Electricity Rate Design for Integrating Distributed Resources Into Energy Systems

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Abstract

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As part of an effort to decarbonize all sectors of the economy, the U.S. electric power grid will undergo many changes over a multi-decade energy transition. On the supply side, large quantities of stochastic renewable energy generation, alongside sources of clean firm generation and fast-acting balancing resources, figure to replace carbon-emitting thermal generators. On the demand side, widespread demand electrification will seek to replace end-use loads that consume fossil fuels. To reliably and economically connect new supply and demand, transmission- and distribution-level infrastructure will need to be expanded and enhanced. Involved with all of this, electricity tariffs, which recover electric utilities' costs from consumers, will play an important role in the energy transition. With the new generation resources and infrastructure that need to be built, electricity tariffs will be the responsible interface for recovering the necessary operational and capital costs. Additionally, electricity tariffs have the ability to pass prices that can influence how consumers invest in and operate distributed resources, which could help balance supply and demand and limit further infrastructure investments.

With the role that electricity tariffs are poised to play in the energy transition, it is imperative to have proper tools available that can help understand the impacts of electricity tariffs. Furthermore, using those tools to provide decision makers with timely policy- and regulatory-relevant insights are critical to ensuring that electricity tariffs and associ-

ated policies are functioning as intended. As such, this dissertation works to advance both the model development and analysis of electricity tariffs and their impacts on consumers' distributed resources. This dissertation introduces an open-source software tool that helps explore the impacts of different value streams, including electricity tariffs, on distributed resource investments and operations. Uniquely, this tool allows users to model multiple different types of electricity tariffs, an opportune capability at a time when new tariff designs are increasingly designed and proposed. Using the open-source software tool, this dissertation also includes two analyses aimed at examining established and proposed electricity tariffs and policies. The first analysis looks into discriminatory technology-specific electricity tariffs implemented in California, finding that a combination of programmatic and structural restrictions limit the value that can be earned by the broader class of flexible distributed resources. The second analysis explores the complementarity of solar and storage resources in the presence of contemporary electricity rates and policies, and reveals deeper insights to the design of electricity rates and asset subsidies.

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DEDICATION

To Elle, who was always there for me.

Chapter 1

INTRODUCTION

1.1 The Current State of the Energy Transition

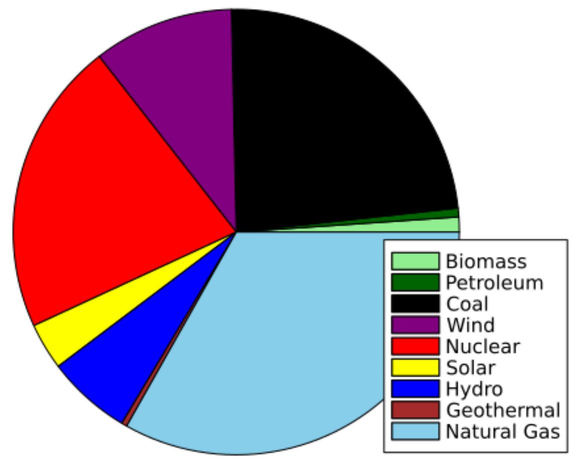
The impacts of human-caused climate change are becoming abundantly clear, with increased instances of extreme heat and natural disasters having deadly effects on society. Climate change has been caused in large part by the continued burning of fossil fuels, which are used in the generation of electricity and are provided directly to many end-use loads across multiple sectors [1]. As such, mitigation efforts are underway to limit fossil fuel use, which ultimately produces carbon dioxide (CO_2) emissions, with the ultimate goal of achieving net-zero CO_2 emissions by 2050 [2]. While effective decarbonization will require a whole-of-economy approach, many large-scale modeling studies have found that vast emissions reductions can be achieved by changing sources of electricity generation to rely on clean energy resources and by electrifying end-use loads across sectors to use that clean electricity [3, 4, 5, 6, 7, 8]. With the electric power sector being responsible for twenty-five percent of all U.S. greenhouse gas emissions in 2021, the second largest share by sector, and the transportation and commercial and residential buildings sectors, which were responsible for twenty-eight percent and thirteen percent of U.S. emissions respectively [9], having ready-to-electrify technologies, the push for clean energy generation and widespread electrification has been widely lauded by climate scientists [2] and pursued by progressive policymakers [3, 7, 10, 11].

Despite lofty clean energy goals and numerous studies, we are still in the early stages of the energy transition. As is shown in Figure 1.1, Lawrence Livermore National Laboratory estimated that around forty-three percent of all quads (or the equivalent of quads for renewable energy resources like solar, wind, geothermal, and hydro) of energy used for electricity generation came from a renewable resource (including biomass) in 2022. The difference between the consumption of fossil fuels and clean energy resources is even more stark when considering that by end-use loads. Lawrence Livermore National Laboratory estimated that a mere fourteen percent[1] of all quads of energy consumed by end-use loads came from a renewable resource (including biomass) or clean electricity in 2022 [12]. Reaching a goal of net-zero emissions by 2050 will require a much quicker shift to zero-carbon resources.

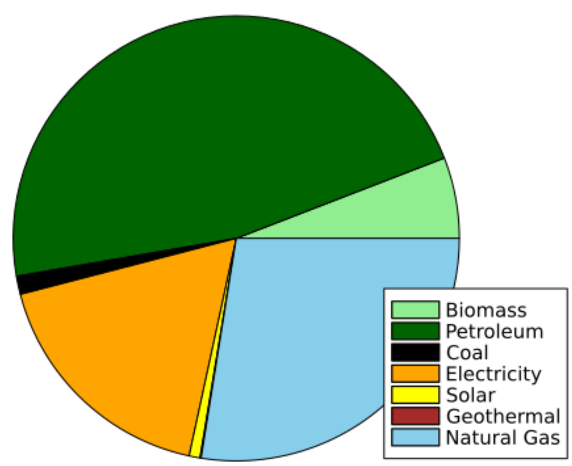
Progress to the energy transition has been stalled by numerous barriers. On the generation side, utility-scale wind, solar, and battery energy storage projects have been constrained by interconnection queue backlogs, zoning and local ordinances, community opposition, and supply chain issues [13, 14, 15, 16]. Newer sources of clean firm and dispatchable supply resources, such as enhanced geothermal systems, long-duration energy storage, and small modular nuclear reactors (SMRs), while promising, are still either speculative with heightened first-of-a-kind costs or in pilot stages exploring one-off participation schemes with individual off-takers [17, 18, 19]. Similar difficulties persist downstream from generation facilities, with aging and insufficient transmission and distribution infrastructure dealing with ever-growing costs, resiliency concerns, right-of-way challenges, community opposition, and supply chain problems [16, 20, 21, 22]. As if these technical, regulatory, and economic concerns were not difficult enough to overcome, there remains the broader institutional challenges, which see unyielding incumbent interests and captured partisan politicians strengthen path dependence and weather critical junctures to ultimately stall the integration of clean energy technologies [20, 23, 24, 25, 26].

Despite all this, overall optimism for the energy transition still remains high. The passage of the Inflation Reduction Act of 2022 and the Infrastructure Investment and Jobs Act of 2021 helped provide strong federal support for decarbonization. Together, both policies are projected to approximately double the pace of annual U.S. decarbonization to about

[1]Note that this quantity may still be generous, as around forty-three percent of the electricity is considered to be clean, per Figure 1.1a. However, with around sixty-four percent of generated electricity being considered as rejected energy, it is unlikely that electricity generated from each fuel type is rejected uniformly.



(a)



(b)

Figure 1.1: Estimated U.S. energy consumption shares in 2022, adapted from Lawrence Livermore National Laboratory's Energy Flow Charts [12]. (a) depicts the share of fuel types used in U.S. electricity generation and (b) depicts the share of fuel types and energy carriers (in the case of electricity) used to meet end-use demand in the residential, commercial, industrial, and transportation sectors.

four percent per year. Both policies are also expected to get the U.S. about thirty-seven percent to forty-one percent below 2005 historical greenhouse gas emissions, which is still off the 2030 target of fifty percent to fifty-two percent below 2005 levels, but is better than the scenario without the policies, which projected to only being about twenty-eight percent below 2005 levels [27]. In the present day, the Inflation Reduction Act has also driven billions of dollars in investments in U.S. manufacturing facilities for clean energy, clean vehicle, building electrification, and carbon management technologies, creating new jobs in the process [28, 29]. Despite the interconnection queue backlogs, 2023 featured the largest capacity increase for solar photovoltaic and battery energy storage installations, with 2024 expected to produce even greater capacity increases [30, 31]. On the demand side, heat pump sales were greater than gas furnaces in 2022, while electric vehicle sales reached a record high in 2023 [29].

1.2 Projecting Future Energy Systems

While impossible to predict perfectly, modeling studies like those mentioned previously can provide an idea of the shape that future energy systems might take. Importantly, these modeling studies can help shape policy and regulatory decisions and drive the national discourse. The following subsections summarize the projected changes to demand, generation, and supporting infrastructure under the impending energy transition.

1.2.1 Demand

As was introduced in Section 1.1, the transportation sector and residential and commercial buildings sector are two of the three greatest emitting sectors in the U.S. [9]. When viewing energy demand together, eighty-six percent of all quads of energy consumed by end-use loads come from carbon-emitting fossil fuels [12]. To meet decarbonization goals, future energy systems are projected to have much greater portions of their demand that are electrified, with those loads then being met by clean electricity. This latter part is critical, and will be a focus of Section 1.2.2, as determining whether an electric load is cleaner than the incumbent technology depends on the electric grid's mix of generation resources at a given time and location [32, 33].

The path to electrifying different sectors will be highly dependent on technology innovation and economics. Currently, there are electric-based technologies that are mature enough to begin displacing incumbent technologies in the light-duty vehicle, building heating and cooling, water heating, and cooking sectors. Through a combination of continued policy support, research and development, and industry learning, costs are anticipated to continue falling [34, 35], making technologies like electric vehicles, air-source heat pumps, and heat pump water heaters become even more attractive. Other sectors, such as heavy-duty vehicles and industrial processes like cement manufacturing and steelmaking, will be more difficult to decarbonize through direct electrification. Some companies are exploring using electricity to produce heat or hydrogen to help with some of these processes, but those applications are still in the nascent stages [36] and will require a reduction in their green premiums to become commercializable [37].

As it is further integrated, demand electrification has the potential to reshape the contemporary profile of net demand, presenting potential operational challenges for utilities and system operators. Exposing the electric grid to large amounts of new demand will not only amplify existing demand peaks [3, 5, 6, 35, 38, 39], but also has the potential to introduce new seasonal demand peaks [5, 35]. Such demand increases threaten to strain existing infrastructure, placing an additional emphasis on the need for more transmission and distribution infrastructure, generation capacity, and operational flexibility. Fortunately, many of the loads that comprise the new electrified demand are anticipated to offer some amount of flexibility. Some loads, such as building heating and cooling, might offer flexibility on the scale of an hour or less, while other loads, such as electric vehicles, might offer flexibility in excess of a day or over multiple days. If managed properly, this flexibility could allow grid operators to shape the newly electrified demand over longer timescales and use the demand's flexibility as a balancing resource over shorter timescales [40].

A barrier to grid operators using demand flexibility is the ability to provide consumers with price signals that reflect grid conditions and incentives that are sufficient enough to elicit participation. This is not a new challenge. Schweppe et al. introduced electricity spot pricing in the 1980s to in part "motivate customers to adjust their own electric energy usage patterns to match utility marginal costs" [41]. Instead, the idea of spot pricing largely stuck for the supply side with the advent of regional electricity markets; the demand side was instead relegated to coarse pricing structures and demand response programs that have not always been well designed. However, recent participatory innovations like distributed energy resource (DER) aggregations and virtual power plants (VPPs) appear better equipped to meet the moment. DER aggregations and VPPs offer flexible loads the opportunity to respond to more dynamic price signals that are better tied to grid conditions [40, 42]. Though it remains to be seen if DER aggregations and VPPs can become pervasive enough to manage large swaths of flexible demand, the functionality they have introduced offers an idea for how utilities and grid operators might be able to tap into the flexibility provided by demand electrification.

1.2.2 Generation

To meet the growing electricity demand and replace existing fossil-fuel-based thermal generators, many sources of clean energy generation will need to be deployed. However, the form and function of these generators will differ from those in traditional power systems. Modeling studies generally agree that future energy systems will be powered in part by large penetrations of variable renewable energy, with wind and solar projected to provide around fifty percent or more of primary energy needs by 2050 [3, 4, 5]. Due to the stochasticity of variable renewable energy sources, other forms of generation will need to not only be clean to meet decarbonization targets, but will also need to complement the operationally cheap and mature wind and solar technologies poised to play a large role. This marks a departure from contemporary generating resources, which are classified by their ability to meet electricity demand in different ways: baseload generators, load-following generators, and peaking generators [43]. While generators in future power systems may share characteristics of those in today's classification, a new taxonomy has arisen to better shape how we think about the

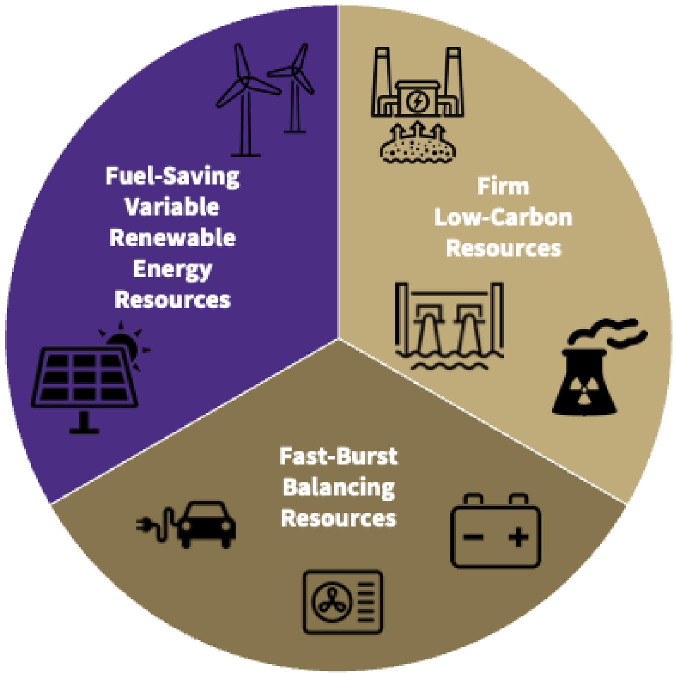


Figure 1.2: Taxonomy of generation resource types in future power systems, adapted from Sepulveda et al. [43].

role the different supply-side resources might play. Sepulveda et al. introduce a classification system, depicted in Figure 1.2, that organizes generators into fuel-saving variable renewable energy resources, firm low-carbon resources, and fast-burst balancing resources [43]. The following subsections describe each of these resource categories in greater detail.

Fuel-Saving Variable Renewable Energy Resources

Fuel-saving variable renewable energy resources describe a classification of resources that includes solar generation (e.g., solar photovoltaic systems, concentrating solar power) and wind generation (e.g., onshore wind turbines, offshore wind turbines). These resources have zero or near-zero operational costs, due in large part to the fact they have no fuel costs, allowing them to replace other generators that have higher operational costs. However, these resources suffer from their weather-dependent variability and their inability to dispatch whenever necessary [43]. This reality contributes to variable renewable energy resources having relatively low capacity factors and a need for overbuilt capacity.

Firm Low-Carbon Resources

Firm low-carbon resources, also commonly referred to as "clean firm resources," describe a classification of resources that includes long-duration energy storage, hydro generation paired with reservoirs, SMRs, enhanced geothermal systems, fossil fuel generators paired with carbon capture and sequestration (CCS), and thermal plants that burn zero-carbon fuels (e.g., hydrogen, biomass, biogas). These resources distinguish themselves by their ability to dispatch over long durations, if necessary, and operate relatively independent from the weather[2] [43]. Firm low-carbon resources are an important complement to fuel-saving variable renewable energy resources, which due to their weather dependence, could potentially go long stretches without being able to supply their otherwise expected capacity. Though the above listed technologies can be classified as firm low-carbon resources, they are not necessarily perfect substitutes for one another. It has been found that building portfolios of different firm low-carbon resources is cost optimal, as each technology still has its own unique characteristics and risks that can be supplemented by and mitigated by, respectively, other firm low-carbon resources [3, 45, 46].

