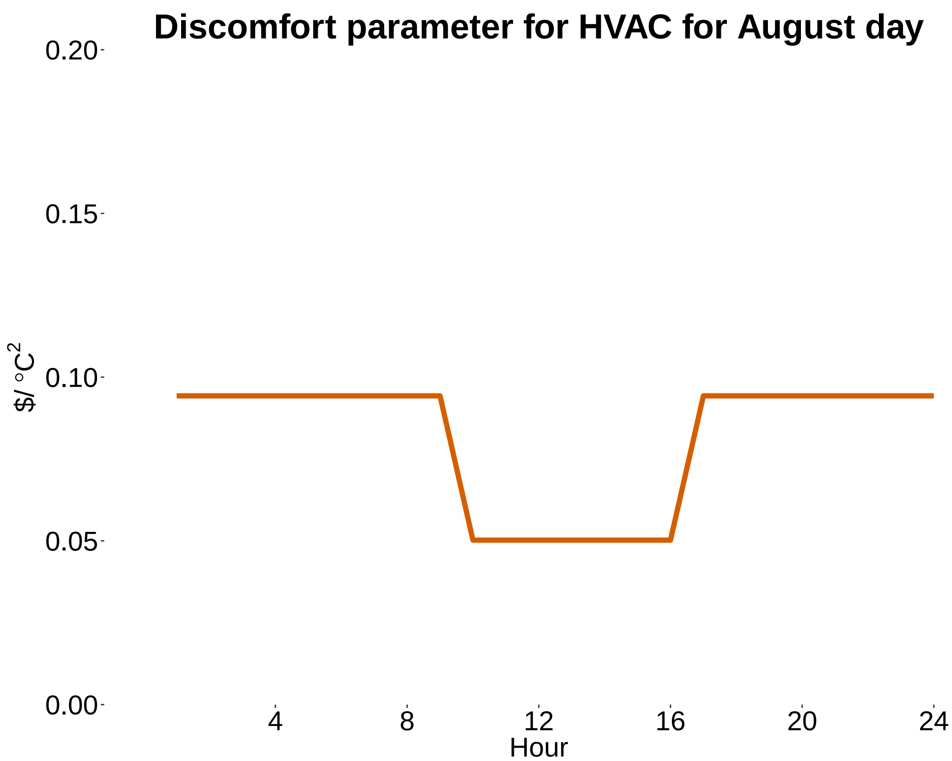

Figure 5.6: Discomfort parameters for the HVAC system. These parameters are quadratic to capture the increasing discomfort as temperatures deviate from customer-set temperatures.

5.2.10 Scenarios analyzed

We first run the optimization model for a single home in the Austin Energy service territory. The purpose of first looking at a single home in isolation is to demonstrate the application of the optimization model and look in detail at how the various metrics change under the different rate structures when the home has certain technologies. Although this household does own solar panels in reality, we hypothetically model the scenarios where it has various combinations of the four distributed energy technologies under five pricing structures. Thus, there are 2^4 or 16 scenarios for each pricing scheme and 80 scenarios overall. Further, the uncontrollable electricity demand of the home is assumed to remain constant across these 80 scenarios regardless of combination of DERs or pricing structure. We solve for the yearly cost incurred by a residential customer (this includes total cost, capital cost, O&M cost, and electricity cost), emissions, energy bought from the grid, and peak grid load for each of these scenarios.

The optimization model is then run in succession for 25 homes in Austin, TX to explore how variations in uncontrollable electricity demand patterns and solar generation capacities affect the metrics analyzed in this study. Again, although all these homes own solar panels in reality, we hypothetically model the scenarios where each of these homes has various combinations of the four distributed energy technologies under the five pricing schemes. We specifically choose homes with solar PV so that actual solar panel sizes and solar generation profiles can be used instead of assuming random values for the scenarios where the household is modeled to have solar capacity.

The input parameters which vary across these homes are the uncontrollable power profile, size of the solar panels, and solar generation (and corresponding parameters which depend on these e.g. the capital cost of solar panels, ITC, value of solar generation, etc.). These values for all 25 homes are obtained from the Pecan Street dataset. Other inputs like the size of the storage systems, discomfort parameters, thermal properties of the home, etc. are kept constant across homes. The distribution of the solar capacities of the homes and the yearly uncontrollable energy consumption can be observed from Figure 5.7. For context, residential solar panels usually range from 3 – 10 kW [109] and the average yearly energy consumption (total, not just uncontrollable) in Austin is 12 MWh [68]. Finally, the metrics recorded for the single-home analysis are also measured for this community-level analysis.

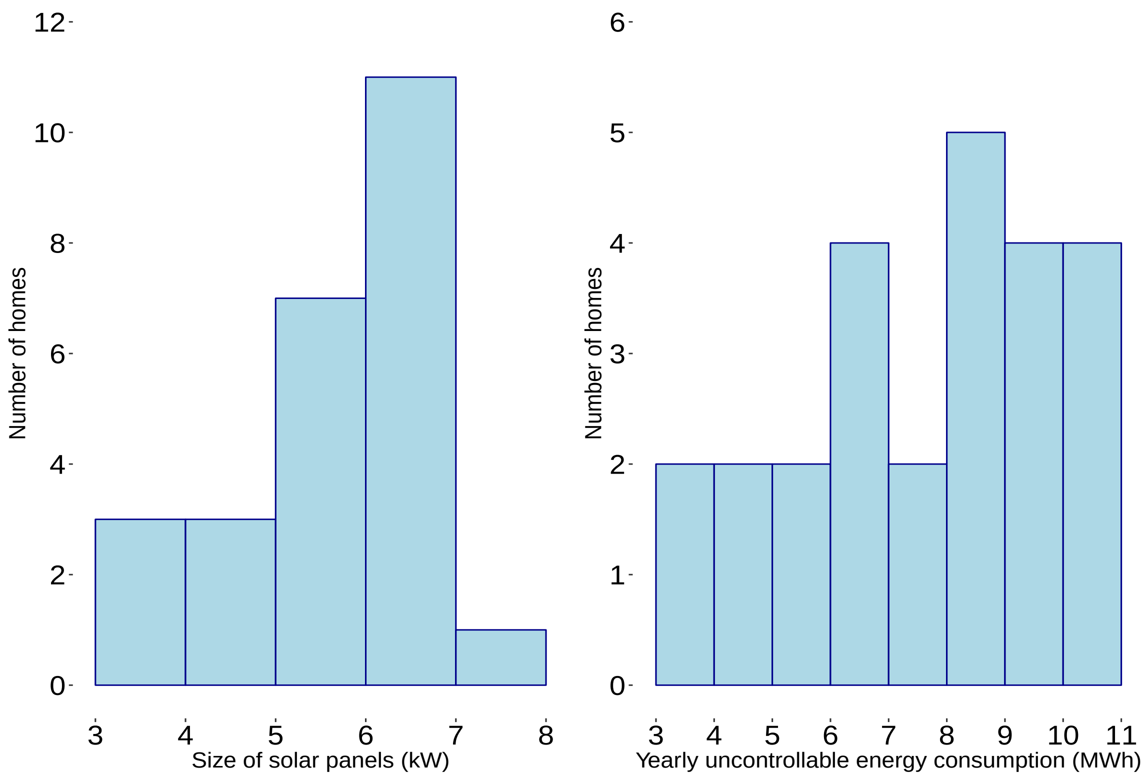

Figure 5.7: Histogram of solar capacities and uncontrollable energy demand of homes for the commmunity-level analysis. The majority of homes have 5-7 kW solar panels.

5.3 Results and discussion

The following subsections describe the results to our optimization model. We start by looking at the single home to illustrate the behavior of the model in detail and then move on to the community of 25 homes. We do not intend to report all the metrics analyzed from each of the 80 possible scenarios in this section since that would become voluminous and tedious for the reader to parse. Instead, we highlight some interesting trends after processing the metrics from scenarios with different combinations of distributed energy technologies under each of the five pricing structures. The time taken for the 'CVXR' solver to solve the optimization problem for each individual home depends on the number of decision variables in each scenario (which again depends on the number of technologies and pricing structure) and ranges from 0.008 s – 31 s.

5.3.1 Single-home analysis

Table 5.3 serves as a quick reference summary for the most significant findings from the single-home analysis. These results (and more) are described in detail in the following subsections.

Table 5.3: Summary of key findings of the single-home analysis (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). The first column lists the significant metrics analyzed in this study. The entries of the table designate the technology combinations corresponding to the optimal (lowest) outcome of each metric under the five pricing structures.

	Tiered	**RTP**	**TOU**	**CPP**	**Demand charge**
Overall Cost	S	HS	S	S	HS
Energy Cost	HSBC	HSBC	HSBC	HSBC	HSBC
Peak Grid Load	SB/SBC	S/SC	SB/SBC	SBC	HBC/HSBC
Annual Energy Bought	HSB/HSBC	HS	HSB/HSBC	HSB/HSBC	HSB

5.3.1.1 Yearly costs to the customer

Under tiered pricing, TOU rates, and CPP, from a purely economic perspective, it is optimal for the residential customer to only install solar panels in their home. The decrease in electricity bills that solar customers experience is enough to offset associated capital and installation costs (when federal and local rebates are accounted for) and make solar panels an economically viable option. The second most cost-effective option for residential customers under all three pricing schemes is to install solar panels and smart thermostats. It is interesting to note that without the investment tax credit and the flat $2,500 rebate offered by Austin Energy, it would be optimal for customers to not install any of the four distributed energy technologies considered in this study. In other words, if these rebates were not available, it would be less expensive for the household to simply draw energy from the grid to meet thermal and electric demand in the home.

The capital costs of both storage systems are still very high at the present day. Thus, although these systems can significantly reduce energy costs (electricity bills), they also drive up the overall expenditure. As these costs decrease in future years as a result of technological innovation and more utilities offer rebates for installing storage systems, these will potentially be a profitable option for residential customers. Another significant reason behind storage systems not being economically viable investments at present is that the VOS tariff essentially disincentivizes investment in storage systems by allowing customers to earn revenue for all solar generation regardless of whether they use the solar electricity in the home, store it on-site, or send it back to the grid. Further, the reduction in annual energy cost obtained by installing storage systems in homes with solar panels is substantially greater without the VOS policy under each of the five pricing structures — the difference is particularly significant under tiered rates, TOU rates, and CPP. This trend can be observed from Table B1 in Appendix B. Thus, the VOS tariff, while encouraging the adoption of solar, actively discourages residential investment in storage systems. If electric utilities wish to support self-consumption of solar electricity in the residential sector, a different compensation mechanism might be necessary.

Under RTP and demand charges, it is cheapest for the residential customer to own solar panels and smart thermostats. This combination is optimal (instead of only solar panels) because the diurnal variability in real-time prices across all months of the year allows significant reduction in annual energy cost as thermal load is shifted across the day (by pre-cooling or pre-heating in the low-price hours). This decrease in energy cost offsets the capital cost of the smart thermostat. The other pricing structures either have constant rates or significant variations only in the summer months, as can be observed from Figure 5.3 in Section 5.2.6. Thus, even as thermostats make the home thermally energy-efficient under tiered rates, TOU rates, and CPP, the energy cost is not lowered to an extent that counterbalances the capital cost of the smart thermostat. Similar to the case with real-time prices, the annual energy cost is significantly lowered under demand charges by distributing the thermal load in the household across each day and lowering the payment corresponding to the peak usage in each month.

The electricity portion of the overall cost is lowest while the overall expenditure is highest for a home with all four technologies under each of the five pricing structures. The capital cost, O&M cost, and electricity cost for a residential customer with different combinations of distributed energy technologies under real-time pricing can be observed from Figure 5.8. The home with solar panels and controllable HVAC has the lowest overall expenditure over the entire year (but only $4 less than the home with solar panels). As the number of technologies installed in the household increases, the energy portion of the overall cost (in gray) decreases while the capital cost portion (in green) increases. In particular, the amortized capital costs of the lithium-ion battery and the ice CTES significantly increase the overall expenses in scenarios with combinations of these technologies. The O&M cost comprises a minor portion of the total expenditure in all cases.

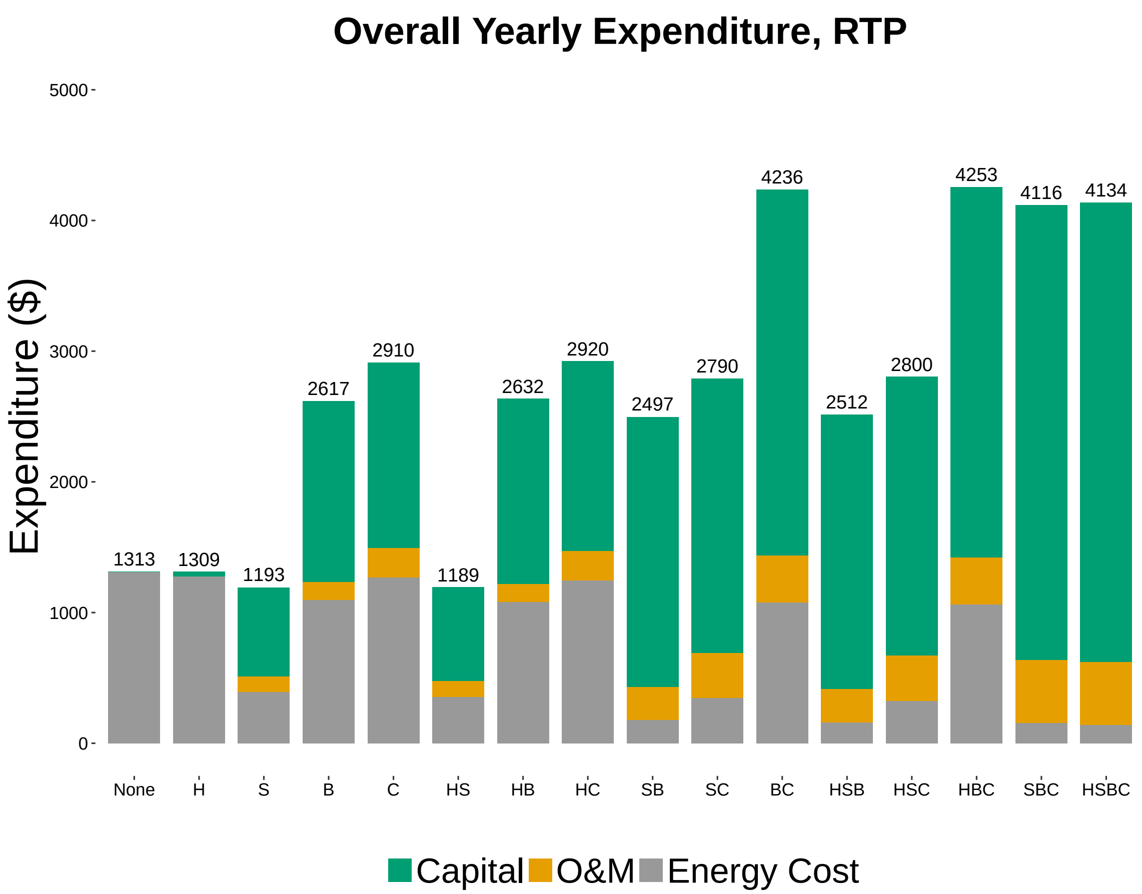

Figure 5.8: Amortized capital, O&M, and yearly energy cost in a home with different combinations of distributed energy technologies under real-time prices (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). The overall expenditure for each technology scenario is labeled in black above the corresponding bar. The energy cost (in gray) is lowest when the household has all four technologies while the overall expenditure is lowest for the case with solar panels and controllable HVAC load.

We would like to acknowledge that the findings from the single home analysis cannot be automatically generalized to apply to all homes as these results depend on the demand profile of the house chosen, properties of the technologies (obtained from literature), discomfort parameters, etc. Thus, these results should not be interpreted globally or out of context. However, since the VOS program isolates the solar investment from the electricity usage profile and other properties of the home, that portion of the analysis can be generalized to other homes with similar solar capacities located in analogous climates.

5.3.1.2 Yearly emissions and energy bought from the grid

Under all five pricing structures considered in this study, solar panels are the main drivers for reducing yearly emissions and energy consumed from the grid. When RTP and demand charges are in effect, the installation of the lithium-ion battery (both in the presence and absence of solar panels) increases the energy consumption from the grid. This occurs because of two reasons: 1) using the battery has the associated disadvantage of efficiency losses and 2) the model chooses to optimally charge the lithium-ion battery from the grid at night when prices are low and discharge to the home during the day when prices are higher. The VOS tariff that exists in the Austin Energy service territory does not differentiate between usage of solar generation and usage of grid electricity. Solar customers get billed for total electricity usage of their home (regardless of whether it comes from the grid or from the solar panels) and receive a VOS credit for the overall solar production. Thus, there is no incentive to self-consume solar electricity and the model chooses to charge the lithium-ion battery from the grid when prices are lowest. In contrast, under tiered rates, TOU rates, and CPP, the lithium-ion battery reduces energy bought from the grid. When tiered rates are in effect, the battery is not charged (either from the grid or solar panels) and only drained throughout the year from the initial energy capacity to meet thermal and electric demand in the home. This occurs because the rates are essentially flat and there is no incentive for utilizing the battery. Rather, power is directly bought from the grid and consumed in the home.

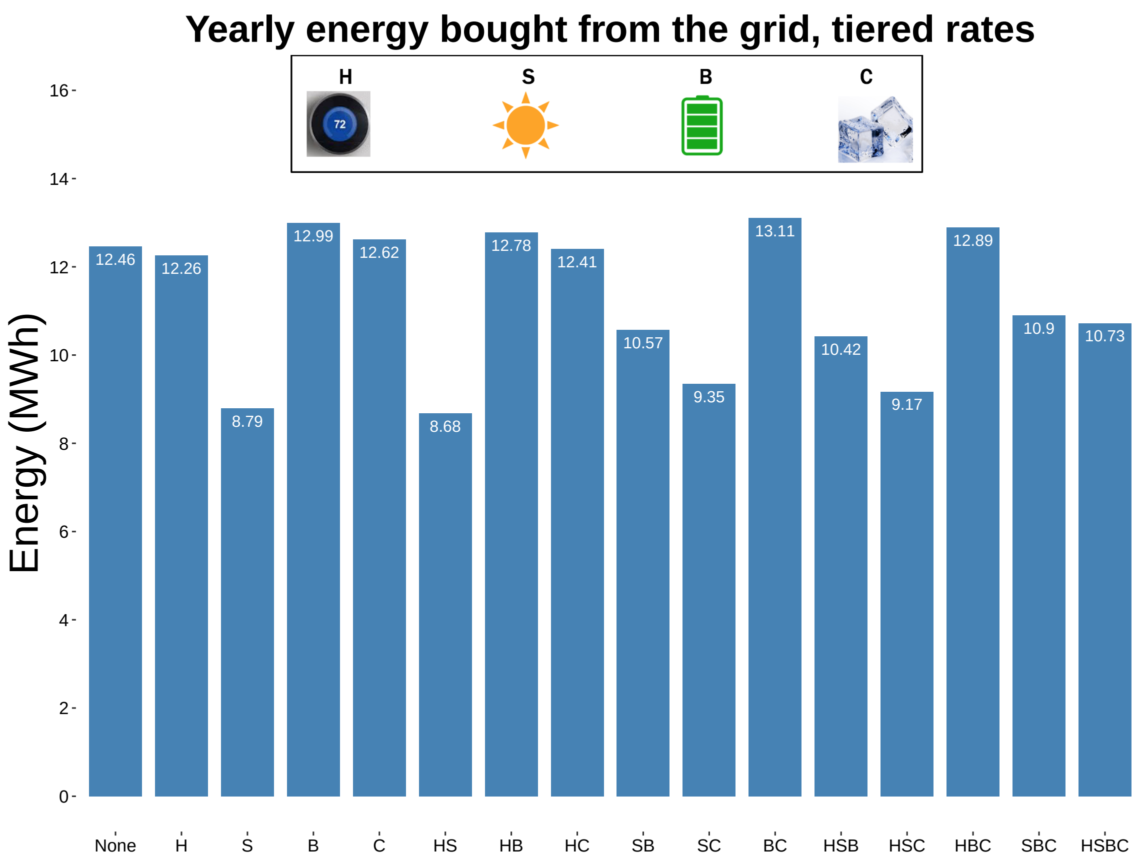

Figure 5.9: Energy bought from the grid over the year of analysis for a home with different combinations of technologies under tiered pricing (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). Solar panels are the main instruments for reducing the energy consumption from the grid. The minimum grid energy bought occurs in two scenarios – when the home has all technologies and when the home has solar panels, lithium-ion battery, and controllable HVAC load (the model chooses to not utilize the CTES under tiered rates).

Under TOU rates and CPP, the battery is charged from the grid during low-price hours and discharged in the course of the high-price hours of the summer months. However, the utilization of the lithium-ion battery is much less than under RTP and demand charges as the diurnal variability of TOU rates and CPP is apparent mainly during the summer months. Thus, although the battery is charged from the grid, the total energy bought from the grid is ultimately lowered under these two pricing schemes. The energy bought from the grid for a representative home under tiered rates and RTP can be observed from Figures 5.9 and 5.10 respectively.

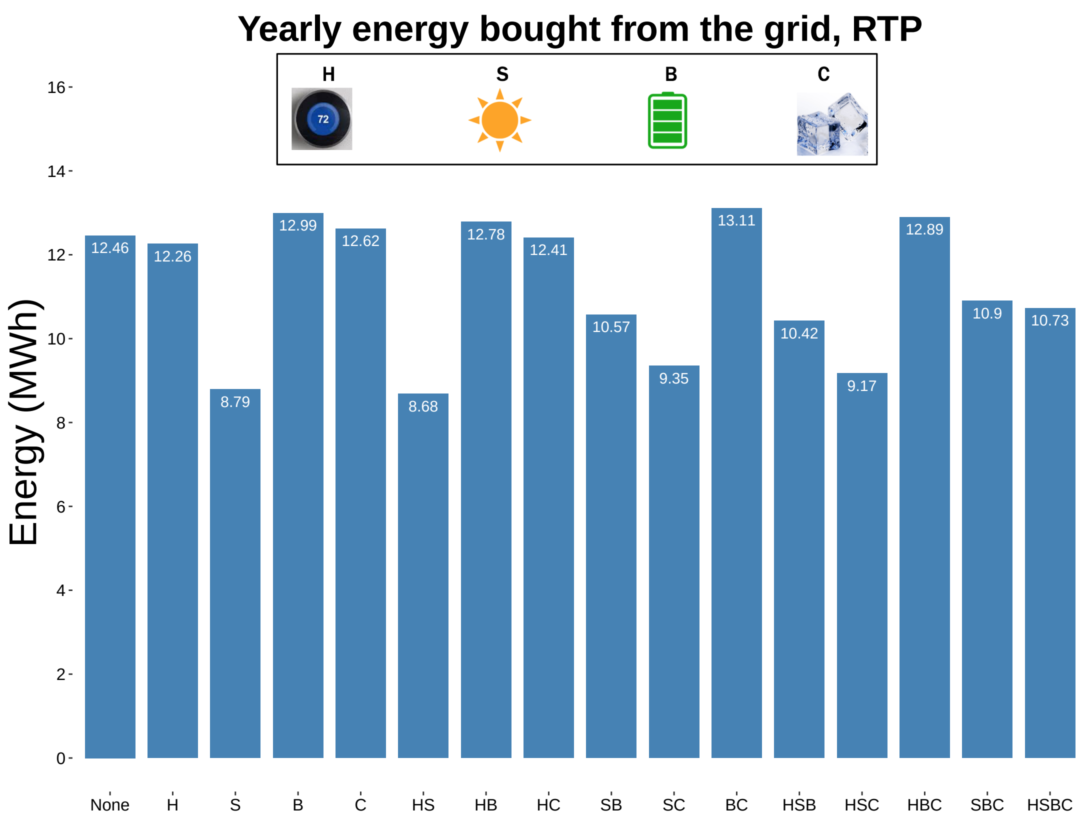

Figure 5.10: Energy bought from the grid over the year of analysis for a home with different combinations of technologies under real-time pricing (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). It is interesting to note that the lowest energy consumption from the grid under this pricing scheme corresponds with the scenario with lowest yearly expenditure – a home with solar panels and controllable HVAC load.