Fast-Burst Balancing Resources

Fast-burst balancing resources describe a classification of resources that includes short-duration energy storage (e.g., intraday-cycling lithium-ion batteries), shiftable flexible demand (e.g., electric vehicles, building heating and cooling, water heating), and sheddable

[2] It should be noted that some clean firm resources could still be impacted by the weather, perhaps just not in the same way that fuel-saving variable renewable energy sources may be. It has been observed in extreme weather events, such as during Winter Storm Uri that hit Texas in February 2021, that even resources typically regarded for their resiliency to weather (e.g., natural gas generators) can be tripped offline due to affected or otherwise malfunctioning equipment [44].

flexible demand. These resources are able to able to provide quick responses (i.e., power injections by battery energy storage systems, demand adjustments by flexible demand resources), but are constrained in how frequently they can respond, either due to technical energy limits (e.g., as is the case with battery energy storage and shiftable flexible demand) or due to the high cost of curtailment (e.g., as is the case with sheddable flexible demand) [43]. Whereas firm low-carbon resources are adept at meeting long-duration shortfalls caused by fuel-saving variable renewable energy resources, fast-burst balancing resources are better suited to meeting shorter term discrepancies between supply and demand, either in steady-state operations for economic considerations [5, 6, 46] or during extreme weather events that cause reliability challenges [47].

When compared to the other two classifications, fast-burst balancing resources differ in that many of their constituent resources may be consumer-owned. Utility-scale energy storage and larger commercial and industrial consumers are typically capable of participating in wholesale-level energy markets, where dynamic prices will be available to better direct decision making. However, the path to participation for behind-the-meter energy storage, which is increasing in penetration [48, 49], and smaller consumers with varying levels of flexible electrified demand is less clear. There is hope that DER aggregators and VPPs may be able to serve a role as intermediaries between consumers and wholesale energy markets [40, 42], but many uncertainties remain in how that relationship may unfold. Even if DER aggregators and VPPs are able to pass consumers compelling price signals, which is no sure thing, the future ubiquity of such participation schemes could be hindered by consumers not wanting to opt in to an external provider or by unfavorable regulatory environments that prevent such programs from being properly established. Regardless of the mechanism, it is critical that incentives offered to fast-burst balancing resources be mutually beneficial to both consumers and the electric grid. Failure to align with the former could cause this large flexible resource to lie dormant, while failure to align with the latter could result in undesirable operational and economic outcomes.

1.2.3 Supporting Infrastructure

To connect the increasing demand and generation resources, large amounts of supporting infrastructure will need to be built and upgraded. As new solar and wind generation is connected to the grid, it will be advantageous for it to be sited in locations with the richest solar and wind resources, respectively. In the U.S., there are rich solar resources in the southwestern part of the country and rich wind resources in the midwestern states. However, with many of the largest load centers being situated along the coasts, large amounts of supporting infrastructure will be needed to connect consumers to these renewable sources of energy. In addition to future interconnection needs born out of generation expansion, the existing transmission system is already experiencing large price differentials between different regional transmission operators, indicating that there is sizable transmission congestion [16]. When modeling the energy transition, many studies identify the need to build many more AC transmission lines and to upgrade the capacity of AC transmission lines along current rights-of-ways [3, 4, 5, 6, 7]. If planners take advantage of the most solar- and wind-rich regions of the country, other studies suggest the buildout of high-voltage DC (HVDC) lines, which are necessary for linkages that might span interconnections and can be economic over long distances [50], due to their potential economic [7, 51] and resilience [52] benefits.

It is not only transmission infrastructure that will need to be upgraded, but distribution infrastructure as well. Demand electrification, particularly due to the projected growth of electric vehicles, and DER adoption will necessitate distribution feeder and substation upgrades [39, 53, 54]. Though some proponents note that managing DERs and flexible demand can help ease the amount of upgrades that may be needed [55, 56], such management will never fully mitigate the need for distribution-level upgrades [53], and that is assuming a best-case scenario where consumers are generally amenable to price signals or load management programs. Inevitably, the capital costs associated with updating the supporting energy infrastructure will be extremely expensive, on the scale of trillions of U.S. dollars when considering combined transmission- and distribution-system upgrades [7, 39, 53].

1.3 The Importance of Electricity Tariffs in the Energy Transition

Electricity tariffs, which are responsible for recovering a retailer's electricity supply costs from consumers, are often largely unheralded when considering the energy transition. However, in light of the challenges described in Section 1.2, electricity tariffs can play an important role. For all of the generation resources and infrastructure that need to be deployed and built, electricity tariffs will largely be the responsible interface for recovering the necessary operational and capital costs. Through the design of these tariffs, there are opportunities in how different costs can be recovered, where passing consumers efficient prices could help serve as a mechanism to engage potential consumer-owned flexible resources. The following subsections expand upon these aspects of electricity rate design.

1.3.1 The Role of Electricity Tariffs in Cost Recovery

The primary role of electricity tariffs is to recover four broadly defined groups of costs: energy costs, generation capacity and ancillary services costs, network costs, and policy and regulatory costs [57, 58]. The magnitude of many of these costs will be affected by the energy transition, and the way they are recovered in electricity tariffs may change as a result.

Energy costs pertain to the cost of generating electricity or the cost of procuring electricity from a wholesale market. These costs vary temporally and spatially, due in part to power-flow physics, the supply-and-demand balance, and fuel costs. Energy costs typically figure to be a smaller share of recoverable costs in future energy systems. In a system where large amounts of demand are electrified, cheap renewable energy resources serve large amounts of electric demand, and sufficient supporting infrastructure is built, it is conceivable that lower demand for fossil fuels should help drive down fuel costs and reduced network congestion could further reduce electricity costs [5, 7]. However, this may not be the case for immediate stages of the energy transition, where there will still be interim needs for fossil fuels on both the supply and demand sides, albeit alongside underused infrastructure and limited supply chains that might result in operational inefficiencies [59] or still be influenced by geopolitical turmoil [60].

Generation capacity and ancillary services costs are associated with the procurement of advanced commitments to ensure a system's reliability. Generation capacity costs have historically been driven by peak demand. However, the projected growth of variable renewable energy resources and flexible electrified demand may cause capacity needs to no longer align with peak demand. Instead, generation capacity requirements may instead by driven by the amount of firm generation capacity that is needed during times of potential generation shortfall [57, 58]. Ancillary services costs, which are already low as a percentage of consumers' bills [58], could get even lower as a glut of fast-burst balancing resources become available and compete to provide frequency regulation and short-term operating reserves.

Network costs largely refer to the fixed distribution and transmission network costs passed to consumers. As supporting infrastructure is built and upgraded, network costs will only continue to grow [3, 7, 61]. This trend is already being observed in the U.S., where recent years have seen delivery costs (i.e., network costs) increase, while power production costs (i.e., energy costs and generation capacity and ancillary services costs) decline [62]. By 2030, it is projected that transmission and distribution costs, along with generation capital expenditures, will be the three greatest retail electricity rate drivers, displacing fuel and purchased power as the primary rate driver [63].

Policy and regulatory costs account for the costs of policy-related initiatives, such as low-income subsidies, energy efficiency, net energy metering, and renewable portfolio standards. Many of these costs are fixed, though that is not always the case as some costs scale with the amount of energy consumed or produced, such as for renewable portfolio standards [57, 58]. As the energy transition progresses and concerns over increasingly high electricity prices persist, it is unlikely that policy and regulatory costs will be decreasing or disappearing.

1.3.2 Pervasive Price Signals from Electricity Tariffs

Electric tariffs play a prominent role in consumers' relationship with energy, providing consumers with the price signals that govern their consumption decisions. However, many of these electricity prices and other incentives have long been misaligned with spatial and temporal conditions on the electricity grid, thereby limiting the role that electric tariffs can play in effectively coordinating the growing mass of distributed flexible resources. Per the U.S. Energy Information Administration (EIA) over ninety percent of U.S. consumers take service under some type of flat rate, which offers consumers a constant volumetric energy charge, independent of considerations for the system, and a small connection charge [64, 65]. It is this type of market inefficiency that has given rise to constructs like DER aggregators and VPPs, which themselves face their own hurdles to widespread implementation, as was further discussed in Section 1.2. Instead, electric utilities and regulators should take advantage of their existing relationship with consumers and provide electric tariffs that provide efficient and cost-reflective prices.

There is a strong body of literature that suggests how electric tariffs could be reformed to better engage the flexibility from consumer-owned flexible resources. Many of these rate proposals center around passing consumers an efficient energy price that more closely resembles the marginal cost of procuring or generating electricity [41, 65, 66, 67, 68, 69, 70, 71]. Updating this rate component is largely necessitated by the increased variability of marginal electricity prices, which is a product of the changing generation mix, and is enabled by improved metering and communication capabilities [65, 67, 68]. Though economists have long preferred passing consumers a real-time energy price, there are many potential options that would be improvements over the incumbent flat rates, such as time-of-use rates, critical peak pricing, or modified real-time prices that include price hedges (e.g., subscription rates, real-time prices with price caps and price floors) [56, 65, 71, 72, 73, 74, 75, 76]. In choosing future energy pricing mechanisms, particularly in the early stages of the reformation process, it will be important to not only consider the theoretical economic efficiency, but the practical efficiency that can be achieved from consumers' behavior and preferences [77]. Though real-time pricing is the theoretical best option, consumers' trepidation over price fluctuations and ability to respond could make a tariff with more predictable prices, such as time-of-use pricing, more effective at procuring the desired responses [65]. Regardless of which mechanism is selected, updating energy prices could help shape consumer demand to better align with changing generation profiles and could potentially elicit responses to real-time system needs, which could support the provision of balancing services.

In addition to fixing how energy prices are passed to consumers, cost-reflective rate proposals also focus on the cost recovery of two other main cost components: capacity costs and fixed costs. Capacity costs are largely recovered inefficiently today, with smaller consumers not seeing any capacity-related cost (these costs are typically lumped in with their volumetric energy cost) and larger consumers being exposed to a non-coincident demand charge, which may or may not align with system needs and might lead to an inefficient use of the network. However, the expected rise of generation and network capacity requirements will necessitate prices that better reflect the cost of that expansion. Popular proposals for recovering these capacity costs include coincident demand charges [65, 67, 68], in which consumers' capacity costs would align with actual system peaks, and dynamic capacity cost recovery schemes [71, 78, 79]. As for fixed costs, some of these costs will by nature be recovered through capacity prices and energy prices. However, remaining fixed costs, such as those pertaining to regulated network costs and policy costs, should be recovered in a way that does not distort the efficiency of the other cost-recovery tools. These costs should be recovered through fixed charges that are independent of the energy and capacity charges [65, 67, 68], with the potential of incorporating equity considerations if the magnitude of fixed charges become overly burdensome on some classes of the customer base [57, 69, 70]. Figure 1.3 provides a depiction of how some of the general cost sources discussed above may be allocated to certain tariff components in an electricity tariff that is more cost-reflective.

1.4 Contributions of This Dissertation

With electricity tariffs poised to play a strong role in the energy transition, it is imperative that there are proper tools available to understand electricity tariffs' impacts and analyses conducted to provide decision makers with policy- and regulatory-relevant insights into electricity rate design. The contributions contained within this dissertation are motivated by

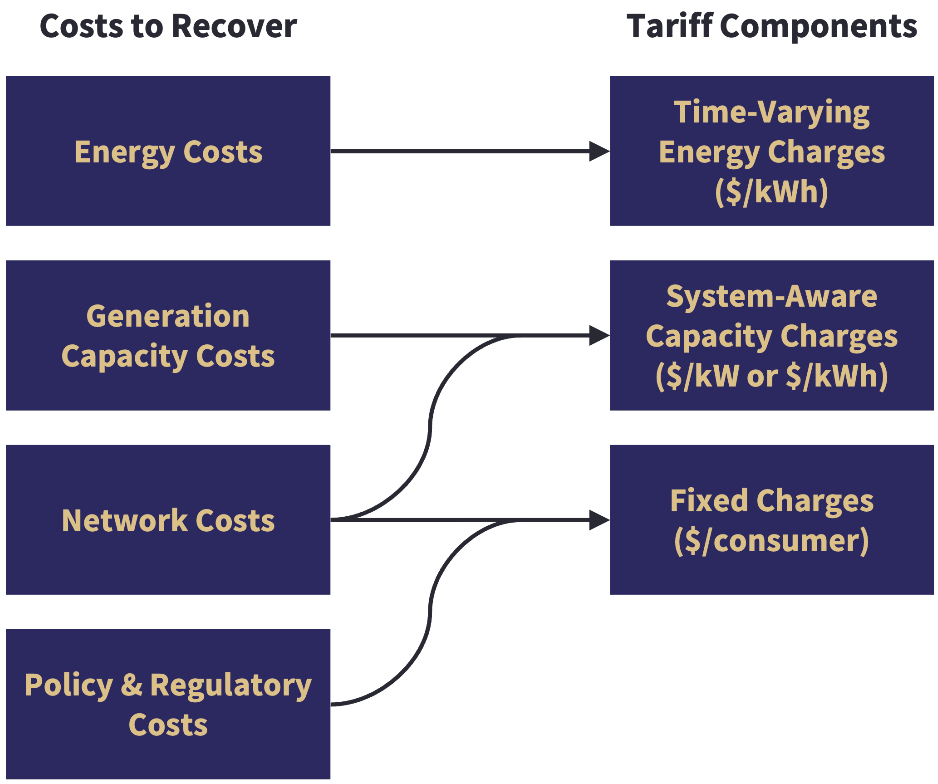


Figure 1.3: Costs that are recovered through an electricity tariff allocated according to the electricity tariff component that recovers those costs in the most cost-reflective way.

the need to expand the quality of modeling and analysis relevant to electricity rates. The following subsections describe this dissertation's contributions in greater detail.

1.4.1 Open-Source Modeling of Consumers' Distributed Resource Decision-Making in the Presence of Multiple Value Streams

As new electricity rates are proposed by regulators and technology-focused incentives are introduced to spur the deployment of distributed resources, it is increasingly important for stakeholders to be able to understand the impacts that new programs have amongst a series of existing value streams. Unfortunately, there is a dearth of open-source tools that effectively allow stakeholders to model various electricity tariffs and evaluate the impact these tariffs may have on DER operation and investment. To address this, Chapter 2 introduces the Distributed Energy Resource Investment and Valuation Engine (DERIVE), an open-source software tool that helps explore the impacts that different value streams, including various electricity rate structures, have on DER investment and operation.

1.4.2 Examining the Impact of Technology-Discriminating Policies on the Valuation of Flexible Distributed Resources

As regulators and electric utilities seek to better shape consumers' net demand profiles, new policies have been introduced that aim to leverage consumers' flexible resources. Under these policies, consumers are provided either a time-varying price signal or an incentive to operate their resources in a way that is beneficial to the operation of the electric power grid. However, some of these policies discriminate against the types of flexible distributed resources that consumers can use to participate, even though the desired consumer actions could be facilitated by other resources. Chapter 3 examines two such policies offered by the Pacific Gas and Electric Company (PG&E) in Northern California. The first case study looks at the Option S for Storage rider of PG&E's B-19 tariff, which is offered exclusively to consumers with battery energy storage despite the fact that consumers with flexible demand resources are able to provide the utility with similar benefits. The second case study explores the impacts of different net energy metering policies, with a particular focus on how net energy metering programs have structurally changed to benefit certain resources over other types of resources.

1.4.3 Analyzing the Complementarity Between Behind-the-Meter Solar and Storage Resources in the Presence of Existing Electricity Tariffs and Policies

Changes to California's net energy metering program have given rise to new concerns over the continued viability of the state's distributed solar industry. The Net Billing Tariff, which is California's successor net energy metering policy, features a shift in its export price signals that limit the export compensation that consumers with only solar photovoltaics can earn.