Under RTP and demand charges, similar to the lithium-ion battery, the ice CTES also increases the energy bought from the grid. However, the magnitude of the increase is less because the ice CTES is only operational from May–September and is capable of solely affecting the cooling demand in the home. On the contrary, the lithium-ion battery can affect both electricity demand and thermal demand (by charging the H&C engine) in the home. The ice CTES is not utilized under tiered rates and CPP since the model finds it optimal to directly meet thermal demand in the home using the H&C engine and avoiding efficiency losses. When TOU rates are in effect, the ice CTES increases the grid energy bought in most technology scenarios. Smart thermostats reduce energy consumption from the grid under all five pricing structures since these make the home thermally energy-efficient.

5.3.1.3 Yearly peak grid load

When tiered rates, RTP, TOU rates, or CPP are in effect, solar panels are the main instruments in reducing peak grid load. The lithium-ion battery minimally reduces this metric under tiered rates and CPP. The peak grid load for the home with different combinations of the four distributed energy technologies under tiered rates can be observed from Figure B.3 in Appendix B. Under RTP, as demonstrated in Figure B.4 in Appendix B, installing a lithium-ion battery increases the yearly peak demand from the grid. This is observed because the goal of the optimization problem is to minimize the cost incurred by the residential customer by charging the lithium-ion battery when prices are low and discharging the battery when prices are high. That target does not necessarily coincide with reducing the peak. With TOU rates, the lithium-ion battery does not alter the peak demand as the battery is mostly utilized in the summer months when the ratio of on-peak to off-peak rates is significant and again, minimizing the overall yearly expenditure is not necessarily equivalent to lowering the peak. The ice CTES does not affect this metric since the peak usage for this particular home occurs in the month of December when the ice CTES is not operational and is comprised mainly of uncontrollable electric load. The installation of smart thermostats under the four pricing schemes does not exhibit a clear trend of lowering or increasing the peak grid load.

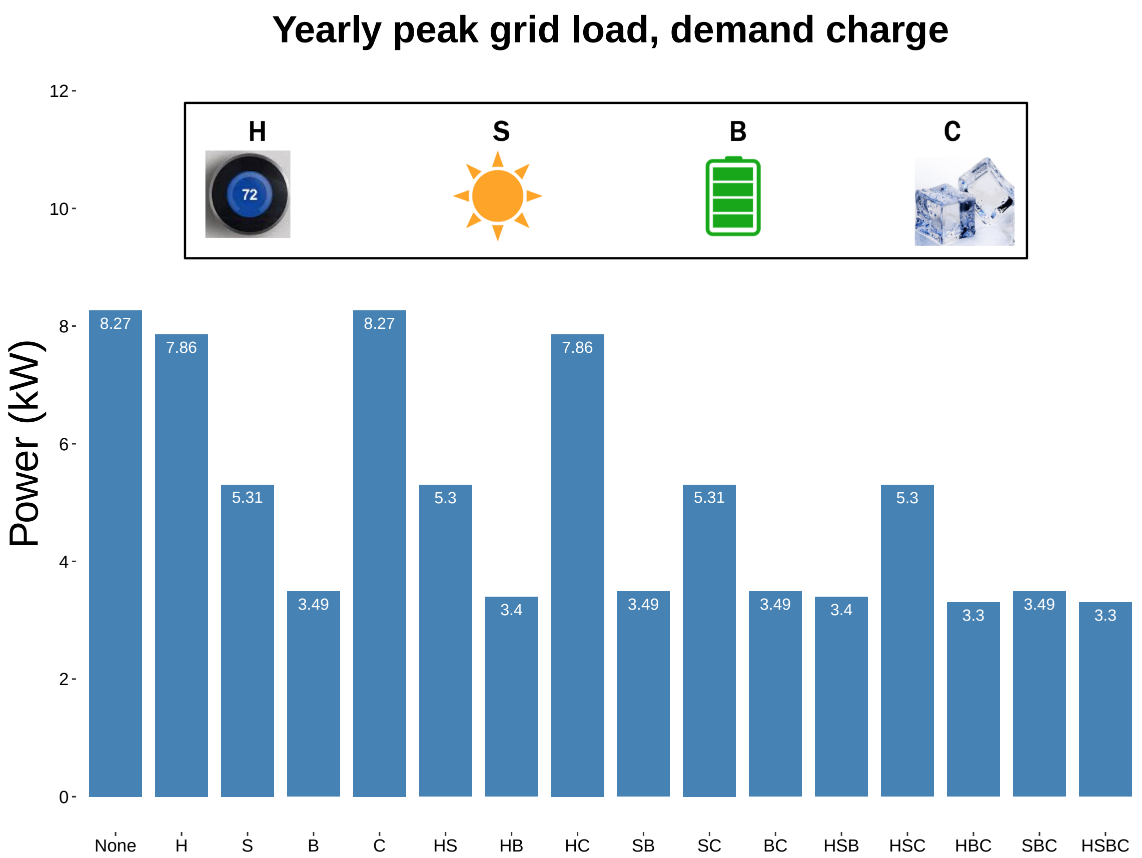

Figure 5.11: Maximum power bought from the grid over the year of analysis for a home with different combinations of technologies under demand charges (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). Lithium-ion batteries are the main drivers in reducing the peak while solar panels can be considered to be secondary drivers. Lithium-ion batteries are able to significantly reduce the peak only under certain rates (like demand charges) and can actually increase the peak under other pricing structures (like RTP).

In contrast, when demand charges are in effect, lithium-ion batteries are the main drivers for reducing yearly peak grid load and flattening the curve, as shown in Figure 5.11. Solar panels are also able to reduce the peak (by a lesser amount) and can be considered to be secondary drivers, even though they are most significant for reducing total grid energy consumption (as mentioned in Section 5.3.1.2). Additionally, smart thermostats slightly lower the peak while the ice CTES does not affect this metric. Under this pricing structure, the model tries to distribute the energy usage in the home equally across the representative day to the extent possible to save the customer from paying a high demand charge each month.

5.3.1.4 Power bought from the grid on a summer day

The power bought from the grid on a representative August day for a home with different combinations of distributed energy technologies under RTP is presented in Figure 5.12. The bright yellow curve represents the scenario without any technologies installed and serves as the 'base' case. The peak grid load in this case occurs at 8 pm, which is also when real-time prices are highest. Solar panels are able to minimally reduce the peak because of the inflexible nature of the timing of solar generation and the peak occurring in the late evening. Ice CTESs lower the peak to a certain extent but potentially create a second peak by charging from the grid around 3–5 am when real-time prices are the lowest. Additionally, ice CTESs are limited in their ability to influence energy consumption from the grid since these storage systems can only have an effect on the cooling demand (and not the electric demand) in the home. Lithium-ion batteries also charge from the grid during the low-price early morning hours and potentially create a second peak of greater magnitude. This observation regarding the storage systems has parallels with the results obtained in Chapter 4 where time-varying prices can have the adverse impact of creating a second higher peak in the residential sector. The power bought from the grid at 8 pm for homes with different technology combinations under RTP and demand charges can be observed from Figures B.1 and B.2 in Appendix B.

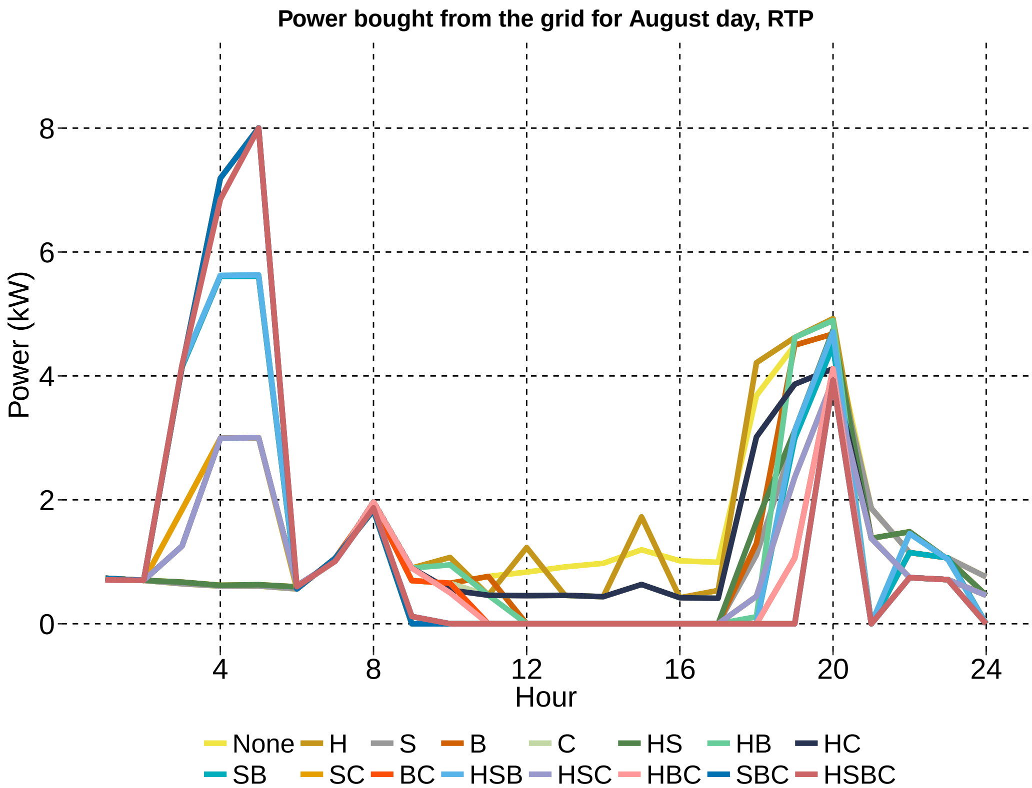

Figure 5.12: Power bought from the grid for the August day under real-time pricing for a home with different combinations of solar panels, lithium-ion batteries, ice CTESs, and controllable HVAC load (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). The two storage systems can potentially create a second (sometimes higher) peak in the early morning hours by charging from the grid when real-time prices are the lowest.

When demand charges are in effect, the lithium-ion battery is the primary technology which spreads the energy usage evenly across the day to the extent possible while still meeting customer comfort constraints. This outcome is different than the results observed under RTP because the goal of minimizing the overall customer expenditure coincides with minimizing the peak usage under this pricing structure. Solar panels are able to reduce the peak negligibly as the maximum grid demand occurs in the late evening. Ice CTESs are also able to lower the peak, albeit by a lesser amount than the lithium-ion batteries since they cannot meet the uncontrollable electric demand in the home, Thus, storage systems are energetically beneficial under demand charges although they drive up overall customer expenditure, as discussed previously in Section 5.3.1.1. If electric utilities plan to subject residential customers to demand charges as an effective load control mechanism, they should offer significant rebates to make investments in these storage systems economically viable.

5.3.2 Community-level analysis

Table 5.4 serves as a quick reference summary for the most significant findings from the community-level analysis in Austin, TX. No consensus can be arrived at regarding the technology combination(s) leading to lowest peak grid load in all or a majority of homes under any of the five electricity rates. Key results from the model runs involving the community of 25 homes under RTP and demand charges are discussed in detail below.

Table 5.4: Summary of key findings of the community-level analysis of 25 homes (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). The first column lists the significant metrics analyzed in this study. The entries of the table designate the technology combinations corresponding to the optimal (lowest) outcome of each metric for a majority of homes under the five pricing structures.

	Tiered	**RTP**	**TOU**	**CPP**	**Demand charge**
Overall Cost	S	HS	S	S	HS
Energy Cost	HSBC	HSBC	HSBC	HSBC	HSBC
Peak Grid Load	–	–	–	–	–
Annual Energy Bought	HSB	HS	HSB	HSB	HS

Under RTP, for all 25 homes, the electricity portion of the overall cost is lowest when households have all four technologies and highest when households do not own any of the technologies. Additionally, we observe that for 20 out of the 25 homes, the overall yearly expenditure is lowest for households with solar panels and controllable HVAC load. These results are consistent with what we observed for the single home analysis in Section 5.3.1.1. There are five homes in the dataset where owning only smart thermostats drives down the overall yearly expenditure to a minimum. For these five households, the VOS credit that customers receive over the entire year is significantly less than the amortized capital and O&M costs that they incur.

Similar to our single home analysis, solar panels are the main instruments in reducing energy bought from the grid and emissions in all 25 homes. Installing lithium-ion batteries and ice CTESs increase the quantity of grid energy consumed in each of these homes to account for efficiency losses. Even in the presence of solar panels, more energy is bought when the storage systems are present since the VOS tariff does not incentivize self-consumption of solar-generated electricity. Thus, the storage systems are charged (from the grid at night) when prices are lowest and not necessarily during the day when prices are higher but solar generation is available. Smart thermostats make the households thermally energy-efficient and reduce the amount of energy bought from the grid in all 25 homes.

Unlike the energy bought from the grid and emissions, a clear pattern regarding the peak grid load in the 25 homes cannot be identified. Under RTP, solar panels lower the yearly peak in some homes significantly, minimally in others while not budging this metric at all in some homes. Lithium-ion batteries increase the yearly maximum grid load in all households because, as mentioned in Section 5.3.1.3, the goal of minimizing the customer expenditure (by charging the battery when prices are low and discharging to the home when prices are high) does not conform with minimizing the peak under this pricing structure. Installing controllable HVAC can either increase or decrease the peak. The ice CTES has no effect in homes where the yearly peak occurs during the winter and a 'temperamental' influence (of either increasing or decreasing the peak) in households with a summer peak. The distributions of the overall customer expenditure, annual energy bought from the grid, consequent emissions, and yearly peak grid load for the 25 homes (with certain technology combinations) under RTP can be observed from Figure 5.13. Under RTP, addition of the two storage systems to homes with solar and smart thermostats has negative effects on all four metrics analyzed. This result further supports the argument presented in Chapter 4 against dynamic pricing potentially being "cure-all" solutions to peak load demand issues.

Under demand charges, for all 25 homes, the electricity portion of the overall cost is lowest when households have all four technologies and highest when households do not own any of the technologies. Additionally, we observe that for a majority (19 out of 25) of homes, the overall yearly expenditure is lowest for households with solar panels and controllable HVAC load. These results are consistent with what we observed for the single home analysis in Section 5.3.1.1. Under demand charges, similar to the single-home analysis, we observe that solar PV is the chief technology responsible for reducing energy bought from the grid and CO_2 emissions for all 25 homes. Further, lithium-ion batteries are the main drivers in reducing the yearly peak grid load in all 25 homes. But unlike the home which we analyze in Section 5.3.1, solar panels act as 'soft drivers' in some homes by also significantly lowering the peak (but by a lesser amount than the lithium-ion battery) while they only negligibly reduce or are unable to affect the yearly maximum in some households.

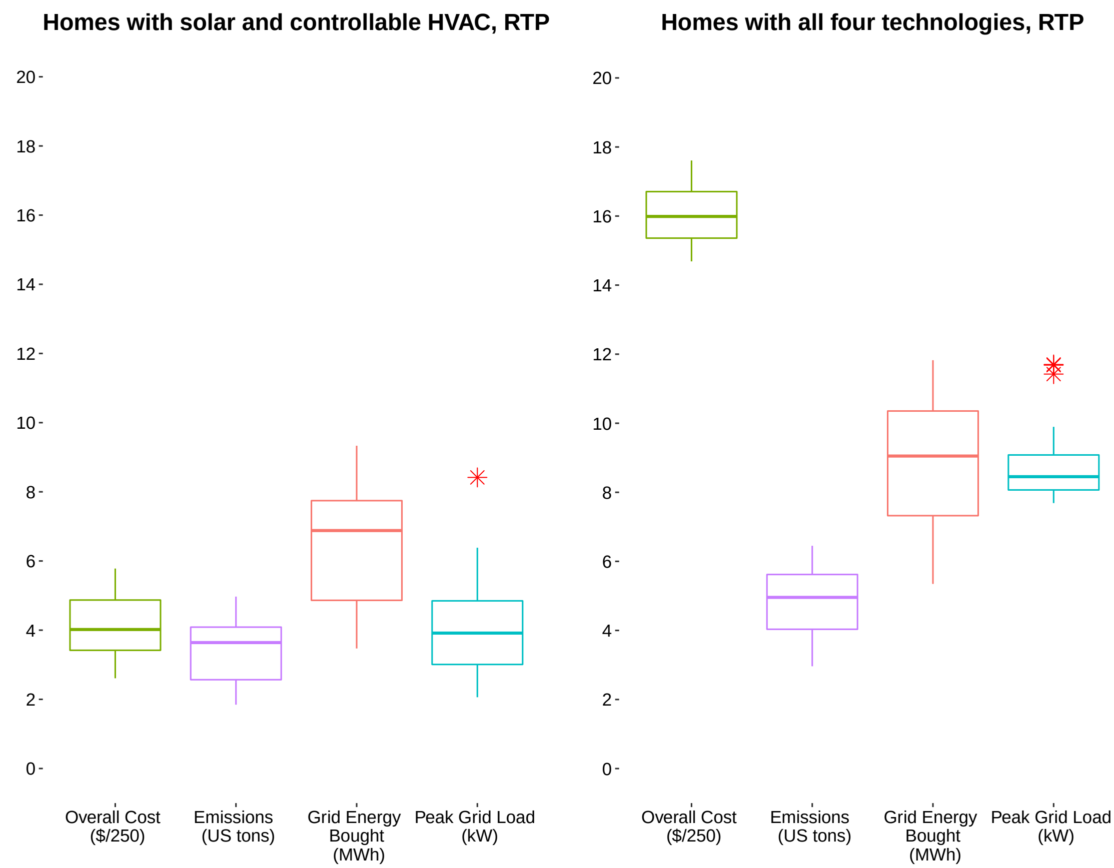

Figure 5.13: Boxplot of overall yearly customer expenditure, annual CO_2 emissions, annual energy bought from the grid, and yearly peak grid load for the 25 homes under RTP in the scenarios where the households have solar panels and smart thermostats (left) and where the households have all four technologies (right). The lower and upper end-point of each box represents the 25th and 75th percentile of the corresponding metric. The solid inner line denotes the median while the whiskers extend to the minimum and maximum values barring outliers. The outliers are represented in red.

5.3.3 Comparison/validation of results with similar literature

Babacan et al. found that when households seek to minimize their electricity costs (and not emissions), grid-connected residential energy storage systems mostly increase greenhouse gas emissions under various utility pricing structures and operation modes, thereby challenging the common notion that increased penetration of

DERs always cleans the electric power system [215]. Similarly, through this analysis, we find that installing lithium-ion batteries and ice batteries could increase energy consumption from the grid and consequent emissions (e.g. under RTP and demand charges). Additionally, a study by Al-Hallaj et al. concluded that out of several chemical and thermal energy storage technologies, lithium-ion batteries deliver the highest value for demand charge reduction [216]. The analysis presented in this chapter also leads to the conclusion that lithium-ion batteries are the primary drivers of lowering demand charges by flattening energy usage. Uddin et al. found that the installation of a coupled photovoltaic lithium-ion battery system in a mid-sized UK family home is not financially profitable [217]. Barcellona et al. investigated the economic viability of installing residential battery storage systems with grid-connected PV plants in Europe and concluded that the present capital costs of batteries are still too high to make the investments profitable [218]. Another study by Lorenzi and Silva [46], mentioned in Section 2.3.2.5, found that, in the presence of modest-sized PV systems, demand response initiatives (which typically have low costs) can provide annual savings to the residential customers while the installation of storage systems causes economic losses because of the high capital cost associated. These outcomes are similar to what we observe in Section 5.3.1.1. Zhang et al. formulated dynamic programming algorithms to quantify the break-even battery capital cost under which residential customers are incentivized to invest in batteries instead of participating in feed-in-tariff or net energy metering programs (and sending excess solar generation back to the grid) [136]. They found at current battery capital cost levels, households should participate in energy sell-back programs rather than investing in batteries [136]. Another study by Carvallo et al. found that under a net-metering scheme, customer-driven decisions about investing in behind-the-meter DERs emphasize the adoption of excess distributed solar and insufficient distributed storage when compared to the true, coordinated system-wide optimum [219]. These results draw parallels with our conclusion that the VOS policy (a form of feed-in-tariff) essentially disincentivizes distributed storage adoption. We highlight the above-mentioned analyses to validate the general trends of our results and strengthen our policy recommendations.

5.4 Limitations

Like any other modeling study, our analysis has some limitations. First, we choose one representative day from each month of our year of analysis using functional boxplots on historical ambient temperature data and annualize the results of our optimization model. The inclusion of variations in ambient temperature, solar generation, electricity prices, and electricity demand within each month could potentially change the results of our study.

In addition, we obtain the capital and O&M costs of the four distributed energy technologies from recent literature. But these costs are rapidly evolving, e.g. the cost of residential solar panels decreased 5% between 2017 and 2018 [109]. Incorporating new prices could potentially change some of the conclusions of this study. Since it is not realistic to update results in real time, our goal is to present a detailed methodology which other energy-system modelers can utilize to rework the analysis in the future and present updated results.

We also assume that certain input parameters like thermal properties of the homes, discomfort parameters, size of the storage systems, customer-specified room temperatures, etc. remain constant across the 25 homes in this analysis. In reality, these parameters will likely differ across homes based on personal preferences, energy usage patterns, income level, etc. Additionally, the one-parameter thermal model of the home in our analysis does not include humidity. The temperature a customer would realistically 'feel' inside a room depends not only on the thermal properties of the home and the ambient temperature (already captured in this study) but also the humidity.

Further, the historical real-time prices which are used in our study are exogenous inputs to the model, instead of being determined endogenously based on supply-demand balance during the course of a model run. As a result, once our model allows the electricity demand profile to deviate from the tiered rate case in response to the dynamic prices, it does not allow the real-time prices to adjust accordingly and cuts off the cycle of feedbacks between demand and price that would likely occur in reality.

Additionally, we assume perfect foresight in this study which means that the model has complete knowledge of past, present, and future electricity prices, ambient temperatures, solar generation patterns, and electricity demand profiles over the period of analysis. Although this simplifying assumption is common in power system modeling [44, 208, 220, 221], it disregards the uncertainties associated with forecasting and potentially underestimates the need for energy storage system investments. Capturing the uncertainties of real-time market prices and future load patterns using a stochastic modeling framework could offer a more realistic assessment of the value of lithium-ion batteries and ice CTESs in the residential sector.

Both the lithium-ion battery and the ice CTES are modeled as 'black boxes.' While we do account for roundtrip charging and discharging efficiencies, loss coefficients, charging limits, and energy capacity bounds (as well as the fact that such an assumption is common in literature), the incorporation of a thermal model of the ice CTES and a chemical model of the battery could make our analysis more detailed and realistic.