While the new price signals figure to create favorable compensation for consumers who also own battery energy storage, the programmatic linkage between solar and storage resources all but ensures that both resources must be built if any are to be built at all. Chapter 4 investigates the complementarity between behind-the-meter solar photovoltaic and battery energy storage operations and investments when exposed to California electricity tariffs and policies, including the new Net Billing Tariff. Additionally, Chapter 4 provides insights to the design of electricity tariffs and asset subsidies.

Chapter 2

THE DISTRIBUTED ENERGY RESOURCE INVESTMENT AND VALUATION ENGINE

2.1 Introduction

Many different factors have led to the increased integration of distributed energy resources (DERs) by consumers. One major influence has been declining equipment and installation costs, with behind-the-meter solar photovoltaics and battery energy storage systems both benefitting [48, 80, 81]. The addition of federal- and state-level support for clean energy technologies has also been helpful, with highlights being the renewed investment tax credits for solar and storage systems and new tax credits for electrification upgrades [10]. In addition to these trends and incentives, which have helped make DERs' still-high capital costs more manageable for consumers to afford, DERs can also reduce the electricity bills consumers incur from increasingly expensive and complicated electricity tariffs.

For consumers, choosing the right DERs to invest in and the appropriate size of those DERs can be a complicated task, especially in light of the many available value streams. For regulators, policymakers, and interest groups, it is also important to understand how proposed rules or policies interact with the existing value stack to help prevent unforeseen complications from arising. This underscores the need for capacity tools, which can help provide interested parties with the objective and factual resources to make their decisions [82]. Due to the differing needs from different stakeholders, there is a need for multiple capacity tools to fit various needs.

In recent years, there has been an increase in capacity tools to help inform consumers, decision makers, and other interested individuals about different DER-related issues. In 2023, the California State Legislature proposed a bill that would require the California Energy

Commission to create a publicly available website that would inform residential consumers about all the energy-related incentive programs available to them [83, 84]. Similarly, the passage of the Inflation Reduction Act of 2022 [10] also spurred efforts to provide consumers with tools that could inform them of different home electrification rebates they could access [85]. The National Renewable Energy Laboratory (NREL) released the System Advisor Model (SAM), an open-source tool that can model different renewable energy technologies for residential, commercial, and utility-scale projects operating under different financial models [86]. Lawrence Berkeley National Laboratory (LBNL) created the Distributed Energy Resources Customer Adoption Model (DER-CAM), which helps users find optimal DER investments for buildings or microgrids [87]. Sandia National Laboratories designed QuEST, an open-source tool for modeling energy storage participation at either the retail level or in wholesale energy markets [88]. Other commercial products exist that can model DER deployment and management under financial models of varying specificity, such as Energy Toolbase's ETB Developer [89] and HOMER Grid [90], but those models require expensive licenses that might be prohibitive to non-corporate stakeholders.

However, despite rising electricity rates in recent years [91] and proposals for a variety of different electric rate structures [72, 92, 93, 73, 94, 71], the publicly available computational models presented above only offer simplistic rate models with limited flexibility for modification. This is problematic considering how influential electricity rates can be in both DER investment and operational decisions. NREL's SAM offers models of flat rates, time-of-use rates, and tiered rates, with the potential to include monthly demand charges (for flat rates and time-of-use rates only) and net energy metering (where excess energy is only sold back at a single flat rate). LBNL's DER-CAM offers similar rate options as SAM, though it also includes the potential for real-time prices and daily demand charges. However, DER-CAM is not open-source, which limits its ability to be modified to work with additional rate models. Sandia's QuEST is the most limited of the discussed publicly available computational tools, only modeling flat and time-of-use rates with monthly demand charges and net energy metering. Though not exactly capacity tools, there are other studies that examine the impacts of different rate structures on DERs [72, 73, 95], but do no share their code or data. This makes it difficult to not only reproduce those studies, but to also build on the developed modeling efforts.

To help address some of these deficiencies, this chapter introduces the Distributed Energy Resource Investment and Valuation Engine (DERIVE)[1]. DERIVE is an open-source software framework and simulation tool that allows users to explore the effects that different rate structures and technology-oriented policies have on the investment and operation of DERs. Similar to the other tools discussed, DERIVE allows users to implement flat rates, time-of-use rates, real-time rates, and monthly and daily demand charges. Additionally, DERIVE includes representations of critical peak pricing and net energy metering that has sell rates greater than the cost of purchasing electricity, a mechanism that is increasingly important to understand in light of the Net Billing Tariff passed by the California Public Utility Commission (CPUC) [96]. Both critical peak pricing and the described version of net energy metering are not modeled in the other computational tools discussed here. Lastly, DERIVE is generally more flexible than the other tools discussed above. Not only are users provided more freedom in how they can design and stack the included rate structures, but the open-source and modular nature of the framework provides users a straightforward way to implement their own rate structure models.

The rest of this chapter is organized as follows. Section 2.2 provides an overview of the DERIVE model, including the tool's capabilities and software structure. Section 2.3 introduces the mathematical formulation of the underlying optimization-based models, discussing the objective function components, constraints, parametric functions, and postprocessing workflows.

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[1] All code for DERIVE is publicly available on GitHub:

L. D. Smith, "Distributed Energy Resource Investment and Valuation Engine (DERIVE)," `https://github.com/lanesmith/DERIVE`.

2.2 Overview

This section describes the capabilities of DERIVE, particularly the different types of analyses that can be considered. Additionally, this section discusses the design considerations that were made for DERIVE to be an effective open-source tool. This section concludes by discussing the structure of DERIVE.

2.2.1 Capabilities

The purpose of DERIVE is to allow users to model the impacts that different electricity rates and technology-oriented incentives have on DER investment and operation. To be clear, the intent of this tool is not to perfectly identify a consumer's optimal DER portfolio or to forecast optimal DER responses with a high degree of certainty, but rather to understand how characteristics of different rate structures and other policies might impact a consumer's DERs and electricity bill. DERIVE is intended to serve as a capacity tool that provides decision-support to any stakeholder interested in understanding the consumer-level impacts of different regulatory or policy decisions.

DERIVE offers users two primary functionalities: (1) determining the operation of a consumer's existing DERs (i.e., the production cost problem) and (2) determining the DERs in which a consumer should invest (i.e., the capacity expansion problem). In the production cost problem, a consumer can optimize the operation of a combination of solar photovoltaics, battery energy storage, and shiftable flexible demand to minimize their total electricity bill, which is comprised of costs from electricity tariffs and credits from incentive programs (e.g., net energy metering). In the capacity expansion problem, a consumer can optimize their investment in a combination of solar photovoltaics and battery energy storage that minimizes their total bill, including the operational costs described in the production cost problem, the annualized investment costs, annual operations and maintenance (O&M) costs, and any subsidies (e.g., investment tax credits).

Depending on the problem type, there are different time scales that can be considered.

For production cost problems, optimization horizons of one day, one month, and one year can be selected. Over each of these horizons, the optimizer has perfect foresight, but physical limitations on battery energy storage systems (through its round-trip efficiency) and shiftable flexible demand (through its energy recovery constraints) curb the advantage that such foresight provides. For capacity expansion problems, users can currently only select an optimization horizon of one year, as it is important consider different months and days of the week together when making the asset sizing decisions. In future iterations, there will be an option for capacity expansion problems to select an optimization horizon of multiple years, where the future years would consider the impact of projected resource degradation, demand growth, and electricity price increases.

2.2.2 Open-Source Software Design

To make studies conducted in DERIVE reproducible, transparent, and easy to access, I made concerted efforts to follow open-source best practices throughout the development. DERIVE is written using the open-source Julia Language [97] with the mathematical optimization formulation integrated using Julia's JuMP package [98]. Through JuMP, different mathematical optimization solvers are supported, including many that are publicly available. Additionally, code is thoroughly documented and commented and specifications are provided to allow users to reproduce the same code environment [99].

Open-source software is important to have across many research disciplines, but especially so for something as public-facing as energy systems research. Due to the nature of power and energy systems, most research and analysis must be conducted using large, complex simulation-based models. Without open-source models and data, there is a lack of transparency, which can erode public trust in institutions and prevent interested parties from ensuring that decision makers are being provided factual information. Open-source software also broadens the pool of potential stakeholders, enabling greater collaboration [100] and allowing better participation, particularly for those who may not otherwise be able to afford expensive licenses or fees [7, 101].

2.2.3 Software Structure

DERIVE reads in technology specifications, programmatic information, electric tariff data, weather data, and demand data that pertain to a simulated consumer's mix of DERs and participating value streams and saves that data in corresponding structs. Using the provided electric tariff data and solar photovoltaic specifications, if considered, electricity price and solar capacity factor profiles are calculated and saved to their respective struct. Following the preprocessing stage, the mathematical optimization model is built based on the technologies that are considered and the selected value stack; the mathematical model formulation is described in detail in Section 2.3. Using a specified solver that is supported by JuMP, the optimization problem is solved and results are passed to a postprocessing stage to extract the electricity bill results, time-series data, and investment results, if necessary.

2.3 Mathematical Model Formulation and Description

This section introduces the nomenclature, objective function components, constraints, parametric functions, and postprocessing workflows that comprise the mathematical model underlying DERIVE. Each of these components are addressed in greater depth in Sections 2.3.1 through 2.3.5.

2.3.1 Nomenclature

The tables included in this section define and describe the nomenclature used in the mathematical modeling introduced in Sections 2.3.2 through 2.3.5. Table 2.1 defines the sets and associated indices, Table 2.2 defines the optimization decision variables, Table 2.3 defines the input parameters, and Table 2.4 defines the supporting expressions.

Table 2.1: Sets and indices included in DERIVE.

Notation	**Description**
$\mathcal{A}$	Set of assets to be considered for investment in the investment model, indexed by a. Depending on user specifications, photovoltaic systems and battery energy storage systems can be considered (i.e., $\mathcal{A} \subseteq \{pv,\ bes\}$).
$\mathcal{B}$	Set of blocks of energy consumption specified in a tiered energy rate, if applicable, indexed by b.
$\mathcal{H}$	Set of time steps included in the critical peak pricing events, if applicable, in the user-defined optimization horizon, indexed by h. The time steps included in this set are a subset of the total time steps included in the optimization horizon (i.e., $\mathcal{H} \subseteq \mathcal{T}$).
$\mathcal{N}$	Set of demand-charge-specific time-of-use periods, indexed by n.
$\mathcal{P}$	Set of points along the current-voltage characteristic curve (also commonly referred to as the "I-V curve") for a photovoltaic module, indexed by p and dependent on $t \in \mathcal{T}$.
$\mathcal{S}$	Set of time steps in which the export price, if applicable, is greater than the energy price, indexed by s. The time steps included in this set are a subset of the total time steps included in the optimization horizon (i.e., $\mathcal{S} \subseteq \mathcal{T}$).
$\mathcal{T}$	Set of time step increments in the user-defined optimization horizon, indexed by t.

Table 2.2: Decision variables included in DERIVE.

Notation	**Description**
$d_{dev}^{dn}(t)$	Deviations by flexible demand from a consumer's demand profile (in kW) at time t that represent curtailing demand or having already met demand during a previous time step.
$d_{dev}^{up}(t)$	Deviations by flexible demand from a consumer's demand profile (in kW) at time t that represent recovering previously unmet demand or preemptively meeting demand that is scheduled to occur at a later time step.
$d_{max}(n)$	Consumer's maximum net demand (in kW) during time-of-use period n, assuming the consumer is exposed to a demand charge.
$d_{shed}(t)$	Consumer's total forced load shed (in kW) during time t.
$d_{tier}(b)$	Consumer's total net energy consumption (in kWh) for block b, assuming the consumer is taking service under a tiered energy rate.
$p_{cha}(t)$	Power (in kW) used to charge the consumer's battery energy storage system during time t.
$p_{dis}^{btm}(t)$	Power (in kW) discharged from the consumer's battery energy storage system during time t for the purpose of meeting the consumer's behind-the-meter demand.
$p_{dis}^{exp}(t)$	Power (in kW) discharged from the consumer's battery energy storage system during time t for the purpose of exporting power to the grid, so long as such exports are allowed.
$p_{pv}^{btm}(t)$	Power (in kW) generated by the consumer's photovoltaic system during time t for the purpose of meeting the consumer's behind-the-meter demand.

Continued on following page

Table 2.2 – continued from previous page

Notation	Description
$p_{pv}^{exp}(t)$	Power (in kW) generated by the consumer's photovoltaic system during time t for the purpose of exporting power to the grid, so long as such exports are allowed.
$J(t)$	State of charge (in kWh) of the consumer's battery energy storage system at time t.
P_{bes}	Power capacity (in kW) of the consumer's battery energy storage system. This term is a decision variable when DERIVE makes investment decisions.
P_{pv}	Power capacity (in kW) of the consumer's photovoltaic system. This term is a decision variable when DERIVE makes investment decisions.
$\zeta_{net}(s)$	Binary indicator variable that equals one when the consumer's net demand at time s is completely met by behind-the-meter assets and equals zero otherwise.
ζ_{pv}	Binary indicator variable that equals one when the consumer does not construct a solar photovoltaic system and equals zero otherwise.

Table 2.3: Parameters included in DERIVE.

Notation	Description
$d(t)$	Consumer's demand (in kW) at time t.
$\overline{d}_{dev}^{dn}(t)$	Maximum amount the consumer's flexible demand can decrease (in kW) relative to the demand profile at time t.

Continued on following page

Table 2.3 – continued from previous page

Notation	Description
$\overline{d}_{dev}^{up}(t)$	Maximum amount the consumer's flexible demand can increase (in kW) relative to the demand profile at time t.
$\overline{d}_{tier}(b)$	Total net energy consumption (in kWh) a consumer can have in block b of a tiered energy rate.
f	Inflation rate.
i	Nominal discount rate.
k	Boltzmann constant, defined as 1.380649x10^{-23} J/K.
$n_d(t)$	Day number at time t.
q	Elementary charge, defined as 1.602176634x10^{-19} C.
r	Real discount rate. This term can be provided as a parameter or can be calculated as an expression when DERIVE is also provided a nominal discount rate and an inflation rate.
C_{cap}^{bes}	Capacity cost (in \$/kW) associated with building a new battery energy storage system.
C_{cap}^{pv}	Capacity cost (in \$/kW) associated with building a new photovoltaic system.
$C_{O\&M}^{bes}$	Fixed operation and maintenance cost (in \$/kW-year) associated with building a new battery energy storage system.
$C_{O\&M}^{pv}$	Fixed operation and maintenance cost (in \$/kW-year) associated with building a new photovoltaic system.
C_{var}^{flexdn}	Variable cost (in \$/kWh) associated with the consumer decreasing demand.
C_{var}^{flexup}	Variable cost (in \$/kWh) associated with the consumer increasing demand.
C_{VOLL}	Variable cost (in \$/kWh) associated with the consumer's value of lost load.

Continued on following page

Table 2.3 – continued from previous page

Notation	Description
$DHI(t)$	Diffuse horizontal irradiance (in W/m^2) observed by the consumer's photovoltaic system at time t.
$DNI(t)$	Direct normal irradiance (in W/m^2) observed by the consumer's photovoltaic system at time t.
E_0	Band-gap energy of the semiconductor (in eV) at 0° K.
G^{nom}	Nominal total irradiance at standard test conditions, defined as 1000 W/m^2.
$GHI(t)$	Global horizontal irradiance (in W/m^2) observed by the consumer's photovoltaic system at time t.
I_{ITC}^{bes}	Investment tax credit percentage available for new battery energy storage systems.
I_{ITC}^{pv}	Investment tax credit percentage available for new photovoltaic systems.
I_{mpp}^{nom}	Current rating (in A) at maximum power during standard test conditions of one of the photovoltaic system's modules.
I_{sc}^{nom}	Short-circuit current rating (in A) during standard test conditions of one of the photovoltaic system's modules.
J_{init}	Initial state of charge (in kWh) of the consumer's battery energy storage system.
$\underline{J}$	Minimum state of charge (in kWh) of the consumer's battery energy storage system.
$\overline{J}$	Maximum state of charge (in kWh) of the consumer's battery energy storage system.
K_I	Current temperature coefficient (in A/K) of one of the photovoltaic system's modules.