Finally, although the uncontrollable power profile and solar generation data are obtained from the Pecan Street dataset, other inputs to the model like the rated power of the HVAC system, thermal properties of the homes, and discomfort parameters are obtained from the literature. Our lack of knowledge about the individual appliances and thermal properties of the homes necessitates the combination of the empirical load data with parameterizations of appliance properties and the thermal model inspired by the literature.

5.5 Summary

This chapter establishes an optimization framework to investigate the interactions among four distributed energy technologies in the residential sector under five electricity pricing structures while accounting for the monetary value of customer comfort levels. Overall yearly expenditure to a customer (including capital, O&M costs, and energy costs), energy consumption from the grid, peak power flowing from the grid to the home, and emissions are recorded for each scenario.

Results show that solar panels are the most cost-effective investments for residential customers under tiered rates, TOU rates, and CPP while a combination of solar panels and smart thermostats is the second-most optimal choice. When RTP and demand charges are in effect, the duo of solar panels and smart thermostats is the most economically viable investment. Installing lithium-ion batteries and ice CTESs in homes with solar panels and smart thermostats can drive down the electricity bills to a minimum but increases the overall expenditure because of the high capital costs of these technologies.

Further, the VOS tariff does not encourage customers to store excess solar electricity in storage systems to use in the home during peak times since solar customers earn a fixed revenue for the total renewable generation regardless of whether it is consumed in the home, stored on-site, or sent back to the grid. Customers are billed on total energy usage and not on the net energy purchased from the grid. Additionally, the operational cost savings from installing storage in a home with solar panels are actually much greater without the VOS incentive. Thus, this rate essentially disincentivizes customer investment in energy storage systems. While the VOS tariff is considered to represent the true value of distributed solar to the utility [128] and mitigate several challenges associated with the more popular net metering policy, the findings of this chapter recommend that policymakers take necessary steps to address the aforementioned concerns.

Solar panels are the main instruments in reducing energy consumption from the grid and consequent CO_2 emissions under all pricing structures. Installing smart thermostats in homes with solar can further reduce these metrics. However, the timing of generation limits the capability of solar panels to substantially lower the peak in many homes. The energetic effects of installing lithium-ion batteries and ice CTESs can be beneficial or detrimental depending upon the household demand profile and the pricing scheme. However, when demand charges are in effect, lithium-ion batteries are the main drivers in reducing peak demand and flattening the load curve. Thus, it is recommended that residential customers invest in solar panels and smart thermostats to minimize their annual expenditure and environmental impact. Further, to the extent that electric utilities wish to support the deployment of distributed technologies to reduce peak loads in the residential sector, the findings of this chapter suggest that they should offer significant rebates to encourage customer investment in storage systems and subject residential consumers to demand charges.

Several avenues for expanding the scope of this study exist. The methodology developed in this chapter has been demonstrated using energy usage and solar generation data for a community of 25 homes in Austin. Since the Pecan Street dataset also contains energy consumption data for homes outside of Texas, a similar analysis can be performed for homes in other locations like Colorado or California to see if the corresponding weather patterns, demand profiles, and electricity pricing structures result in significantly different conclusions. The study can also be replicated to analyze the effect of other residential pricing schemes like variable peak pricing (e.g. offered by Oklahoma Gas & Electric) or peak time rebates.

This study is modeled from the perspective of the residential customer, i.e the goal of the analysis is to minimize the costs incurred by a household over the period of a year. The results are then interpreted to highlight implications for the utility. In contrast to the current formulation, the optimization model could also be framed from the point of view of the utility, where the objective would be to minimize yearly expenditure for the utility. Additionally, the problem can be formulated as a bilevel model between the electric utility and residential customers, which would allow for a complete cost-benefit analysis of peak load reduction strategies and evaluation of whether the benefits of these strategies at the grid scale justify the costs.

Finally, apart from lithium-ion batteries, lead acid batteries are also commonly used at the residential scale. These are much less expensive than lithium-ion batteries, but have a shorter lifespan and lower depth of discharge [222]. The performance of these batteries could be evaluated to analyze how they affect customer expenditure and energy consumption from the grid when used on their own or in conjunction with the other technologies.

Chapter 6

Conclusions and Future Work

The goal of this dissertation was to develop a techno-economic method for evaluating the effect of DERs, like solar panels and energy storage systems, and demand response on the electricity distribution grid. This goal was achieved by modeling various installed local distributed solar and storage capacities, residential dynamic electricity prices, detailed operating models of commonly-used household appliances and storage systems, and customer discomfort/inconvenience parameters. The major findings of the three research objectives detailed in Chapters 3–5 are summarized below.

6.1 Summary of results

Research Objective 1: The focus of this objective (detailed in Chapter 3) was to develop a generalized tool to forecast the change of 4 coincident peak loads and corresponding TCOS obligations based on varying amounts of solar and storage capacity over a 10-year period for utilities within ERCOT. Historical demand data, annual energy consumption, TSP transmission rates, and future annual energy projections were used to statistically forecast future demand patterns and transmission rates. The effect of current levels of installed solar and storage on future 4CP loads and

Some sections of this chapter were adapted from the journal article: A. Bandyopadhyay, B. D. Leibowicz, E. A. Beagle, M. E. Webber, As one falls, another rises? Residential peak load reduction through electricity rate structures, *Sustainable Cities and Society*, 2020 [3]. The majority of this paper's research, analysis, and writing were completed by the author of this dissertation. The co-authors contributed to defining the direction of this project and editing the manuscript.

TCOS obligations were investigated. The major findings from this portion of the analysis are as follows:

- Solar panels are limited in their ability to reduce 4CP load because the peak event generally occurs in the late evening hours [70] and does not align well with solar generation patterns. However, the corresponding reductions in TCOS obligations are significant. An increase of 20 MW of distributed solar can reduce the corresponding TCOS obligations by an average of $180,000 every year over a 10-year period.
- If storage systems are fully charged before the peak event, the reduction in 4CP loads as a result of increase in local storage capacity is significant. An increase in 5 MW (10 MWh) of distributed storage can lower TCOS obligations by an average of $400,000 every year over the ten years.

Research Objective 2: The focus of this objective (detailed in Chapter 4) was to develop a method to model price-based demand response in the residential sector while incorporating the monetary value of customer discomfort of deviation from set-point temperatures and inconvenience of running appliances at certain times of the day. Four different electricity pricing structures were evaluated and four types of controllable loads were considered. Sensitivity analysis was performed by varying the discomfort/inconvenience parameters for the different controllable loads to analyze their effect on the peak residential electricity demand. The major findings from this portion of the analysis are as follows:

- Dynamic pricing shifts the residential peak away from the time of overall peak load but can have the adverse impact of making the residential peak higher.

- Time-varying prices do not reduce overall household energy consumption. These rates incentivize concentration of appliance usage within low-price hours.

- Dynamic prices might not be "cure-all" solutions to high peak demand issues in the electricity sector as several studies suggest [182–184]. Implementing these rate structures could lead to other potential problems.

- The ramp rate of power delivered from the distribution grid to the home is greater for the time-varying rates than for the constant rate case, which points to electric utilities needing to deploy energy generators that can be dispatched quickly [223].

Research Objective 3: The focus of this objective (detailed in Chapter 5) was to develop a method to model the interactions among four technologies in the residential sector — solar panels, lithium-ion batteries, ice CTESs, and smart thermostats — under price-based demand response. Five different electricity pricing schemes were evaluated and implications on customer expenditure, peak grid demand, energy consumption from the grid, and emissions in homes with different combinations of the four technologies were recorded. The major findings from this portion of the analysis are as follows:

- Residential customers should invest in solar panels and smart thermostats to minimize their yearly expenditure and environmental footprint.

- The capital costs of lithium-ion batteries and ice CTESs are still too high at present for their installations to be economically profitable for typical residential customers under any pricing structure.

- The VOS policy disincentivizes customer investment in energy storage systems as solar customers earn a fixed revenue for the total renewable generation whether they consume it in the home or not.

- Solar panels are the main instruments in reducing energy consumption from the grid and CO_2 emissions. However, they are limited in their ability to decrease peak grid load across multiple homes.

- Lithium-ion batteries and ice CTESs can increase or decrease the peak grid load depending on the household demand profile and pricing scheme.

- Lithium-ion batteries are the main drivers to avoid high demand charges by spreading the net energy demand in the home (and power bought from the grid) evenly to the extent possible without incurring significant customer discomfort.

Several cross-cutting observations emerge from the findings of the three research objectives of this dissertation. First, solar panels, while environmentally beneficial and cost-effective, are limited in their ability to significantly reduce peak demand because of the inflexible nature of timing of generation. Secondly, energy storage systems are more effective at reducing peak load if the agent minimizing costs faces some monetary penalty for a high peak e.g. TCOS obligations or residential demand charges. Finally, while dynamic prices are effective at shifting the timing of the peak, they can have the negative impact of creating a second higher peak by encouraging concentration of appliance usage or charging of storage systems during low-price hours.

6.2 Final conclusions and future work

The electricity distribution sector is changing with increasing penetration of rooftop solar, onsite storage, rising EV adoption, smart meters, two-way communication between the customer and the utility, dynamic pricing, and utility rebates and incentives. As the transformation continues, the impact of these transitions and new 'players' on the electricity sector must be investigated. As a whole, this body of work demonstrates the energetic and economic value streams of DERs and effectiveness of price-based demand response initiatives.

Utilities can use the modeling framework and concepts presented here to anticipate the effects of alternative electricity rate structures on the timing and magnitude of peak load in the residential sector. Further, the analysis can help utilities make decisions about dynamic rate design and strategies for increased adoption of DERs. Additionally, homeowners can utilize the methodology and tools developed in this dissertation to evaluate the economic viability of investing in distributed energy technologies and optimally control their appliances in response to more complex residential electricity rate structures that might be in place in the future.

Future work could expand the research scope beyond some of the assumptions used in this dissertation. Potential research avenues that could add to the conclusions of each chapter have already been discussed in the individual chapters. In an overall sense, the impact of DERs apart from the ones modeled here, like small wind turbines or flywheel batteries, and other pricing structures, like variable peak pricing or peak time rebates, could be analyzed. The methods developed here can also be demonstrated using case studies from regions of the country other than Austin, TX to assess how different regional prices, weather patterns, and variability in demand affect the findings. Further, this dissertation mainly focuses on the cost effectiveness of reducing and/or shifting peak load using solar panels, energy storage systems, and price-based demand response initiatives. A comprehensive cost-benefit analysis would allow energy system modelers to quantify the benefits of each of these strategies at the grid-scale. Finally, integrating the results of the computational analyses presented in this dissertation with findings from experimental or survey-based studies could magnify the practical relevance of this body of work.

Appendices

Appendix A

Additional Results and Figures for Chapter 4

A.1 Results for single home with no solar panels

Table A1: Differences in peak load timing and characteristics for a sample home without solar panels on the summer peak day of 2017 for four electricity pricing structures. Similar to the analysis of a home with solar panels, dynamic prices shift the timing of the residential peak but increase its magnitude.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	9:30 am	3:45 am	10 pm	7 pm
Peak Load (kW)	6.13	10.59	7.69	7.78
Energy Consumption (kWh)	104.72	105	104.44	104.27
Greatest Ramp Rate (kW/min)	0.09	0.49	0.29	0.33

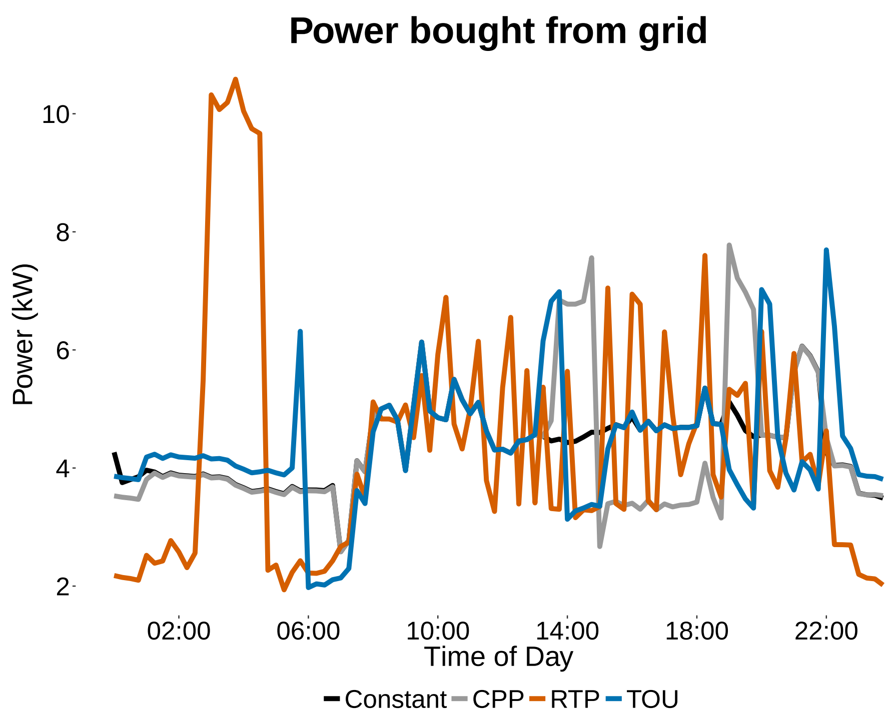

Figure A.1: Power bought from the grid on the summer peak day of 2017 for a sample home without solar panels under four different pricing structures.

A.2 Operational levels for the four appliances in 100 homes

This section describes the power consumed by the four end-use appliances - HVACs, EWHs, EVs, and PPs - for the community of 100 single-family detached homes in Austin, TX under four different electricity pricing structures on the summer peak day. Other key results for the community-wide analysis can be found in Section 4.3.2.

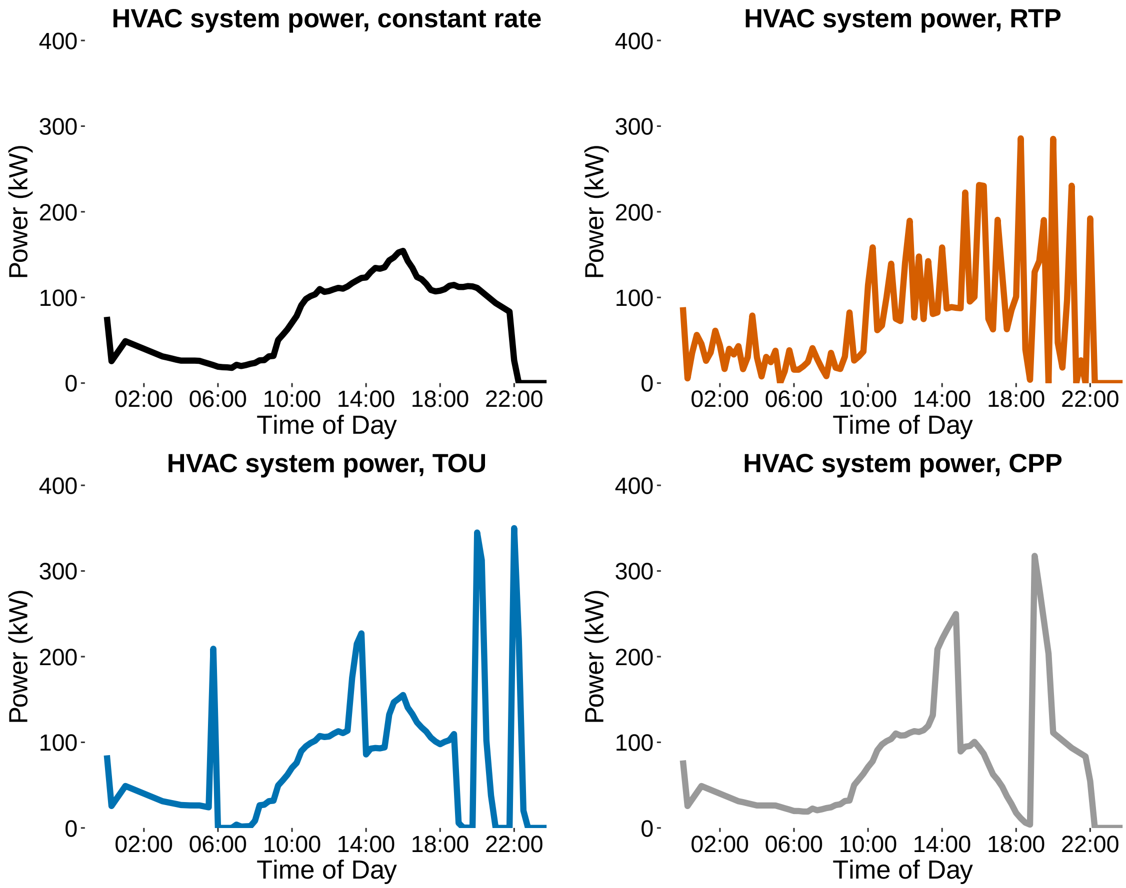

Figure A.2: Power utilized by HVAC systems on the summer peak day of 2017 for the community of 100 single-family detached homes under four different pricing structures.

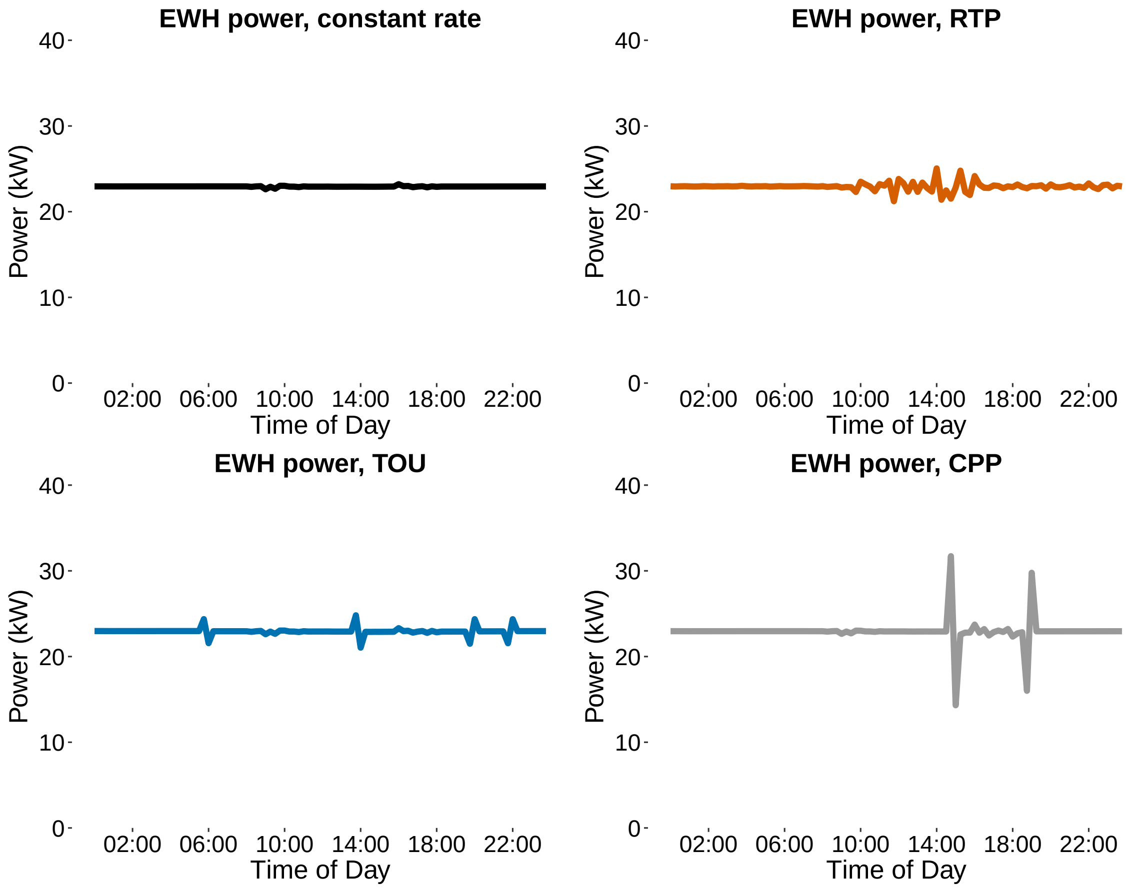

Figure A.3: Power utilized by EWH systems on the summer peak day of 2017 for the community of 100 single-family detached homes under four different pricing structures.

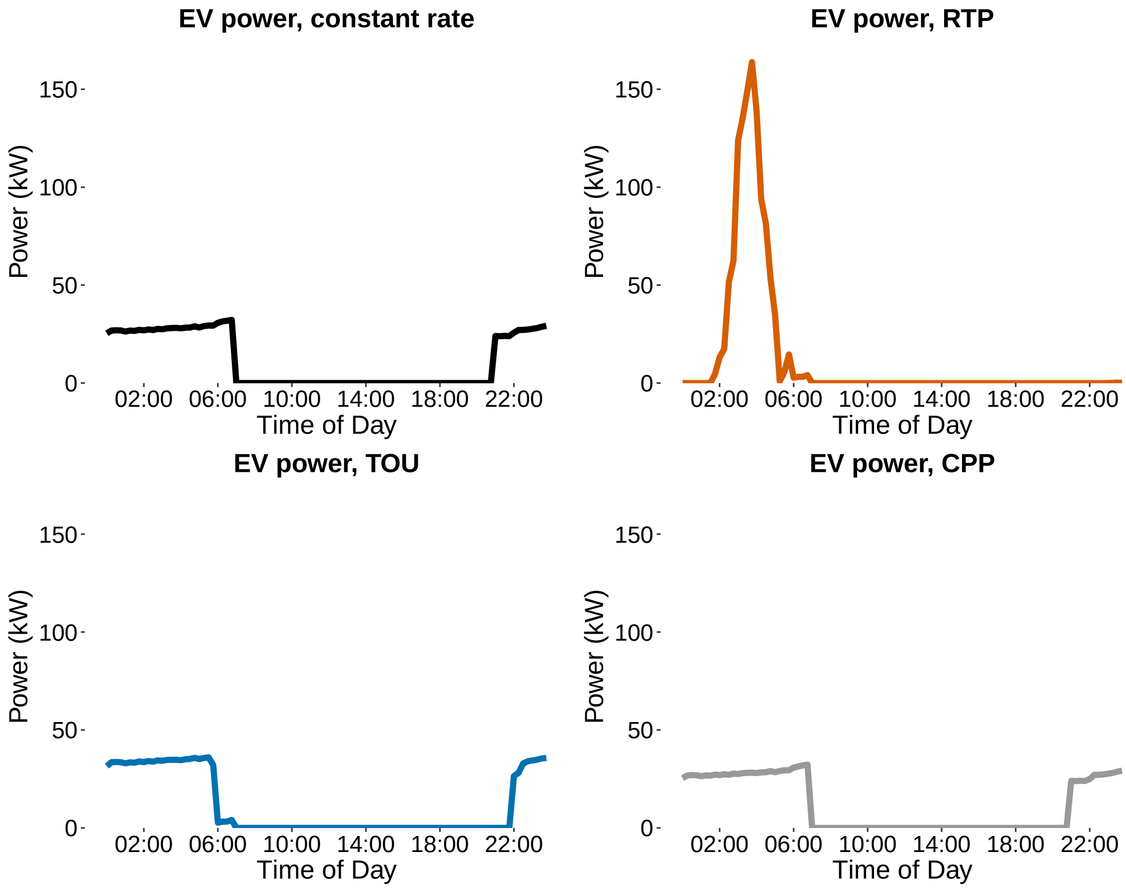

Figure A.4: Charging schedule of EVs on the summer peak day of 2017 for the community of 100 single-family detached homes under four different pricing structures.