Continued on following page

Table 2.3 – continued from previous page

Notation	Description
K_V	Voltage temperature coefficient (in V/K) of one of the photovoltaic system's modules.
L_{bes}	Period (in years) over which the consumer's battery energy storage system investment is amortized.
L_{pv}	Period (in years) over which the consumer's photovoltaic system investment is amortized.
LAT	Consumer's latitude.
$LONG$	Consumer's longitude.
LTM	Local time meridian, as determined by the time zone in which the consumer resides.
N_c	Number of series-connected cells in one module of the consumer's photovoltaic system.
P_{bes}	Power capacity (in kW) of the consumer's battery energy storage system. This term is a parameter when DERIVE only makes operation decisions.
P_{mpp}^{nom}	Power rating (in W) at maximum power during standard test conditions of one of the photovoltaic system's modules.
P_{pv}	Power capacity (in kW) of the consumer's photovoltaic system. This term is a parameter when DERIVE only makes operation decisions.
$\overline{P}_{bes}$	Maximum power capacity (in kW) of the consumer's battery energy storage system. This term is a parameter when DERIVE makes investment decisions.
$\overline{P}_{pv}$	Maximum power capacity (in kW) of the consumer's photovoltaic system. This term is a parameter when DERIVE makes investment decisions.

Continued on following page

Table 2.3 – continued from previous page

Notation	Description
$T(t)$	Temperature (in K) observed by the consumer's photovoltaic system at time t.
T^{nom}	Nominal temperature at standard test conditions, defined as 298.15 K.
V_{mpp}^{nom}	Voltage rating (in V) at maximum power during standard test conditions of one of the photovoltaic system's modules.
V_{oc}^{nom}	Open-circuit voltage rating (in V) during standard test conditions of one of the photovoltaic system's modules.
α_{E_g}	Constant used in the relation between temperature and the semiconductor's band-gap energy.
β_{E_g}	Constant used in the relation between temperature and the semiconductor's band-gap energy.
η_{bes}^{dis}	Self discharge rate of the consumer's battery energy storage system.
η_{bes}^{rte}	Round-trip efficiency of the consumer's battery energy storage system.
η_{inv}	Efficiency of the inverter used by the consumer's photovoltaic system.
μ_{fix}	Either the total number of days in the year or the total number of months in the year depending on whether the fixed charge π_{fix} is levied by day or by month, respectively.
π_{cpp}	Penalty (in \$/kWh) levied on the consumer's net energy consumption during critical peak pricing events, which are defined by the hours $h \in \mathcal{H}$.
$\pi_{dem}(n)$	Demand charge (in \$/kW) placed on the consumer's maximum net demand during demand-charge-specific time-of-use period n.
$\pi_{en}(t)$	Energy charge (in \$/kWh) placed on the consumer's net energy consumption during time t.

Continued on following page

Table 2.3 – continued from previous page

Notation	Description
$\pi_{exp}(t)$	Export price (in \$/kWh) offered as compensation for the consumer's eligible energy exports, so long as the consumer is participating in a net energy metering program.
π_{fix}	Fixed charge (in \$/day or \$/month) levied on consumers. Also commonly referred to as a "customer charge." May be charged per day or per month.
π_{nbc}	Price (in \$/kWh) of the non-bypassable charges levied by utilities on consumers participating in a net energy metering program.
$\pi_{tier}(b)$	Charge (in \$/kWh) placed on the consumer's net energy consumption for block b of a tiered energy tariff. This charge is in addition to that levied by the time-of-use energy charge $\pi_{en}(t), \forall t \in \mathcal{T}$.
ρ	Ground reflectance coefficient.
Γ	Time linkage coefficient for relating power and energy quantities. If a simulation has time steps of one hour, then $\Gamma = 1$. If a simulation has time steps of thirty minutes, then $\Gamma = 2$. If a simulation has time steps of fifteen minutes, then $\Gamma = 4$.
Δ	Length (in hours) of the demand recovery period for the consumer's flexible demand.

Table 2.4: Expressions included in DERIVE.

Notation	Description
a_d	Diode ideality constant.

Continued on following page

Table 2.4 – continued from previous page

Notation	Description
$d_{max}^{prev}(n)$	The consumer's maximum net demand (in kW) during demand-charge-specific time-of-use period n if the optimization horizon is less than the duration of n and previous maximum net demand needs to be tracked.
$d_{net}(t)$	Consumer's net demand (in kW) at time t.
$p_{exp}(t)$	Consumer's total energy exports (in kWh) at time t.
r	Real discount rate. This term is an expression when DERIVE is provided a nominal discount rate and an inflation rate.
$CF_{pv}(t)$	Capacity factor profile of the consumer's photovoltaic system at time t.
$CT(t)$	Clock time (in minutes) at time t.
$E(t)$	Equation of time at time t.
$E_g(t)$	Band-gap energy of the semiconductor (in J) at time t.
E_g^{nom}	Nominal band-gap energy of the semiconductor (in J) during standard test conditions.
$G(t)$	Total irradiance (in W/m^2) observed by the consumer's photovoltaic system at time t.
$G_{BC}(t)$	Beam irradiance on the collector of the consumer's photovoltaic system at time t.
$G_{DC}(t)$	Diffuse irradiance on the collector of the consumer's photovoltaic system at time t.
$G_{RC}(t)$	Reflected irradiance on the collector of the consumer's photovoltaic system at time t.
$H(t)$	Hour angle at time t.
$I(t, p)$	Output current of one of the photovoltaic system's modules at point p along the I-V curve and time t.

Continued on following page

Table 2.4 – continued from previous page

Notation	Description
$I_0(t)$	Saturation current used in the single-diode model of one of the photovoltaic system's modules at time t.
I_0^{nom}	Nominal saturation current during standard test conditions used in the single-diode model of one of the photovoltaic system's modules.
$I_{pv}(t)$	Photo current used in the single-diode model of one of the photovoltaic system's modules at time t.
I_{pv}^{nom}	Nominal photo current during standard test conditions used in the single-diode model of one of the photovoltaic system's modules.
$P_{mpp}(t,p)$	Maximum power output by one of the photovoltaic system's modules at time t.
$R_p(t)$	Shunt resistance used in the single-diode model of one of the photovoltaic system's modules at time t.
R_p^{nom}	Nominal shunt resistance during standard test conditions used in the single-diode model of one of the photovoltaic system's modules.
R_s	Series resistance used in the single-diode model of one of the photovoltaic system's modules.
$ST(t)$	Solar time (in hours) at time t.
$V(t,p)$	Terminal voltage of one of the photovoltaic system's modules at point p along the I-V curve and time t.
$V_t(t)$	Thermal voltage (in V) of one of the photovoltaic system's modules at time t.
V_t^{nom}	Nominal thermal voltage (in V) during standard test conditions of one of the photovoltaic system's modules.
$\beta(t)$	Solar altitude angle at time t.

Continued on following page

Table 2.4 – continued from previous page

Notation	**Description**
$\delta(t,n)$	Indicator variable that equals one when the time t aligns with the demand-charge-specific time-of-use period n and zero otherwise.
$\delta_s(t)$	Solar declination angle at time t.
$\phi_s(t)$	Solar azimuth angle at time t.
$\theta(t)$	Incidence angle between the Sun and the collector face of the consumer's photovoltaic system at time t.
Π_{dem}	Total annual demand charge (in \$), evaluated in postprocessing.
Π_{en}	Total annual energy charge (in \$), evaluated in postprocessing.
Π_{fix}	Total annual fixed charge (in \$), evaluated in postprocessing.
Π_{nbc}	Total annual non-bypassable charges (in \$), evaluated in postprocessing.
Π_{nem}	Total annual revenue (in \$) associated with participating in a net energy metering program, evaluated in postprocessing.
Π_{total}	Total annual electricity bill (in \$), evaluated in postprocessing.
Σ	Collector tilt angle of the consumer's photovoltaic system.

2.3.2 Objective Functions

The objective function created by an instance of DERIVE is largely dependent on the problem type specified by the user: production cost or capacity expansion. Under the production cost formulation, the objective function is generally defined as the difference between the total operating costs, such as purchasing electricity and incurring programmatic penalties, and the total operating revenues, such as selling electricity and earning programmatic incentives. Under the capacity expansion formulation, the general objective function specified for the production cost model is augmented to include costs associated with asset investments and revenues obtained through different incentive structures. Through the optimization formulation, the objective functions defined by both problem types are minimized.

The objective functions are further dependent on the types of assets the simulated consumer owns or procures and the mechanisms under which the simulated consumer takes service. The following subsections provide the mathematical formulations and descriptions of the objective function components needed to represent the asset and mechanism models currently included in DERIVE. Depending on mechanism adoption and asset deployment, the objective function is a sum of the relevant objective function components provided herein.

Time-Varying Energy Charges

Time-varying energy charges are incurred by consumers taking service under a utility's electricity tariff. Equation 2.1 models the consumer's energy charge over the user-specified optimization horizon.

$$\frac{1}{\Gamma} \cdot \sum_{t \in \mathcal{T}} \pi_{en}(t) \cdot d_{net}(t) \tag{2.1}$$

where

$$d_{net}(t) = d(t) - p_{pv}^{btm}(t) + p_{cha}(t) - p_{dis}^{btm}(t) + d_{dev}^{up}(t) - d_{dev}^{dn}(t) - d_{shed}(t), \qquad \forall t \in \mathcal{T} \tag{2.2}$$

As shown in Equation 2.1, the time-varying energy charge at a given time t is the product of the energy price at that time, $\pi_{en}(t)$, and the consumer's net demand at that time, $d_{net}(t)$, which is defined in Equation 2.2. To find the time-varying energy charge over the entire user-defined optimization horizon, each product corresponding to time steps $t \in \mathcal{T}$ is summed together.

In DERIVE, the time-varying energy prices are provided as an array of preprocessed parameters and the net demand values are provided as an array of JuMP expressions. Each JuMP expression is comprised of some combination of parameters and JuMP variables depending on the combination of mechanisms considered and assets deployed. Due to the generic structure of Equation 2.1, the time-varying energy price can represent a slew of different options, including flat rates, time-of-use (TOU) rates, and real-time energy prices. For flat energy charges, users would provide electricity tariff parameters such that $\pi_{en}(t) = \pi_{en}$, $\forall t \in \mathcal{T}$, where π_{en} is a time-independent energy price. For TOU energy charges, $\pi_{en}(t)$ would equal energy prices that correspond to the TOU price for each $t \in \mathcal{T}$. For real-time energy prices, the consumer would be assumed to be a price taker and $\pi_{en}(t)$ would refer to a user-provided array of real-time energy prices.

Non-Coincident Demand Charges

While energy charges are incurred by all consumers taking service under a utility's rate structure, non-coincident demand charges[2] are not levied in the same manner. Oftentimes, demand charges are only present in tariffs targeted towards larger consumers, such as commercial or industrial consumers. For consumers exposed to non-coincident demand charges, Equation 2.3 models the demand charge over the specified optimization horizon.

$$\sum_{n \in \mathcal{N}} \pi_{dem}(n) \cdot d_{max}(n) \tag{2.3}$$

As shown in Equation 2.3, the non-coincident demand charge for a given TOU period n is the product of the demand price in that TOU period, $\pi_{dem}(n)$, and the consumer's maximum demand during that TOU period, $d_{max}(n)$. To find the non-coincident demand charge over the entire optimization horizon, each product corresponding to TOU periods $n \in \mathcal{N}$ is summed together.

With demand charges often considering consumers' maximum demand over a period of a month, which is the standard billing period, the optimization horizon is often set to be one month [92, 93]. However, this has the potential to produce overly optimistic results, as

[2] I use the term "non-coincident demand charges" to better juxtapose the demand charges modeled in DERIVE (and offered by many electric utilities) and demand charges that are actually based on consumers' coincident peak demand. The demand-charge-specific time-of-use demand charges modeled in DERIVE are often used as a proxy for a coincident demand charge in practice, but they are still not a true coincident demand charge, hence the decision to label these demand charges as "non-coincident demand charges."

the simulated consumer is being granted perfect foresight over a long period. In addition to that suspension of reality, it is not uncommon for other optimization horizons to need to be considered. For instance, simulations focused on evaluating consumers' operating costs may prefer a shorter optimization horizon, which can be beneficial as it limits consumers from having unrealistically omnipotent foresight. Conversely, longer optimization horizons are necessary for investment and deployment problems, where the impacts of large capital investments and seasonal variances are vital to consider.

As such, DERIVE enables users to model optimization horizons of one day, one month, and one year. For optimization horizons of less than one month, the potential for the optimization horizon to be less than at least one of the periods over which maximum demand charges are considered (e.g., maximum monthly demand charges) necessitates an assumption to be made. For optimization horizons of one day, it is assumed that consumers can consider the maximum demand in their current optimization horizon and the maximum demand from previous optimization horizons in the relevant evaluation period. Under this assumption, the consumer is not allowed to look ahead of the current optimization horizon to speculate about relevant future maximum demands. Additionally, demand charges for periods greater than one day (e.g., monthly maximum demand charges) are weighted in order to limit the prevalence of the demand charge relative to the energy charge, which is being evaluated daily instead of monthly under scenarios where the optimization horizon is one day. For example, if a particular month has thirty days, the monthly maximum demand charge would be divided by thirty; energy charges and daily demand charges, if included, would not need to be scaled.

Critical Peak Pricing Charges

Critical peak pricing (CPP) is a tariff rider that can be included alongside a consumer's selected energy charges. Typical CPP programs include two cost-related components that affect a consumer's electricity bill: (1) a penalty associated with energy consumption during a finite number of CPP events and (2) a reduction in energy charges during some utility-defined period of time outside of CPP events. For consumers participating in a CPP program, Equation 2.4 models the former cost component while the latter cost component is addressed during the preprocessing of the provided energy charges.

$$\frac{1}{\Gamma} \cdot \pi_{cpp} \cdot \sum_{h \in \mathcal{H}} d_{net}(h) \tag{2.4}$$

As shown in Equation 2.4, the penalty associated with energy consumption during CPP events, which are defined by the hours $h \in \mathcal{H}$, is the product of the CPP surcharge, π_{cpp}, and the sum of the consumer's net demand, d_{net}, during the CPP event.

Tiered Energy Charges

Tiered energy rates provide surcharges based on preestablished blocks of monthly or daily energy consumption. These surcharges are in addition to the energy rates provided in a commonly structured flat or TOU tariff. Typically, the magnitude of the surcharge increases as the consumer's total energy consumption, represented by the discrete blocks, increases. Equation 2.5 models the surcharges levied on consumers who take service under a tiered energy rate.

$$\sum_{b \in \mathcal{B}} \pi_{tier}(b) \cdot d_{tier}(b) \tag{2.5}$$

As shown in Equation 2.5, the surcharge associated with block b of consumption is the product of the price associated with that block, $\pi_{tier}(b)$, and the consumer's total net energy consumption in that block, $d_{tier}(b)$. To find the total surcharge levied on the consumer, each product corresponding to block $b \in \mathcal{B}$ is summed together.