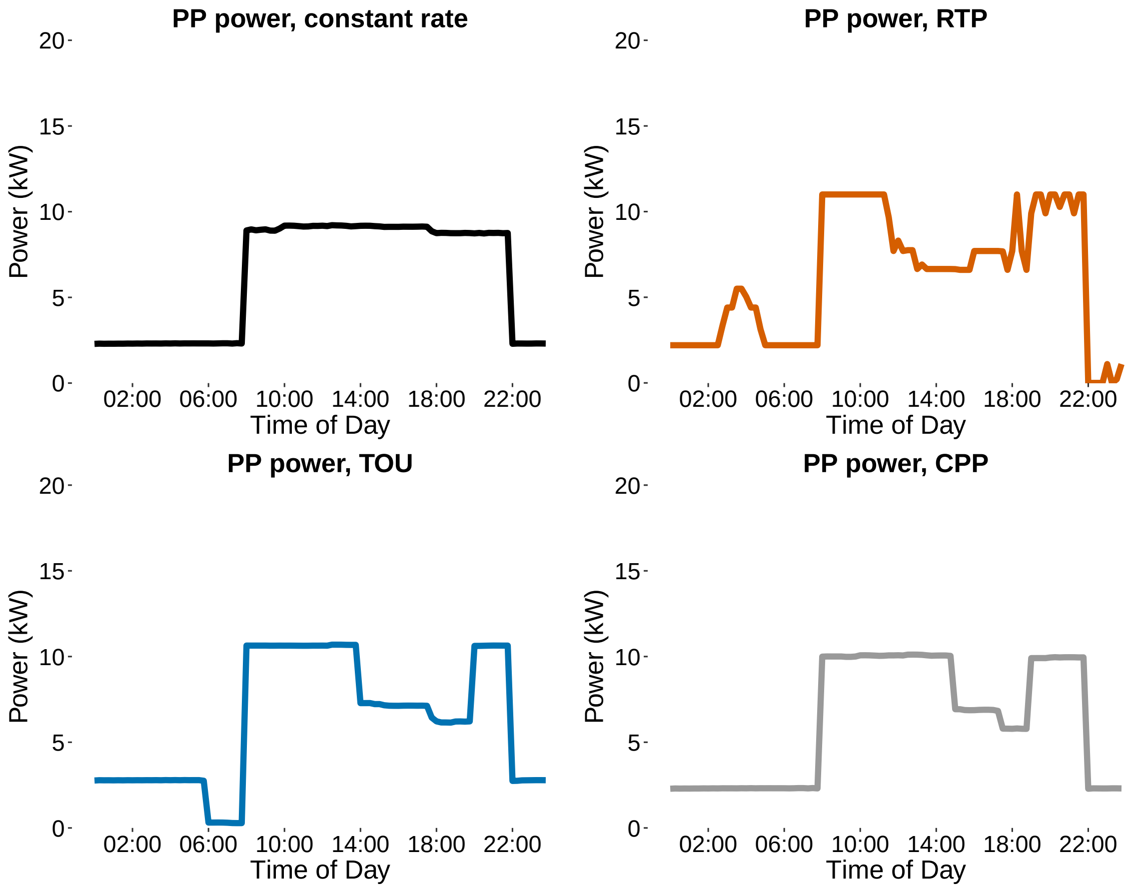

Figure A.5: Power utilized by PPs on the summer peak day of 2017 for the community of 100 single-family detached homes under four different pricing structures.

A.3 Winter day results

The section describes the power bought from the grid for the community of 100 single-family detached homes in Austin, TX on the winter minimum peak day under three different pricing structures (CPP is only valid for the summer day as Austin lies in a summer load peaking state), the timing and value of peak demand, energy consumption, and greatest ramp rate. The Austin Energy systemwide electricity peak on this day occurred at 1:50 pm.

Table A2: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes on the winter minimum peak day of 2017 for three electricity pricing structures. RTP shifts the timing of the residential peak but increases its magnitude. TOU rates do not shift the timing of the peak but create a lower peak.

	Constant rate	**RTP**	**TOU**
Timing of Residential Peak Load	6:30 pm	3 am	6:30 pm
Residential Peak Load (kW)	174	217	172
Energy Consumption (kWh)	2179	2215	2240
Greatest Ramp Rate (kW/min)	2.7	12.1	10.8

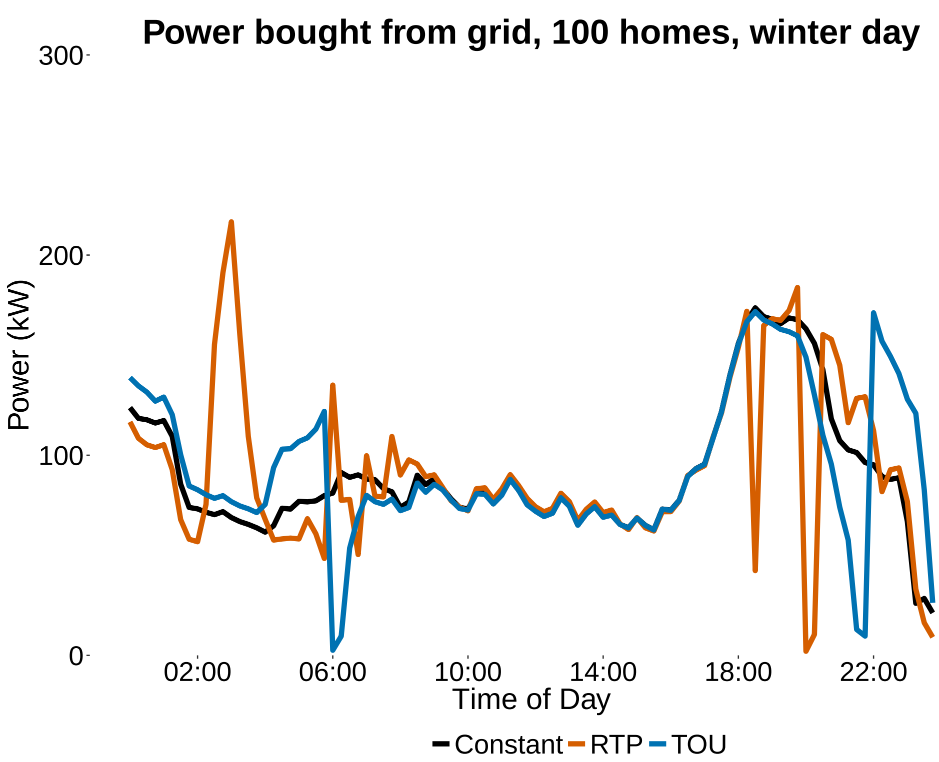

Figure A.6: Power bought from the grid on the winter minimum peak day of 2017 for the community of 100 single-family detached homes under three different pricing structures.

A.4 Community-level analysis on summer peak day: solar capacity sensitivity

Table A3: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with 25% of homes having solar panels) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	7:45 pm	6:15 pm	10 pm	7 pm
Residential Peak Load (kW)	268	458	512	496
Energy Consumption (kWh)	4184	4199	4220	4193
Greatest Ramp Rate (kW/min)	4.1	19.4	23.6	24.5

Table A4: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with 50% of homes having solar panels) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	9:15 pm	8 pm	10 pm	7 pm
Residential Peak Load (kW)	283	444	538	469
Energy Consumption (kWh)	3970	3992	4002	3977
Greatest Ramp Rate (kW/min)	4.2	19.0	24.3	23.3

Table A5: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with 75% of homes having solar panels) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	9:15 pm	8 pm	10 pm	7 pm
Residential Peak Load (kW)	300	451	553	457
Energy Consumption (kWh)	3724	3749	3755	3729
Greatest Ramp Rate (kW/min)	4.3	19.6	24.6	22.8

Table A6: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with 100% of homes having solar panels) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	9:15 pm	8 pm	10 pm	7 pm
Residential Peak Load (kW)	274	424	530	392
Energy Consumption (kWh)	2677	2701	2705	2681
Greatest Ramp Rate (kW/min)	3.9	19.9	24.7	20.6

A.5 Community-level analysis on summer peak day: EV sensitivity

Table A7: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with no homes having EVs) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	7:30 pm	6:15 pm	10 pm	7 pm
Residential Peak Load (kW)	257	430	486	474
Energy Consumption (kWh)	3679	3688	3715	3687
Greatest Ramp Rate (kW/min)	4.0	18.5	22.9	23.8

Table A8: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with 10% of homes having EVs) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	7:30 pm	6:15 pm	10 pm	7 pm
Residential Peak Load (kW)	268	439	504	485
Energy Consumption (kWh)	3809	3821	3844	3817
Greatest Ramp Rate (kW/min)	4.1	18.7	23.2	24.1

Table A9: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with 20% of homes having EVs) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	7:45 pm	8 pm	10 pm	7 pm
Residential Peak Load (kW)	266	436	518	475
Energy Consumption (kWh)	3796	3812	3829	3803
Greatest Ramp Rate (kW/min)	4.1	18.8	23.7	24.0

Table A10: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with 30% of homes having EVs) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	9:15 pm	8 pm	10 pm	7 pm
Residential Peak Load (kW)	288	445	544	465
Energy Consumption (kWh)	3874	3894	3905	3880
Greatest Ramp Rate (kW/min)	4.1	19.3	24.2	23.1

Table A11: Differences in residential peak load timing and characteristics for the community of 100 single-family detached homes (with 40% of homes having EVs) on the summer peak day of 2017 for four electricity pricing structures.

	Constant rate	**RTP**	**TOU**	**CPP**
Timing of Peak Load	9:15 pm	8 pm	10 pm	7 pm
Residential Peak Load (kW)	297	447	547	457
Energy Consumption (kWh)	3742	3766	3773	3747
Greatest Ramp Rate (kW/min)	4.2	19.4	24.3	22.8

Appendix B

Additional Results and Figures for Chapter 5

B.1 Savings in annual energy cost obtained by installing a lithium-ion battery with and without the VOS incentive

Table B1: Annual energy cost ($) of a residential customer with only solar panels and with the combination of solar panels and lithium-ion battery in the presence and absence of the VOS incentive under the five pricing structures. The operational cost savings from installing a lithium-ion battery are much greater when the VOS tariff is not available — particularly under tiered rates, TOU rates, and CPP. Thus, the VOS policy actively discourages the adoption of distributed storage.