Net Energy Metering Credits

Net energy metering (NEM) provides consumers with credits for energy exports from their qualifying sources of renewable generation. For consumers participating in a NEM program, Equation 2.6 models the revenue earned from energy exports over the specified optimization horizon.

$$-1 \cdot \frac{1}{\Gamma} \cdot \sum_{t \in \mathcal{T}} \pi_{exp}(t) \cdot p_{exp}(t) \tag{2.6}$$

where

$$p_{exp}(t) = p_{pv}^{exp}(t) + p_{dis}^{exp}(t), \qquad \forall t \in \mathcal{T} \tag{2.7}$$

As shown in Equation 2.6, the NEM revenue at a given time t is the product of the NEM export price signal at that time, $\pi_{exp}(t)$, and the consumer's total exports at that time, $p_{exp}(t)$, which are described by Equation 2.7. To find the NEM revenue over the entire optimization horizon, each product corresponding to time steps $t \in \mathcal{T}$ is summed together. This representation of NEM revenue differs from previous implementations [92, 93], which were able to take advantage of the fact that the export price was never greater than the energy price. The previous implementations represented exports in part by using a linear representation of the pointwise maximum of the consumer's net demand and zero. However, the introduction of export prices that exceed the energy price caused the linear representation of the pointwise maximum to be driven to infinity. The NEM export revenue model contained herein addresses that practical infeasibility.

The value of the export price signal is dependent on the particular NEM program in which a consumer is participating. DERIVE includes representations of three iterations of NEM programs, which are currently offered or were at one time offered by utilities across the United States. The first NEM program, colloquially referred to as "NEM 1.0," provides consumers with an export price that is equal to the consumer-facing energy price (i.e., $\pi_{exp}(t) = \pi_{en}(t), \forall t \in \mathcal{T}$). The second program, referred to as "NEM 2.0," provides consumers with an export price that is also equal to the consumer's energy price, though consumers are still responsible for paying non-bypassable charges, regardless of the credits earned through NEM. Non-bypassable charges are a small component of consumers' energy charges (e.g.,

\$0.02/kWh to \$0.03/kWh in the Pacific Gas and Electric Company (PG&E) service territory) and are intended to make DER owners help support their share of public-purpose costs [102, 103]. In PG&E, non-bypassable charges include the Public Purpose Program Charge, the Nuclear Decommissioning Charge, the Competition Transition Charge, and the Wildfire Fund Charge. To reflect the presence of inescapable non-bypassable charges, the export price signal under "NEM 2.0" is set to equal the consumer-facing energy price minus the volumetric price of the non-bypassable charges (i.e., $\pi_{exp}(t) = \pi_{en}(t) - \pi_{nbc}, \forall t \in \mathcal{T}$). Finally, the third NEM program, referred to as "NEM 3.0," is modeled after the CPUC's Net Billing Tariff and bases its export price signal on the values determined using an avoided cost calculator [96, 104]. The values returned from an avoided cost calculator better reveal the value of consumers' exports to the electric grid as opposed to export prices that rely solely on retail energy prices. However, in a seeming adherence to the "Bonbright Principle" of "predictability of the rates themselves" [66], the dynamic output of the avoided cost calculator is averaged by month, weekdays versus weekends and holidays, and hour of the day, thereby creating predictable monthly rate structures. The export price under "NEM 3.0" is equal to the hourly prices determined from the averaged avoided cost calculator output minus the volumetric price of non-bypassable charges, similar to "NEM 2.0" and as specified by the CPUC and PG&E [96, 105].

In the cases of export prices that account for non-bypassable charges (i.e., "NEM 2.0" and "NEM 3.0"), note that the export price used in the objective function is a slight abstraction. In reality, consumers still receive the whole export price (i.e., the export price without the adjustment for non-bypassable charges) for their exports. However, since any bill credits generated from a consumer's exports can only be used to offset that consumer's energy charges sans the non-bypassable charges [96, 102], it is important for the impact of the non-bypassable charges to be considered when determining whether to self-consume or to export excess generation. Accounting for the non-bypassable charges in the export prices helps to better convey the value of self-consuming excess generation to avoid needing to pay for non-bypassable charges on grid-purchased energy.

Variable Costs on Shiftable Flexible Demand

Shifting flexible demand consumption may introduce costs to consumers, either as a real operational cost or in the form of an inconvenience cost. For consumers with shiftable flexible demand resources, Equation 2.8 models the cost associated with shifting demand from the consumer's baseline demand profile.

$$\frac{1}{\Gamma} \cdot \sum_{t \in \mathcal{T}} \left[C_{var}^{flexdn} \cdot d_{dev}^{dn}(t) + C_{var}^{flexup} \cdot d_{dev}^{up}(t) \right] \tag{2.8}$$

As shown in Equation 2.8, the cost associated with shifting flexible demand is comprised of two components: a cost associated with the amount (in kWh) of curtailed demand relative to the baseline demand at a given time and a cost associated with the amount (in kWh) of additional demand relative to the baseline demand at a given time. It is not required for both or any of the cost parameters to be nonzero, as some consumers may not incur costs when making such operational decisions or may be economically indifferent to when consumption occurs (though may still be bound by technical operating constraints, as modeled by Equations 2.32 through 2.35).

Variable Costs on Forced Sheddable Demand

Similar to the cost of shifting flexible demand, there is also often a cost associated with shedding demand. However, unlike the model for the shiftable flexible demand resource, this model of sheddable demand is considered more for reliability purposes rather than for economics. As such, the cost associated with shedding demand will not be an inconvenience or operational cost, but rather the consumer's value of lost load. For consumers in which sheddable demand is being considered, Equation 2.9 models the cost associated with curtailing the consumer's demand.

$$\frac{1}{\Gamma} \cdot \sum_{t \in \mathcal{T}} C_{VOLL} \cdot d_{shed}(t) \tag{2.9}$$

As shown in Equation 2.9, the cost associated with shedding demand at a given time t is the product of the consumer's value of lost load, C_{VOLL}, and the amount of demand the consumer is curtailing at that time, $d_{shed}(t)$. To find the total cost of shedding demand over the optimization horizon, each product corresponding to time steps $t \in \mathcal{T}$ is summed together.

As noted above, this model of sheddable demand is intended to represent reliability considerations instead of economic ones. As such, the consumer's value of lost load is typically one to three orders of magnitude larger than the energy price (e.g., [106] estimates values of lost load between \$12/kWh to \$190.7/kWh for medium and large commercial and industrial consumers). Under these costs, consumers would not economically shed load during steady-state conditions. However, during outage conditions where the cost of purchasing electricity from the grid is modeled to approach infinity, load shedding will be the cost optimal decision unless sufficient DER capacity is built.

Asset Capital Costs

Investing in DERs is capital-intensive, with a large capital cost due upfront and subsequent fixed operations and maintenance (O&M) costs due annually over the course of the DER's lifespan. However, since DERIVE considers a capacity expansion problem over the course of one year, I consider an annualized capital cost to prevent a distortion in the consumer's total cost, which also includes the cost of the consumer's annual electricity bill. When considering the capacity expansion problem, Equation 2.10 models the annualized capital cost and annual fixed O&M cost associated with investing in a combination of solar photovoltaics and battery energy storage.

$$\sum_{a \in \mathcal{A}} \left[\frac{r \cdot (1+r)^{L_a}}{(1+r)^{L_a} - 1} \cdot C_{cap}^{a} \cdot P_a + C_{O\&M}^{a} \cdot P_a \right] \tag{2.10}$$

where

$$r = \frac{i - f}{1 + f} \tag{2.11}$$

As shown in Equation 2.10, there are two cost components within the summation: the first is the annualized capital cost and the second is the annual fixed O&M cost. The annualized capital cost of DER asset a is the product of the capital recovery factor, the capital cost per kilowatt of installed capacity, and the installed capacity. The capital recovery factor is a ratio that helps define the equal annual capital cost payments at a real discount rate r over the amortization period L_a of asset a (e.g., the lifespan of asset a, a loan repayment period). From Equation 2.11, the real discount rate is defined in terms of the nominal discount rate i (i.e., the rate at which money can be borrowed) and the expected inflation rate f. The annual fixed O&M cost is the product of the fixed O&M cost per kilowatt of installed capacity and the installed capacity. These cost calculations are repeated for each asset $a \in \mathcal{A}$ for which the consumer considers investing.

Investment Tax Credits

The passage of the Inflation Reduction Act of 2022 renewed the investment tax credits that can be claimed for solar photovoltaic systems and battery energy storage systems [10]. Additionally, the Inflation Reduction Act removed some of the restrictions originally placed upon battery energy storage systems. Under previous iterations of the investment tax credit, battery energy storage needed to be charged by a paired solar photovoltaic system entirely to claim the entire tax credit or be charged by a paired solar photovoltaic system at least 75% of the time to claim a portion of the tax credit [107]. When considering the capacity expansion problem, Equation 2.12 models the annualized investment tax credit associated with investing in a combination of solar photovoltaics and battery energy storage. Similar to the asset capital costs, the investment tax credit is annualized to prevent it from distorting the consumer's total cost.

$$-1 \cdot \sum_{a \in \mathcal{A}} \left[\frac{r \cdot (1+r)^{L_a}}{(1+r)^{L_a} - 1} \cdot I_{ITC}^{a} \cdot C_{cap}^{a} \cdot P_a \right] \tag{2.12}$$

As shown in Equation 2.12, the investment tax credit provided to asset a is the product of the capital recovery factor, the tax credit fraction (e.g., 0.3 if the consumer is eligible to earn the whole tax credit as of 2024), the capital cost per kilowatt of installed capacity, and the installed capacity. This calculation is repeated for each asset $a \in \mathcal{A}$ for which the consumer considers investing.

2.3.3 Constraints

Similar to the formulation of the objective function, the constraints established by an instance of DERIVE are dependent on the problem type specified by the user, the assets owned or procured by the simulated consumer, and the mechanisms under which the simulated consumer takes service. The constraints shown in the following subsections represent a combination of technical operating limitations and programmatic rules and regulations to which consumers and their assets must adhere.

Demand-Related Variable Definitions

To properly model the financial aspects of consumer participation in electricity tariffs, two demand-related variables are introduced to the optimization model: an expression representing the consumer's net demand, d_{net}, and a decision variable representing the consumer's maximum net demand during different TOU periods, d_{max}. Equations 2.13 through 2.16 provide constraints on both of these variables so that they may adequately represent the physical and financial quantities.

$$d_{net}(t) \geq 0, \qquad \forall t \in \mathcal{T} \tag{2.13}$$

$$\delta(t,n) \cdot d_{net}(t) \leq d_{max}(n), \qquad \forall t \in \mathcal{T}, \quad \forall n \in \mathcal{N} \tag{2.14}$$

$$d_{max}(n) \geq 0, \qquad \forall n \in \mathcal{N} \tag{2.15}$$

$$d_{max}^{prev}(n) \leq d_{max}(n), \qquad \forall n \in \mathcal{N} \tag{2.16}$$

Equation 2.13 ensures that the consumer's net demand is nonnegative. Due to the definition of net demand provided by Equation 2.2 and the fact that the consumer's exports are represented separately, net demand should never realistically be a negative quantity. The constraint introduced by Equation 2.13 is necessary to prevent net demand from being driven to be negative, which could occur to help reduce the consumer's bill associated with TOU energy charges (Equation 2.1) and critical peak pricing charges (Equation 2.4).

Equations 2.14 through 2.16 place constraints on the variable representing the consumer's maximum net demand. Equations 2.14 and 2.15 define the consumer's maximum net demand during different TOU periods $n \in \mathcal{N}$, ensuring that the maximum net demand is the largest net demand quantity during each TOU period and is nonnegative, respectively. The δ in Equation 2.14 is a constant indicator parameter that aligns with the specified TOU periods, equaling one when time t aligns with period n and zero otherwise. Equation 2.16 helps model the consumer's maximum net demand when DERIVE's optimization horizon is over one day and the electricity tariff has monthly demand charges. This equation ensures that the maximum net demand is equal to either that day's largest net demand or the largest net demand from a previous day, whichever is greater. The previous optimization horizon's maximum net demand d_{max}^{prev} is updated at the end of each daily simulation and is set equal to zero for days at the beginning of the month.

Solar Photovoltaic System

Solar photovoltaic systems are modeled primarily through the use of weather-dependent capacity factor profiles. When multiplied by the capacity of the consumer's solar photovoltaic system, the capacity factor profiles help reveal the amount of generation the photovoltaic system is able to produce during each hour. Equations 2.17 through 2.20 describe the constraints for operating and investing in the consumer's solar photovoltaic system.

$$p_{pv}^{btm}(t) \geq 0, \qquad \forall t \in \mathcal{T} \tag{2.17}$$

$$p_{pv}^{exp}(t) \geq 0, \qquad \forall t \in \mathcal{T} \tag{2.18}$$

$$p_{pv}^{btm}(t) + p_{pv}^{exp}(t) \leq \eta_{inv} \cdot P_{pv} \cdot CF_{pv}(t), \qquad \forall t \in \mathcal{T} \tag{2.19}$$

$$0 \leq P_{pv} \leq \overline{P}_{pv} \tag{2.20}$$

Equations 2.17 and 2.18 ensure that the photovoltaic system generation for meeting behind-the-meter demand and for providing grid exports are nonnegative. Equation 2.19 provides the upper bound for the total amount of generation that the solar photovoltaic system can produce at a given time t. The upper bound is the product of the inverter's efficiency; the photovoltaic system's capacity (in kW), which may be a parameter or a decision variable depending on the problem type; and the capacity factor profile. Setting the total possible generation at each time t as the upper bound allows for curtailment to take place, if necessary. If the consumer is not participating in a net energy metering program, Equation 2.18 is not active and the total generation defined in Equation 2.19 is equal to just the generation that is intended to meet the behind-the-meter demand. When the solar photovoltaic system capacity is a decision variable, Equation 2.20 sets bounds on the photovoltaic system capacity. In particular, Equation 2.20 ensures that the photovoltaic system capacity is nonnegative with an upper bound that can be specified by the user, if desired.

Battery Energy Storage System

Battery energy storage systems are modeled using physics-based equations that govern the energy flows entering and exiting the technology. Equations 2.21 through 2.31 describe the constraints for operating and investing in the consumer's battery energy storage system.

$$0 \leq p_{cha}(t) \leq P_{bes}, \qquad \forall t \in \mathcal{T} \tag{2.21}$$

$$p_{cha}(t) \leq p_{pv}^{btm}(t), \qquad \forall t \in \mathcal{T} \tag{2.22}$$

$$p_{dis}^{btm}(t) \geq 0, \qquad \forall t \in \mathcal{T} \tag{2.23}$$

$$p_{dis}^{exp}(t) \geq 0, \qquad \forall t \in \mathcal{T} \tag{2.24}$$

$$p_{dis}^{btm}(t) + p_{dis}^{exp}(t) \leq P_{bes}, \qquad \forall t \in \mathcal{T} \tag{2.25}$$

$$p_{dis}^{exp}(s) \leq P_{bes} - \left[d(s) - p_{pv}^{btm}(s)\right], \qquad \forall s \in \mathcal{S} \tag{2.26}$$

$$J(t) = (1 - \eta_{bes}^{dis}) \cdot J(t-1) + \frac{1}{\Gamma} \cdot \left[\eta_{bes}^{rte} \cdot p_{cha}(t) - p_{dis}^{btm}(t) - p_{dis}^{exp}(t)\right], \qquad \forall t \in \mathcal{T} > 0 \tag{2.27}$$

$$J(t) = (1 - \eta_{bes}^{dis}) \cdot J_{init} + \frac{1}{\Gamma} \cdot \left[\eta_{bes}^{rte} \cdot p_{cha}(t) - p_{dis}^{btm}(t) - p_{dis}^{exp}(t)\right], \qquad t = 0 \tag{2.28}$$

$$\underline{J} \leq J(t) \leq \overline{J}, \qquad \forall t \in \mathcal{T} \tag{2.29}$$

$$J(|\mathcal{T}|) \geq J_{init} \tag{2.30}$$

$$0 \leq P_{bes} \leq \overline{P}_{bes} \tag{2.31}$$

Equation 2.21 establishes bounds on the charging power (in kW) of the battery energy storage system. If the battery energy storage system is restricted from charging using grid electricity and must charge from the consumer's co-located solar photovoltaic system, Equation 2.22 provides an additional upper bound on the battery energy storage system's charging power that ensures it is no greater than the power produced by the solar photovoltaic system for behind-the-meter consumption at any time t. Equations 2.23 through 2.25 establish bounds on the discharging power (in kW) of the battery energy storage system. Like with the solar photovoltaic system model, the discharging power of the battery energy storage system model is separated into a component for meeting behind-the-meter demand and a component for exporting power to the grid, if applicable. Equations 2.23 and 2.24 ensure that the respective discharging powers are nonnegative. Equation 2.25 sets the upper bound of the total discharging power to be the power rating of the battery energy storage system.

If the integer variables and constraints associated with the net energy metering representation are relaxed,[3] Equation (2.26) places a cap on the power the battery energy storage

[3] Refer to the subsection on net energy metering constraints for a more thorough discussion of the integer variables and constraints integrated into the model.

system is able to export. The upper bound of Equation (2.26) is established such that the battery energy storage systems must reserve some of its capacity to help serve the net demand not met by a solar photovoltaic system, if applicable.[4] As can be seen, Equation (2.26) is only applied during time steps where $\pi_{exp}(t) > \pi_{en}(t)$, as those are the time steps in which the battery energy storage system might be incentivized to violate the net energy metering program requirements if those requirements are not enforced through integer variables and constraints. While Equation (2.26) will not necessarily require net demand to be completely met before the consumer can export to the grid, it at least helps limit some of the unrealistic compensation a consumer can earn through its program violations.

Equations 2.27 through 2.30 describe the energy balance of the battery energy storage system at time t. Equations 2.27 and 2.28 govern the battery energy storage system's state of charge, with the latter describing the first time step (i.e., $t = 0$) and the former describing all successive time steps (i.e., $\forall t \in \mathcal{T} > 0$). Equation 2.29 establishes bounds on the battery system's state of charge. This allows users to set bounds other than what may be technically feasible, which could allow battery management strategies that better promote proper battery health to be implemented. Equation 2.30 ensures that the battery energy storage system's final state of charge is no less than the initial state of charge, which helps avoid perverse battery management schemes (e.g., completely discharging the battery energy storage system at the end of the optimization horizon, regardless of the initial state of charge, in order to myopically minimize the electricity bill in that period) from occurring.

When the battery energy storage system power capacity is a decision variable, Equation 2.31 sets bounds on the battery system power capacity. In particular, Equation 2.31 ensures that the battery system power capacity is nonnegative with an upper bound that can be specified by the user, if desired. The battery energy storage system's energy capacity is not co-optimized alongside the power capacity. Instead, energy capacity is determined by multiplying a specified duration (in hours) by the power capacity. This is done to account for

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[4] If a solar photovoltaic system is not considered in the model alongside the battery energy storage system, then the upper bound of Equation (2.26) is adjusted to be $P_{bes} - d(s)$, $\forall s \in \mathcal{S}$.

the more standardized battery energy storage system sizes and data availability on investment costs [80].

Shiftable Flexible Demand

Flexible demand for the purposes of a consumer's personal economics is modeled as being shiftable as opposed to sheddable, where the former indicates that all deviations from the consumer's baseline demand profile must be balanced out and the latter indicates that demand can be curtailed without being recovered. Additionally, flexible demand is modeled to represent a portfolio of technology-agnostic resources that are defined by their percentage of demand that is flexible and their load recovery duration. Though some technology-specific precision may be lost, this representation allows consumers with greater diversity to be considered. Equations 2.32 through 2.35 describe the constraints for operating the consumer's shiftable flexible demand resources.

$$0 \leq d_{dev}^{dn}(t) \leq \overline{d}_{dev}^{dn}(t), \qquad \forall t \in \mathcal{T} \tag{2.32}$$

$$0 \leq d_{dev}^{up}(t) \leq \overline{d}_{dev}^{up}(t), \qquad \forall t \in \mathcal{T} \tag{2.33}$$

$$\sum_{t \in \mathcal{T}} \left[d_{dev}^{up}(t) - d_{dev}^{dn}(t) \right] = 0 \tag{2.34}$$

$$\sum_{\tau=k}^{\Delta+k-1} \left[d_{dev}^{up}(\tau) - d_{dev}^{dn}(\tau) \right] \geq 0, \qquad k = 1, ..., |\mathcal{T}| - \Delta + 1 \tag{2.35}$$

Equations 2.32 and 2.33 establish bounds on the demand deviation decision variables that are responsible for curtailing and increasing demand relative to the consumer's baseline demand profile, respectively. Both demand deviation terms are nonnegative, with the upper bounds being set either by user-provided profiles or by multiplying the consumer's baseline demand profile by a user-provided value that describes the percentage of demand that is flexible. This latter representation can be conservative, as demand bottlenecks can appear during low-demand periods. However, since this model of shiftable flexible demand is intended to mimic a portfolio of technology-agnostic flexible resources, I believe such a consideration is useful since such a portfolio of assets will likely experience bouts of intermittent availability.

Equations 2.34 and 2.35 require demand deviations to be balanced over different time scales. Equation 2.34 requires total demand deviations to be balanced over the course of the optimization horizon. In other words, the total demand curtailments must equal the total demand increases. Equation 2.35 requires demand deviations over rolling time periods of user-specified length to be nonnegative, meaning that demand increases can be greater than demand curtailments if deemed optimal. The length of the time period is intended to equal the load recovery duration (in hours) of the shiftable flexible demand.

Sheddable Demand

Sheddable demand is modeled as a reliability consideration instead of an economic tool. Consumers will only shed demand when the cost of curtailing demand (i.e., the value of lost load) is less than the energy cost. With typical values of lost load, such a situation is only likely to occur during (1) outage scenarios when the energy price is set arbitrarily high to indicate that load must be curtailed if not met by DERs or (2) potentially in a scenario where the consumer is exposed to real-time prices and the energy price is at or near the price cap. Equation 2.36 describes the constraint placed on the amount of load that can be curtailed.

$$0 \leq d_{shed}(t) \leq d(t), \qquad \forall t \in \mathcal{T} \tag{2.36}$$

Equation 2.36 establishes bounds on the decision variables that are responsible for curtailing demand. The amount of load that is shed is nonnegative, with an upper bound equal to the consumer's baseline demand profile.

Tiered Energy Rates

Tiered energy rates are modeled in a way that allows them to work alongside other types of electricity rates, as is common in practice. As such, a separate decision variable that helps track the energy consumption in each tier $b \in \mathcal{B}$ is established: $d_{tier}(b)$. Equations 2.37 and 2.38 describe the constraints placed upon the tiered energy consumption decision variables.

$$0 \leq d_{tier}(b) \leq \overline{d}_{tier}(b), \qquad \forall b \in \mathcal{B} \tag{2.37}$$

$$\sum_{b \in \mathcal{B}} d_{tier}(b) = \frac{1}{\Gamma} \cdot \sum_{t \in \mathcal{T}} d_{net}(t) \tag{2.38}$$

Equation 2.37 establishes bounds on the tiered energy consumption decision variables. These decision variables are nonnegative and have an upper bound that is dictated by the total consumption allowed in a given tier. Equation 2.38 makes the total energy consumption in each of the tiers equal to the consumer's total energy consumption over the optimization horizon. In conjunction with Equation 2.5, Equations 2.37 and 2.38 help ensure that the tiers corresponding to the cheapest penalties are fully used (i.e., the maximum allowable consumption in each tier is realized) before consuming energy in a tier associated with a more expensive penalty.

Net Energy Metering

With the two-product modeling scheme DERIVE uses to simulate solar photovoltaic systems and battery energy storage systems, whereby the energy used to meet behind-the-meter consumption and the energy used for grid exports are represented by separate decision variables, it is imperative that two particular requirements of net energy metering programs are specified. The first requirement is fundamental to net energy metering programs: consumers can only export generated energy that exceeds their consumption needs at a given time. This requirement prevents exports from occurring when a consumer's behind-the-meter resources have not met their entire demand at a time t, something an optimization algorithm may otherwise enable if the export price exceeds the cost of consumption (i.e., $\pi_{exp}(t) > \pi_{en}(t)$). The second requirement is that consumers must have a behind-the-meter renewable energy generating facility (e.g., a solar photovoltaic system) to participate in net energy metering. Net energy metering programs want to credit consumers for the clean energy they are producing rather than providing an additional arbitrage incentive that may or may not contribute to perverse emissions outcomes. For problems that consider asset investment, this requirement prevents a consumer from participating in net energy metering with only a battery energy storage system. Equations 2.39 through 2.42 describe the constraints introduced to represent the two requirements described above.

$$\zeta_{net}(s) = 1 \Rightarrow d_{net}(s) \leq 0, \qquad \forall s \in \mathcal{S} \tag{2.39}$$

$$p_{exp}(s) \leq \zeta_{net}(s) \cdot \left[\overline{P}_{pv} + \overline{P}_{bes}\right], \qquad \forall s \in \mathcal{S} \tag{2.40}$$

$$\zeta_{pv} = 1 \Rightarrow P_{pv} \leq 0 \tag{2.41}$$

$$p_{exp}(t) \leq \left[1 - \zeta_{pv}\right] \cdot \left[\overline{P}_{pv} + \overline{P}_{bes}\right], \qquad \forall t \in \mathcal{T} \tag{2.42}$$

Equations 2.39 and 2.40 prevent grid exports if the consumer's net demand is not completely satisfied by the behind-the-meter assets. Equation 2.39 provides the constraint for the indicator variable $\zeta_{net}(s)$, which equals one when the consumer's net demand is completely satisfied by the behind-the-meter resources and equals zero otherwise for each time step s. Equation 2.40 places an arbitrary upper bound on the grid exports expression. This upper bound is the product of the indicator variable $\zeta_{net}(t)$ and the sum of the maximum allowable solar photovoltaic system and battery energy storage system capacities. The upper bound is selected so that exports are not restricted (as they would otherwise be determined through other physical and economic considerations pertaining to each asset type) when $\zeta_{net}(s) = 1$, but are prevented when $\zeta_{net}(s) = 0$.

Note that only a subset of time steps, denoted by the set $\mathcal{S}$, is considered in Equations 2.39 and 2.40 as opposed to the full set of time steps, $\mathcal{T}$. When the export price exceeds the energy price, the optimizer may allow export behavior that is prohibited by net energy metering programs, namely the ability to produce exports before the consumer's own demand needs are completely sated. However, export prices only exceed energy prices during a subset of all time steps. In times when the energy price is greater than the export price, the optimizer prescribes self-consumption until the consumer's net demand is driven to zero, which is not problematic behavior under net energy metering programs. Therefore, to help limit some of the computational burden incurred by introducing the binary indicator variables ζ_{net}, I only create enough binary indicator variables to appropriately constrain the time steps when export prices exceed energy prices.

Equations 2.41 and 2.42 prevent grid exports if a solar photovoltaic system is not constructed. Equation 2.41 provides the constraint for the indicator variable ζ_{pv}, which equals one when the consumer does not construct a solar photovoltaic system and equals zero otherwise. Similar to Equation 2.40, Equation 2.42 places an arbitrary upper bound on the grid exports expression. This upper bound is the product of the difference between one and the indicator variable ζ_{pv} and the sum of the maximum allowable solar photovoltaic system and battery energy storage system capacities. The upper bound is selected so that exports are not restricted when $\zeta_{pv} = 0$, but are prevented when $\zeta_{pv} = 1$. These constraints are only necessary in the scenario where a battery energy storage system is allowed to charge using grid power and export to the grid, an interconnection scheme that is not supported at the retail level under net energy metering.

Independent of the two-product modeling scheme employed by DERIVE to simulate solar photovoltaic systems and battery energy storage systems, there is another net energy metering program requirement that an optimizer may violate if the model is not properly constrained. Net energy metering 3.0 programs (e.g., the California Public Utilities Commission's Net Billing Tariff) produce credits that, over a year, may potentially only be allowed to offset a consumer's energy charges net of their non-bypassable charges [105]. In the production cost formulation, constraining the model to enforce such behavior is not necessary nor simple to include. It is unnecessary because the size of the consumer's assets are predetermined and the true amount of the consumer's net energy metering credits can be determined during postprocessing.[5] Even if that accounting were useful to include in real-time, attempting to consider the annual true-up of net energy metering credits over optimization horizons of one month or one day would prove to be complicated, especially since there are certain months and days of the week where the value of the export price signal is greater than others. However, it is important to include a constraint that limits the annual net energy metering credits that can be collected when considering the capacity expansion formulation. Setting a cap on the net energy metering credits is important when trying to decide how to size a consumer's solar photovoltaic and battery energy storage assets, especially since a failure to do so may result in oversized assets. Additionally, the fact that the capacity expansion model has an optimization horizon of one year makes the implementation of such a constraint relatively straightforward. Equation (2.43) describes the constraint that enforces this net energy metering program rule.

$$\sum_{t \in \mathcal{T}} \pi_{en}(t) \cdot d_{net}(t) - \sum_{t \in \mathcal{T}} \pi_{exp}(t) \cdot p_{exp}(t) \geq \pi_{nbc} \cdot \sum_{t \in \mathcal{T}} d_{net}(t) \tag{2.43}$$

As is shown in Equation (2.43), the cap on annual net energy metering credits is enforced by requiring the difference in the annual energy charges and the annual net energy metering revenues to be no less than the annual non-bypassable charges.

2.3.4 Parametric Functions

DERIVE contains multiple parametric functions that are calculated independently of the optimization model, but are critical to the simulations being representative of the physical and financial phenomena under consideration. The following subsections describe these parametric functions in depth.

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[5]Refer to Section 2.3.5 for a discussion on the postprocessing that occurs following a simulation.

Solar Photovoltaic Capacity Factor Profiles

The solar photovoltaic capacity factor profiles are important for helping to indicate the amount of generation a solar photovoltaic system is providing at a given time t. In a production cost model, the capacity factor profiles are multiplied by the known solar photovoltaic system capacity to reveal the produced time-series generation. In a capacity expansion model, the capacity factor profiles are instead multiplied by the solar photovoltaic system capacity decision variable to help determine the system size. Creating the solar photovoltaic capacity factor profiles depends on three main components: weather data, solar photovoltaic module specifications, and solar photovoltaic module placement. Equations 2.44 through 2.75 show the process for determining the solar photovoltaic capacity factor profile prior to running a simulation in DERIVE. Broadly, Equations 2.44 through 2.56 reveal the process of calculating the total solar irradiance realized by the collector of the solar photovoltaic system. Unless otherwise noted, these equations and the methodology for calculating the total solar irradiance were sourced from [108].