	Solar	**Solar & Battery**	**Savings in Energy Cost ($)**	**Solar**	**Solar & Battery**	**Savings in Energy Cost($)**
	VOS	**VOS**	–	**no VOS**	**no VOS**	–
Tiered	399	378	21	900	510	390
RTP	392	177	215	925	489	437
TOU	397	367	30	889	503	386
CPP	401	381	20	899	510	389
Demand charge	398	144	254	1030	528	502

B.2 Power bought from the grid on a representative summer day

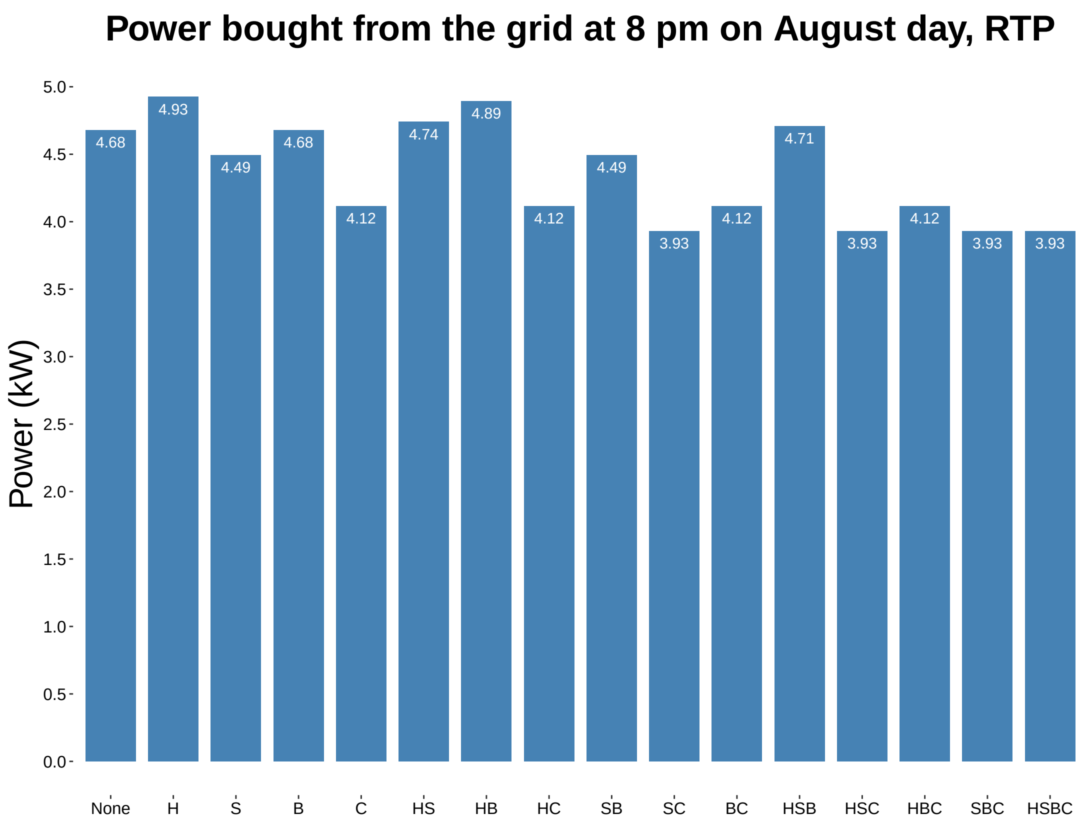

Figure B.1: Power bought from the grid at 8 pm (when prices are highest and the load profile peaks for the scenario with no technologies) for the August day under RTP for a home with different combinations of solar panels, lithium-ion batteries, ice CTESs, and controllable HVAC load (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES).

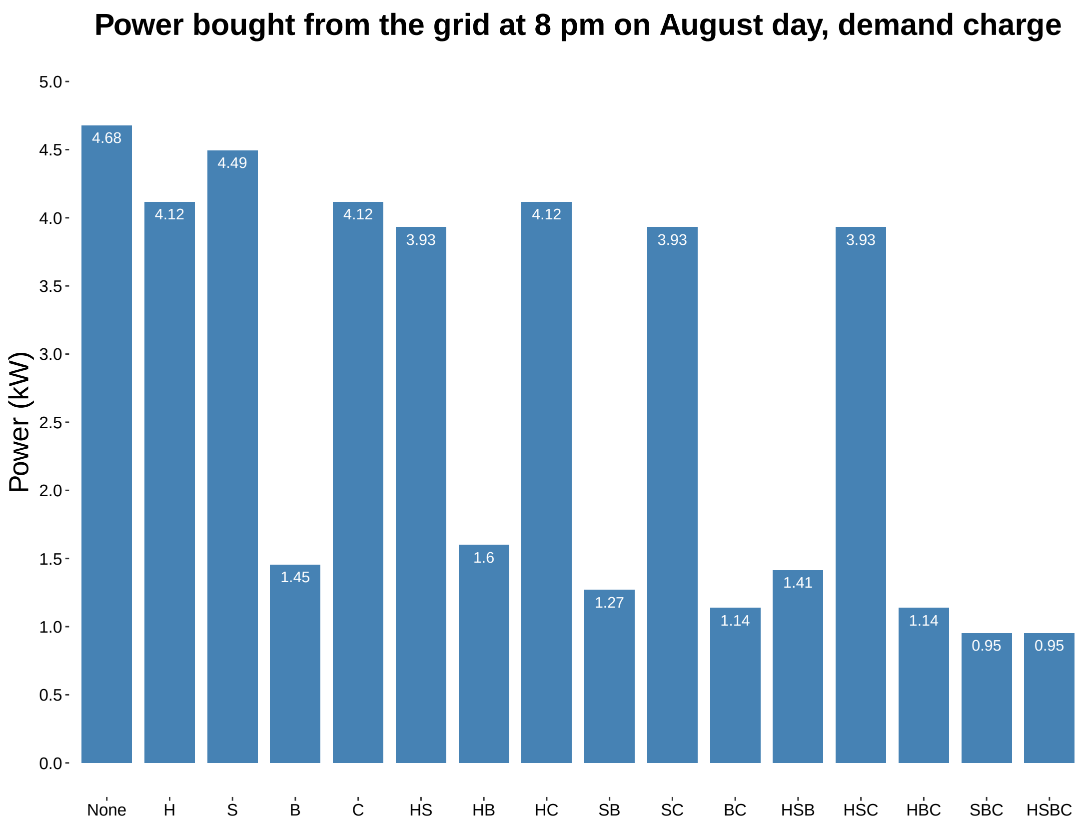

Figure B.2: Power bought from the grid at 8 pm (when the load profile peaks for the scenario with no technologies) for the August day under demand charges for a home with different combinations of solar panels, lithium-ion batteries, ice CTESs, and controllable HVAC load (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). Lithium-ion batteries are most effective at flattening the load profile and reducing the peak.

B.3 Peak grid load

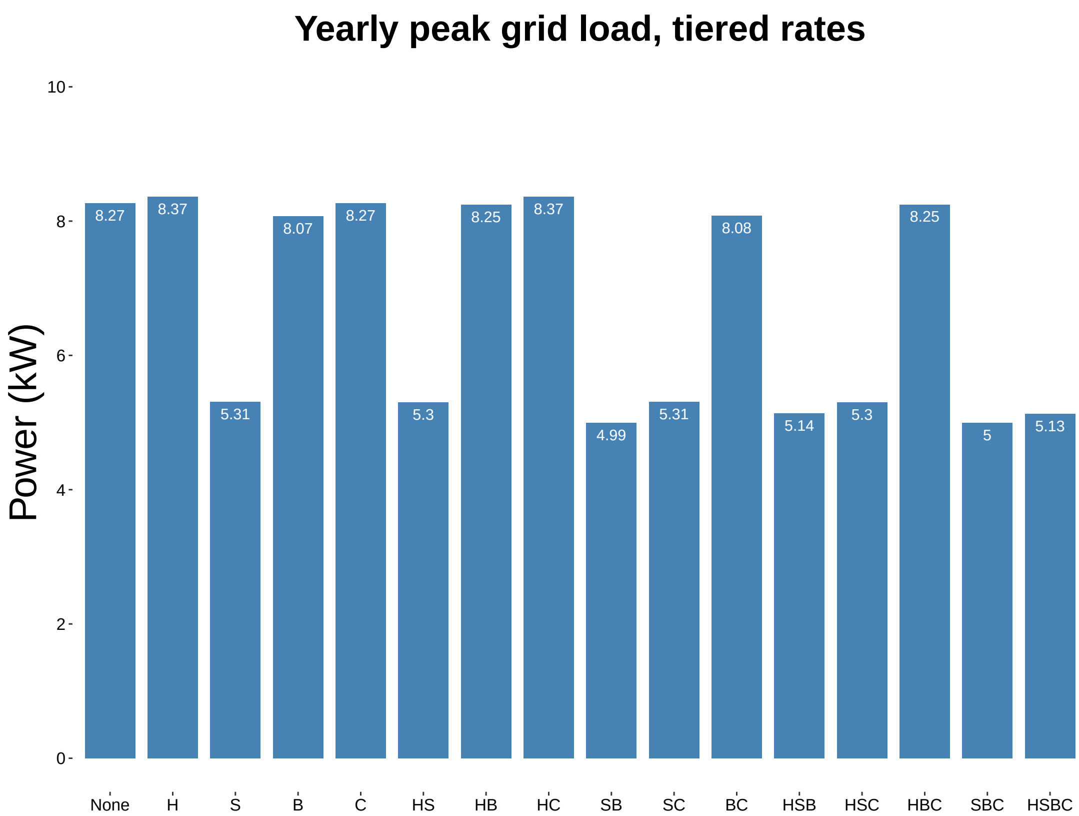

Figure B.3: Maximum power bought from the grid over the year of analysis for a home with different combinations of technologies under tiered rates (H=Ccontrollable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). Solar panels are the main instruments for reducing the peak. The minimum peak occurs in the scenario where the home has solar panels and li-ion battery.

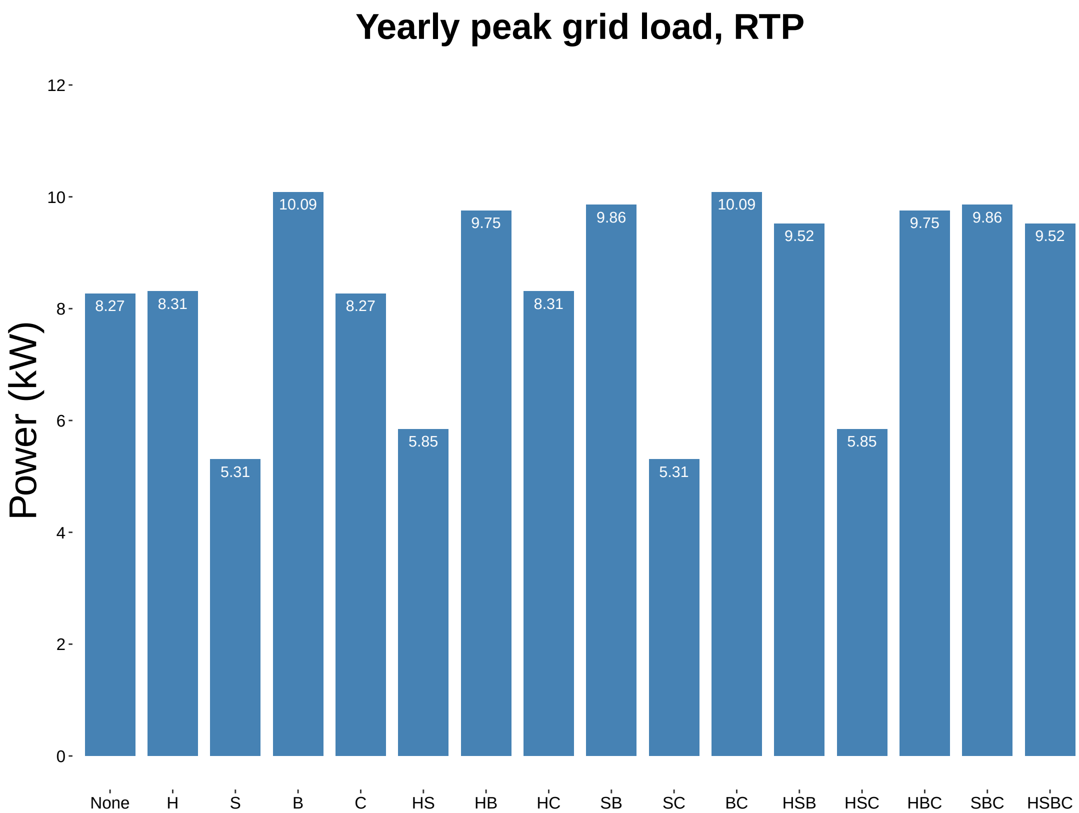

Figure B.4: Maximum power bought from the grid over the year of analysis for homes with different combinations of technologies under real-time prices (H=Controllable HVAC, S=Solar panels, B=Lithium-ion battery, C=Ice CTES). Solar panels are the main instruments for reducing the peak. The other technologies do not reduce the peak because the goal under this pricing scheme is to minimize overall customer expenditure which does not coincide with minimizing the peak.

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