$$\delta_s(t) = 23.45 \cdot \sin\left(\frac{360}{365} \cdot [n_d(t) - 81]\right), \qquad \forall t \in \mathcal{T} \tag{2.44}$$

$$E(t) = 9.87 \cdot \sin[2 \cdot B(t)] - 7.53 \cdot \cos[B(t)] - 1.5 \cdot \sin[B(t)], \qquad \forall t \in \mathcal{T} \tag{2.45}$$

$$B(t) = \frac{360}{364} \cdot [n_d(t) - 81], \qquad \forall t \in \mathcal{T} \tag{2.46}$$

$$ST(t) = \frac{CT(t) + 4 \cdot (LTM - LONG) + E(t)}{60}, \qquad \forall t \in \mathcal{T} \tag{2.47}$$

$$H(t) = 15 \cdot [12 - ST(t)], \qquad \forall t \in \mathcal{T} \tag{2.48}$$

$$\beta(t) = \sin^{-1}(\cos[LAT] \cdot \cos[\delta_s(t)] \cdot \cos[H(t)] + \sin[LAT] \cdot \sin[\delta_s(t)]), \qquad \forall t \in \mathcal{T} \tag{2.49}$$

$$\phi_s(t) = \begin{cases} \sin^{-1}\left(\frac{\cos[\delta_s(t)] \cdot \sin[H(t)]}{\cos[\beta(t)]}\right), & \text{if } \cos[H(t)] \geq \frac{\tan[\delta_s(t)]}{\tan[LAT]} \\ 180 - \sin^{-1}\left(\frac{\cos[\delta_s(t)] \cdot \sin[H(t)]}{\cos[\beta(t)]}\right), & \text{otherwise} \end{cases}, \qquad \forall t \in \mathcal{T} \tag{2.50}$$

$$\Sigma = 1.3793 + LAT \cdot [1.2011 + LAT \cdot (-0.014404 + LAT \cdot 0.000080509)] \tag{2.51}$$

$$\cos[\theta(t)] = \begin{cases} \cos[\beta(t)] \cdot \cos[\phi_s(t) - \phi_c] \cdot \sin[\Sigma] + \sin[\beta(t)] \cdot \cos[\Sigma], & \text{fixed} \\ 1, & \text{2-axis} \\ \sqrt{1 - (\cos[\beta(t)] \cdot \cos[\phi_s(t)])^2}, & \text{1-axis HNS} \\ \sqrt{1 - (\cos[\beta(t)] \cdot \cos[\phi_s(t)])^2}, & \text{1-axis HEW} \\ \cos[\delta_s(t)], & 1 - \text{axis PNS} \\ \sin[\beta(t) + \Sigma], & \text{1-axis VERT} \end{cases}, \forall t \in \mathcal{T} \tag{2.52}$$

$$G_{BC}(t) = DNI(t) \cdot \cos[\theta(t)] \tag{2.53}$$

$$G_{DC}(t) = \begin{cases} DHI(t) \cdot \left(\frac{1+\cos[\Sigma]}{2}\right), & \text{fixed} \\ DHI(t) \cdot \left(\frac{1+\sin[\beta(t)]}{2}\right), & \text{2-axis} \\ DHI(t) \cdot \left[\frac{1+\left(\frac{\sin[\beta(t)]}{\cos[\theta(t)]}\right)}{2}\right], & \text{1-axis HNS} \\ DHI(t) \cdot \left[\frac{1+\left(\frac{\sin[\beta(t)]}{\cos[\theta(t)]}\right)}{2}\right], & \text{1-axis HEW} \\ DHI(t) \cdot \left(\frac{1+\sin[\beta(t)-\delta_s(t)]}{2}\right), & \text{1-axis PNS} \\ DHI(t) \cdot \left(\frac{1+\cos[\Sigma]}{2}\right), & \text{1-axis VERT} \end{cases}, \quad \forall t \in \mathcal{T} \tag{2.54}$$

$$G_{RC}(t) = \begin{cases} GHI(t) \cdot \rho \cdot \left(\frac{1-\cos[\Sigma]}{2}\right), & \text{fixed} \\ GHI(t) \cdot \rho \cdot \left(\frac{1-\sin[\beta(t)]}{2}\right), & \text{2-axis} \\ GHI(t) \cdot \rho \cdot \left[\frac{1-\left(\frac{\sin[\beta(t)]}{\cos[\theta(t)]}\right)}{2}\right], & \text{1-axis HNS} \\ GHI(t) \cdot \rho \cdot \left[\frac{1-\left(\frac{\sin[\beta(t)]}{\cos[\theta(t)]}\right)}{2}\right], & \text{1-axis HEW} \\ GHI(t) \cdot \rho \cdot \left(\frac{1-\sin[\beta(t)-\delta_s(t)]}{2}\right), & \text{1-axis PNS} \\ GHI(t) \cdot \rho \cdot \left(\frac{1-\cos[\Sigma]}{2}\right), & \text{1-axis VERT} \end{cases}, \quad \forall t \in \mathcal{T} \tag{2.55}$$

$$G(t) = G_{BC}(t) + G_{DC}(t) + G_{RC}(t), \qquad \forall t \in \mathcal{T} \tag{2.56}$$

Equation 2.44 calculates the solar declination angles at different time steps t. Equation 2.45 determines the equation of time, which helps account for the differences between solar time and local clock time, with Equation 2.46 serving as an intermediate calculation. Equation 2.47 indicates the solar time in terms of the local clock time, taking into account corrections from the equation of time and a longitude correction. Equation 2.48 determines the hour angle, which is the difference in degrees between the Sun's meridian and the local meridian. Equations 2.49 and 2.50 calculate the altitude and azimuth angles of the Sun, respectively. The conditional in Equation 2.50 is included to help account for the ambiguity of the inverse sine function [108].

To this point, the described equations have focused on identifying the angle of the Sun with respect to the solar photovoltaic system's collector. Using information on the Sun's relative positioning, the positioning of the consumer's solar photovoltaic system, and solar irradiance data, the total solar irradiance realized by the collector of the solar photovoltaic system can be determined. If unspecified by the user, Equation 2.51 uses a third-order polynomial fit to set a tilt angle for the solar photovoltaic system's panels. This polynomial fit relates Northern Hemisphere latitudes and solar photovoltaic system tilt angles from simulations using fixed-tilt systems in the National Renewable Energy Laboratory's PVWatts Calculator [109]. Equation 2.52 determines the cosine of the incidence angle, which is the angle difference between the solar beam radiation and the reference frame that is normal to the collector face of the solar photovoltaic system. Equation 2.52 contains many different values for the cosine of the incidence angle depending on the solar photovoltaic system's tracking technology: fixed tilt, two-axis tracking, one-axis horizontal tracking along the North-South directions, one-axis horizontal tracking along the East-West directions, one-axis polar-mounted tracking along the North-South directions, and one-axis vertical-mounted tracking with a fixed tilt angle. Equations 2.53, 2.54, and 2.55 calculate the beam irradiance, diffuse radiation, and reflected radiation, respectively, on the collector of the solar photovoltaic system. As with Equation 2.52, Equations 2.54 and 2.55 also have different possible irradiance values depending on the modeled tracking technology. Equation 2.56 produces the total irradiance realized by the collector of the solar photovoltaic systems at time t [108].

The solar photovoltaic system is modeled using the single-diode equivalent circuit model of a photovoltaic cell. The single-diode equivalent circuit model is known to produce accurate and realistic representations of photovoltaic cells [108] and has been used in well-regarded solar photovoltaic system simulation models [110, 111]. Equations 2.57 through 2.73 describe the single-diode equivalent circuit model and the solution methods necessary for solving the resulting nonlinear system of equations.

$$I(t,p) = I_{pv}(t) - I_0(t) \cdot \left(e^{\frac{V(t,p)+I(t,p)\cdot R_s}{V_t(t)\cdot a_d}} - 1 \right) - \frac{V(t,p)+I(t,p)\cdot R_s}{R_p}, \qquad \forall t \in \mathcal{T}, \quad \forall p \in \mathcal{P} \tag{2.57}$$

$$I_{pv}^{nom} = I_{sc}^{nom} \tag{2.58}$$

$$I_{pv}(t) = (I_{pv}^{nom} + K_I \cdot [T(t) - T^{nom}]) \cdot \frac{G(t)}{G^{nom}}, \qquad \forall t \in \mathcal{T} \tag{2.59}$$

$$V_t^{nom} = \frac{N_c \cdot k \cdot T^{nom}}{q} \tag{2.60}$$

$$V_t(t) = \frac{N_c \cdot k \cdot T(t)}{q}, \qquad \forall t \in \mathcal{T} \tag{2.61}$$

$$E_g^{nom} = \left[E_0 - \frac{\alpha_{E_g} \cdot (T^{nom})^2}{T^{nom} + \beta_{E_g}} \right] \cdot q \tag{2.62}$$

$$E_g(t) = \left[E_0 - \frac{\alpha_{E_g} \cdot T(t)^2}{T(t) + \beta_{E_g}} \right] \cdot q, \qquad \forall t \in \mathcal{T} \tag{2.63}$$

$$a_d = \frac{K_V - \frac{V_{oc}^{nom}}{T^{nom}}}{V_t^{nom} \cdot \left[\frac{K_I}{I_{pv}^{nom}} - \frac{3}{T^{nom}} - \frac{E_g^{nom}}{k \cdot (T^{nom})^2} \right]} \tag{2.64}$$

$$I_0^{nom} = \frac{I_{pv}^{nom}}{e^{\frac{V_{oc}^{nom}}{a_d \cdot V_t^{nom}}} - 1} \tag{2.65}$$

$$I_0(t) = I_0^{nom} \cdot \left[\frac{T(t)}{T^{nom}} \right]^3 \cdot e^{\frac{\frac{E_g^{nom}}{T^{nom}} - \frac{E_g(t)}{T(t)}}{k}}, \qquad \forall t \in \mathcal{T} \tag{2.66}$$

Equation 2.57 is the current output by a solar photovoltaic system, dependent on the solar photovoltaic system's terminal voltage at time t and for the point along the I-V curve p. Equations describing the single-diode equivalent circuit model are largely sourced from De Soto et al. [112] and Villalva et al. [110]. The equations that estimate the solar photovoltaic system's parameters (a_d, R_s, and $R_p(t)$, which are described in Equations 2.64, 2.68, and 2.70, respectively) are sourced from Femia et al. [113]. Equations 2.58 and 2.59 model the nominal photo-induced current at standard test conditions (i.e., a nominal temperature of 25 °C and a total solar irradiance of 1000 W/m^2) and the photo-induced current at time t, respectively. Note that the time dependence of the photo-induced current is due to the time dependence introduced by weather data such as temperature and total solar irradiance. Equations 2.60 and 2.61 model the nominal thermal voltage at standard test conditions and the thermal voltage at time t, respectively. Equations 2.62 and 2.63 model the nominal band-gap energy at standard test conditions and the band-gap energy at time t, respectively. Equation 2.64 models the diode ideality constant. Equations 2.65 and 2.66 model the nominal saturation current at standard test conditions and the saturation current at time t, respectively.

To help solve the above system of equations in an analytical way, I use the principal branch of the Lambert W function, W_0, which is the solution to the equation $f(x) = x \cdot e^x$. Though the Lambert W function offers a solution to a problem of a similar form to that presented in Equation 2.57, it is especially useful for its efficient solution methods, such as those presented in [114]. As such, use of the Lambert W function for efficiently solving the single-diode equivalent circuit model has been popular, as is evidenced by the model presented by Femia et al. [113] and the implementation of the popular Python-based version of the open-source PVLIB software [111]. As is shown below, some of the remaining parameters can be identified using the Lambert W function and a change of variables. Ultimately, this enables Equation 2.57 to be rewritten in an explicit form that is straightforward to solve.

$$x = W_0\left(\frac{V_{mpp}^{nom}\left[2 \cdot I_{mpp}^{nom} - I_{pv}^{nom} - I_0^{nom}\right] \cdot e^{\frac{V_{mpp}^{nom} \cdot \left[V_{mpp}^{nom} - 2 \cdot a_d \cdot V_t^{nom}\right]}{a_d^2 \cdot [V_t^{nom}]^2}}}{a_d \cdot I_0^{nom} \cdot V_t^{nom}}\right) + 2 \cdot \frac{V_{mpp}^{nom}}{a_d \cdot V_t^{nom}} - \frac{(V_{mpp}^{nom})^2}{a_d^2 \cdot (V_t^{nom})^2} \tag{2.67}$$

$$R_s = \frac{x \cdot a_d \cdot V_t^{nom} - V_{mpp}^{nom}}{I_{mpp}^{nom}} \tag{2.68}$$

$$R_p^{nom} = \frac{x \cdot a_d \cdot V_t^{nom}}{I_{pv}^{nom} - I_{mpp}^{nom} - I_0^{nom} \cdot (e^x - 1)} \tag{2.69}$$

$$R_p(t) = R_p^{nom} \cdot \frac{G^{nom}}{G(t)}, \qquad \forall t \in \mathcal{T} \tag{2.70}$$

$$V_{oc}(t) = V_{oc}^{nom} + K_V \cdot [T(t) - T^{nom}], \qquad \forall t \in \mathcal{T} \tag{2.71}$$

$$\psi(t,p) = \frac{R_s \cdot R_p(t) \cdot I_0(t) \cdot e^{\frac{R_p(t)\cdot[R_s\cdot(I_{pv}(t)+I_0(t))+V(t,p)]}{a_d\cdot V_t(t)\cdot[R_s+R_p(t)]}}}{a_d \cdot V_t(t) \cdot [R_s + R_p(t)]}, \qquad \forall t \in \mathcal{T}, \quad \forall p \in \mathcal{P} \tag{2.72}$$

$$I(t,p) = \frac{R_p(t) \cdot [I_{pv}(t) + I_0(t)] - V(t,p)}{R_s + R_p(t)} - \frac{a_d \cdot V_t(t) \cdot W_0(\psi(t,p))}{R_s}, \qquad \forall t \in \mathcal{T}, \quad \forall p \in \mathcal{P} \tag{2.73}$$

Equation 2.67 provides a change of variable that relies on the principal branch of the Lambert W function, W_0, and is used to help solve for two of the solar photovoltaic system's parameters: the series resistance, R_s, and the time-varying shunt resistance, $R_p(t)$ [113]. Equation 2.68 models the series resistance of the single-diode equivalent circuit model. Equation 2.69 models the nominal shunt resistance of the single-diode equivalent circuit model at standard test conditions. Though both Equations 2.68 and 2.69 utilize nominal parameters at standard test conditions, the shunt resistance used in the single-diode equivalent circuit model is sensitive to changes in the time-varying solar irradiance, while the series resistance is not [112]. As such, the series resistance can be identified once with parameters evaluated at standard test conditions. The shunt resistance must be modified to consider the time-varying solar irradiance, as is modeled in Equation 2.70. Equation 2.71 models the time-varying open-circuit voltage, which serves as the upper bound on the voltage values $V(t,p)$ for each set of points $\mathcal{P}$ that comprise an I-V curve. Equation 2.72 provides a change of variable that relies on the principal branch of the Lambert W function, W_0, and is used to help make Equation 2.57 able to be solved explicitly [111]. That explicit representation of the solar photovoltaic system's current output is shown in Equation 2.73.

Having the voltage values of the I-V curve, which are set to be values between zero and the time-varying open-circuit voltage established in Equation 2.71, and the current values of the I-V curve, which are determined based on Equation 2.73, allows for the power produced by the solar photovoltaic system to be determined. Equations 2.74 and 2.75 introduce the solar photovoltaic system's produced power and capacity factor profile, respectively.

$$P_{mpp}(t) = \max_{p \in \mathcal{P}} \left[I(t,p) \cdot V(t,p) \right], \qquad \forall t \in \mathcal{T} \tag{2.74}$$

$$CF_{pv}(t) = \frac{P_{mpp}(t)}{P_{mpp}^{nom}}, \qquad \forall t \in \mathcal{T} \tag{2.75}$$

Equation 2.74 models the ability of a solar photovoltaic system's maximum power point tracker to identify the maximum power output along the I-V curve. Finally, Equation 2.75 describes the time-varying capacity factor profile of the modeled solar photovoltaic system. The capacity factor profile takes the power output from the characteristic photovoltaic system and divides it by that characteristic photovoltaic system's nameplate capacity.

Net Energy Metering 3.0 Export Price Profiles

To determine the NEM 3.0 export price profiles, I follow the methodology prescribed by the California Public Utility Commission's guidance in their proposed Net Billing Tariff [96]. I combine the different component outputs of the E3 avoided cost calculator [104] to create an hourly composite price profile. Then, based on the simulation year, I create an annual hourly price profile, where prices are set based on the composite price's average value for each month, weekdays versus weekends and holidays, and each hour of the day. In other words, each month has forty-eight different prices calculated, twenty-four prices corresponding to each hour on weekdays and twenty-four prices corresponding to each hour on weekends and holidays. Finally, in accordance with guidance from the CPUC and PG&E, the volumetric price that recovers non-bypassable charges is subtracted from the hourly export prices [96, 105]. As was discussed in Section 2.3.2, non-bypassable charges are accounted for in the NEM 3.0 export price signal to help influence consumer decision making with regards to self-consuming or exporting excess energy.

2.3.5 Postprocessing Workflows

Following the solution of one of its constituent optimization problems, DERIVE produces pertinent summary statistics and data. For both the production cost and capacity expansion problems, DERIVE creates two files: one that contains the time-series results for relevant decision variables, expressions, and parameters and another that shows the consumer's total electricity bill and bill components. Unique to the capacity expansion problem, DERIVE also creates a file that reveals resultant investment costs and quantities. Both the time-series results and the investment results are straightforward to create, as those files essentially contain either preestablished parameters or direct optimization results. However, the electricity bill results require a little more care since their calculation deviates slightly from the price components introduced in Section 2.3.2.

In modeling the different price components to which consumers are exposed, there are design decisions that must be made to convey the impact of certain prices without necessarily incorporating the full complexity of the total accounting. Some, but not all, price components will resemble a price component included in Section 2.3.2. Equations (2.76) through (2.81) reveal the bill components included in an example[6] of the total electricity bill calculation portion of the postprocessing workflow[7].

$$\Pi_{en} = \frac{1}{\Gamma} \cdot \sum_{t \in \mathcal{T}} \pi_{en}(t) \cdot d_{net}(t) \tag{2.76}$$

$$\Pi_{nbc} = \frac{1}{\Gamma} \cdot \pi_{nbc} \cdot \sum_{t \in \mathcal{T}} d_{net}(t) \tag{2.77}$$

$$\Pi_{dem} = \sum_{n \in \mathcal{N}} \pi_{dem}(n) \cdot d_{max}(n) \tag{2.78}$$

$$\Pi_{fix} = \mu_{fix} \cdot \pi_{fix} \tag{2.79}$$

$$\Pi_{nem} = \frac{1}{\Gamma} \cdot \sum_{t \in \mathcal{T}} \left[\pi_{exp}(t) + \pi_{nbc}\right] \cdot p_{exp}(t) \tag{2.80}$$

[6]For brevity, this example includes a consumer exposed to energy charges, demand charges, and fixed charges who is participating in a net energy metering 3.0 program. If all programs modeled in this chapter were considered, then bill components for a critical peak pricing program and a tiered energy tariff would also be included.

[7]Please note and excuse the slight abuse of notation in Equations (2.76) through (2.81). To avoid creating new sets for the time step increments in a year and the demand-charge-specific time-of-use periods over a year, the established set notation $\mathcal{T}$ and $\mathcal{N}$, respectively, are used.

$$\Pi_{total} = \Pi_{en} + \Pi_{dem} + \Pi_{fix} - \min\{\Pi_{nem}, \Pi_{en} - \Pi_{nbc}\} \tag{2.81}$$

Equation (2.76) calculates the consumer's total annual energy charge. Equation (2.77) calculates the consumer's total annual non-bypassable charges, which are a subset of the consumer's total annual energy charge. Equation (2.78) calculates the consumer's total annual demand charge. Equation (2.79) calculates the consumer's total annual fixed charge. Equation (2.80) calculates the total annual credits a consumer earned from their exports in a net energy metering program. Note that the export price is no longer reduced in each time step t by the volumetric price used to recover the non-bypassable charges[8]. In the optimization formulation, the volumetric price of the non-bypassable charges is considered in the export price signal of the relevant net energy metering programs to convey the potential value reduction of net energy metering credits if non-bypassable charges make up a large part of the consumer's bill. This inclusion makes it so that self-consumption of generated energy (i.e., energy produced from a behind-the-meter solar photovoltaic system or discharged by a battery energy storage system) can be more attractive in the optimization problem, something that attempts to capture the realism of a consumer attempting to avoid incurring additional non-bypassable charges. Equation (2.81) calculates the consumer's total electricity bill, comprised of the bill components specified in Equations (2.76) through (2.80)[9]. As can be seen, this equation accounts for the reality of net energy metering credits only being able to recover the portion of a consumer's energy charges that do not include the non-bypassable charges [96, 103].

[8] In net energy metering programs that do not ensure the recovery of non-bypassable charges (e.g., NEM 1.0 programs), $\pi_{nbc} = 0$ in Equation (2.80).

[9] Note that the quantity of net energy metering credits that can be recovered and used to help offset the total electricity bill are calculated to reflect the example's selection of a net energy metering 3.0 program.

Chapter 3

EXAMINING THE IMPACTS OF TECHNOLOGY-DISCRIMINATING POLICIES ON THE VALUE OF FLEXIBLE DISTRIBUTED RESOURCES

3.1 Introduction

Over the coming decades, the push to decarbonize every sector of the U.S. economy will create drastic changes in how electricity is generated and consumed. On the supply side, large amounts of variable renewable energy generation are expected to be integrated to the electric grid [3, 4, 5]. These resources, which are cheap to operate but dependent on the weather, will need to be supported in part by flexible resources (e.g., battery energy storage, shiftable flexible demand) that can help meet brief demand shortfalls or respond to necessary economic signals [43]. On the demand side, the push towards widespread electrification will seek to replace resources that consume fossil fuels (e.g., internal combustion engine vehicles, natural gas-fueled furnaces) with resources that consume electricity (e.g., electric vehicles, air-source heat pumps) [34]. Electrification of transportation and building heating and cooling demand is projected to introduce thousands of terawatt-hours of consumption by 2050 [35], with new electrified demand both magnifying existing demand peaks and introducing new seasonal and temporal demand peaks [5, 38].

Fortunately, there are some promising solutions to help address the projected growth in electrified demand and the impending variability created by large-scale renewable energy integration. Many sources of electrified demand will be able to offer some level of flexibility, ranging on the scale of hours to days [35]. Additionally, the continued deployment of distributed energy resources (DERs) like solar photovoltaics (PVs) and battery energy storage (BES), which consumers can install to reduce their electricity bills and provide backup power, provides a potential trove of flexibility [40]. By tapping into the flexibility offered by electrified demand and other DERs, consumers' net demand profiles can be shaped to limit demand peaks and better align with the available generation mix.

One way that electric utilities have tried to help shape consumer net demand profiles in response to changing grid conditions is through the use of electric tariffs. An increasing number of utilities have begun to incorporate time-varying pricing mechanisms into their electricity tariffs to encourage consumption during times that can benefit the grid and, in turn, reduce operational costs for the utility. Though some of the proposed and implemented mechanisms may be less dynamic price signals (e.g., time-of-use energy prices, time-based demand charges) than their economic ideals (e.g., real-time pricing, coincident demand charges), even the coarser offerings have typically been regarded as having efficiency improvements over traditional flat rates while still offering consumers predictability in their electricity prices [72, 71]. Some utilities, in response to the growth in access and affordability of DERs and flexible demand resources, have even begun to offer technology-specific tariffs that are designed to encourage the deployment and operation of particular technologies.

However, some recent technology-oriented tariffs appear to be discriminatory in nature, focusing on the flexibility benefits of BES over those of general flexible demand resources. Pacific Gas and Electric Company (PG&E), the investor-owned utility that serves the majority of Northern California, offers the Option S for Storage rider to its B-19 tariff, which provides commercial consumers with BES lower demand charges on maximum daily demand and maximum demand during time-of-use periods [115]. This allows consumers with flexibility afforded by their BES to have a potentially significant reduction in the demand charges on their monthly electricity bill. Another example comes from the California Public Utilities Commission (CPUC), which recently introduced the Net Billing Tariff as a successor to the Net Energy Metering (NEM) 2.0 program. Concerns over cost shifts created by NEM 2.0 caused the CPUC to transition to the Net Billing Tariff, which changed the export compensation offered to consumers. While NEM 2.0 allowed a renewable energy generating facility to export excess generation and be compensated at the retail energy price (so long as non-bypassable charges are not offset), the Net Billing Tariff instead sets the export price according to the output of an avoided cost calculator, which is intended to better account for the benefits a distributed energy resource provides the grid [96]. This shift in export pricing schemes affects consumers with behind-the-meter solar PVs, as the export price signals that align with the solar generating hours are now much lower than they were under NEM 2.0. Now, a BES system is necessary if consumers want to export excess solar generation during the highest-priced hours.

While other flexible resources, such as shiftable flexible demand, are not perfect substitutes for BES, the tariffs described above do not solely leverage the technological capabilities of BES that make it a unique resource. For instance, BES can potentially serve as a backup power source to consumers, but there is nothing in the B-19 Option S tariff nor the Net Billing Tariff that encourages BES operation to hedge against potential outages; in fact, any capacity reserved in the event of an outage is capacity that is not helping reduce demand charges nor being used to store excess solar energy for later exports. Instead, these tariffs strive to have consumers use their BES to reduce net consumption during certain hours, a capability that is hardly unique. Shiftable flexible demand is also capable of shifting consumer demand to reduce consumption during peak-period times and enabling the self-consumption of solar energy when it is less valuable to the grid (at least as determined by an avoided cost calculator).

The motivation for this chapter is to examine the impacts that the discriminatory BES-specific policies have on commercial consumers with different asset mixes. To better understand the benefit of offering these tariffs exclusively to consumers with BES, I use the DER Investment and Valuation Engine (DERIVE) [116] to expose consumers with BES and consumers with shiftable flexible demand to the technology-specific policies. Modeling the impact of electricity rates on DERs is itself not new to the literature. Schittekatte et al. [72] consider the effectiveness of a time-of-use tariff and a time-of-use tariff paired with critical peak pricing in getting flexible demand resources to respond in a way that mimics decision making under real-time pricing. Spiller et al. [73] examine the impact that a flat tariff, a time-of-use tariff, a real-time pricing tariff, and two separate cost-reflective tariffs have on DER adoption and operation. Reeve et al. [117] model BES and flexible demand interactions with a flat rate and a distribution-level market mechanism to understand how each rate influences resource operation and system costs. Darghouth et al. [118] and Darghouth et al. [119] explore how different rate structures paired with NEM can influence electricity bill savings and PV adoption. However, these studies ultimately focus on modeling rates that are designed to be largely technology-agnostic, which do not reveal the types of impacts that I explore herein.

This chapter builds on the previous electricity rate analysis and DER modeling literature to examine the design considerations of technology-specific electricity rates and understand their impacts on DERs as a result. This chapter presents two case studies, the first, which looks at the implications of extending the BES-centric B-19 Option S tariff to shiftable flexible demand resources, and the second, which seeks to understand the impacts that the Net Billing Tariff has on different classes of distributed flexible resources. In addition to the insights offered about these specific policies, this chapter helps demonstrate the capabilities of DERIVE in being able to model and simulate complex rate structures for analytical purposes.

The rest of this chapter is organized as follows. Section 3.2 describes the mathematical model used to minimize the electricity bill of a consumer with a combination of PV, BES, and shiftable flexible demand resources. Section 3.3 presents the case study design and results for the first case study: "Should Storage-Centric Tariffs be Extended to Commercial Flexible Demand?[1]" Section 3.4 presents the case study design and results for the second case study: "Effects of Net Metering Policies on Distributed Energy Resource Valuation and Operation." Section 3.5 concludes the chapter.

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[1] A previous version of this case study was published in:

L. D. Smith and D. S. Kirschen, "Should Storage-Centric Tariffs be Extended to Commercial Flexible Demand?," in *2021 IEEE Power & Energy Society General Meeting (PESGM)*, (Denver, CO), 2022.

3.2 Mathematical Formulation

I define a mixed-integer linear program (MILP) to determine the minimum electricity bill, comprised of costs associated with time-of-use (TOU) rates and revenues associated with NEM, for a consumer with a combination of PV, BES, and shiftable flexible demand resources. Within the MILP, asset operation is optimized to achieve the minimum bill, while a simulated demand profile and a PV capacity factor profile are provided as parameters. The MILP is formulated as follows:

$$\min. \quad \sum_{n \in \mathcal{N}} \pi_{dem}(n) \cdot d_{max}(n) + \sum_{t \in \mathcal{T}} \pi_{en}(t) \cdot d_{net}(t) - \sum_{t \in \mathcal{T}} \pi_{exp}(t) \cdot \left[p_{pv}^{exp}(t) + p_{dis}^{exp}(t) \right] \tag{3.1}$$

subject to:

$$d_{net}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{3.2}$$

$$\zeta_{net}(s) = 1 \Rightarrow d_{net}(s) \leq 0, \qquad \forall s \in \mathcal{S} \tag{3.3}$$

$$p_{pv}^{exp}(s) + p_{dis}^{exp}(s) \leq \zeta_{net}(s) \cdot (P_{pv} + P_{bes}), \quad \forall s \in \mathcal{S} \subseteq \mathcal{T} \tag{3.4}$$

$$\delta(t, n) \cdot d_{net}(t) \leq d_{max}(n), \quad \forall t \in \mathcal{T}, \quad \forall n \in \mathcal{N} \tag{3.5}$$

$$d_{max}(n) \geq 0, \quad \forall n \in \mathcal{N} \tag{3.6}$$

$$p_{pv}^{btm}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{3.7}$$

$$p_{pv}^{exp}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{3.8}$$

$$p_{pv}^{btm}(t) + p_{pv}^{exp}(t) \leq \eta_{inv} \cdot P_{pv} \cdot CF_{pv}(t), \quad \forall t \in \mathcal{T} \tag{3.9}$$

$$0 \leq p_{cha}(t) \leq P_{bes}, \quad \forall t \in \mathcal{T} \tag{3.10}$$

$$p_{dis}^{btm}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{3.11}$$

$$p_{dis}^{exp}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{3.12}$$

$$p_{dis}^{btm}(t) + p_{dis}^{exp}(t) \leq P_{bes}, \quad \forall t \in \mathcal{T} \tag{3.13}$$

$$J(t) = J(t-1) + \eta_{bes}^{rte} \cdot p_{cha}(t) - p_{dis}^{btm}(t) - p_{dis}^{exp}(t), \quad \forall t \in \mathcal{T} > 0 \tag{3.14}$$

$$J(t) = J_{init} + \eta_{bes}^{rte} \cdot p_{cha}(t) - p_{dis}^{btm}(t) - p_{dis}^{exp}(t), \quad t = 0 \tag{3.15}$$

$$\underline{J} \leq J(t) \leq \overline{J}, \quad \forall t \in \mathcal{T} \tag{3.16}$$

$$J(|\mathcal{T}|) \geq J_{init} \tag{3.17}$$

$$p_{cha}(t) \leq p_{pv}^{btm}(t), \quad \forall t \in \mathcal{T} \tag{3.18}$$

$$0 \leq d_{dev}^{dn}(t) \leq \overline{d}_{dev}^{dn}(t), \quad \forall t \in \mathcal{T} \tag{3.19}$$

$$0 \leq d_{dev}^{up}(t) \leq \overline{d}_{dev}^{up}(t), \quad \forall t \in \mathcal{T} \tag{3.20}$$

$$\sum_{t \in \mathcal{T}} \left[d_{dev}^{up}(t) - d_{dev}^{dn}(t) \right] = 0 \tag{3.21}$$

$$\sum_{\tau=k}^{\Delta+k-1} \left[d_{dev}^{up}(\tau) - d_{dev}^{dn}(\tau) \right] \geq 0, \quad k = 1, ..., |\mathcal{T}| - \Delta + 1 \tag{3.22}$$

where

$$d_{net}(t) = d(t) - p_{pv}^{btm}(t) + p_{cha}(t) - p_{dis}^{btm}(t) + d_{dev}^{up}(t) - d_{dev}^{dn}(t), \ \forall t \in \mathcal{T} \tag{3.23}$$

Equation (3.1) is the objective function, reflecting the consumer's total electricity bill. The first summation pertains to the tariff's demand charges, the second summation describes the tariff's energy charge, and the third summation represents the NEM revenue, where the value of the export price signal π_{exp} varies depending on the NEM version being considered. Note that BES exports p_{dis}^{exp} may be prohibited depending on the scenario under consideration.

Constraints (3.2) – (3.6) describe bounds placed on demand-related values and expressions. Constraint (3.2) prevents the consumer's net demand, which is defined in Equation (3.23) and does not include exports p_{pv}^{exp} and p_{dis}^{exp}, from being exported to the grid. Differing from [92] and [93], exports and behind-the-meter consumption are disaggregated to avoid the practical infeasibility that occurs when export prices are greater than energy prices (i.e., $\pi_{exp}(t) > \pi_{en}(t)$), as is possible under the CPUC's Net Billing Tariff. Constraints (3.3) and (3.4) ensure there are only exports if the consumer's assets have already met the net demand. Constraints (3.5) and (3.6) define the maximum demand during different periods. The δ in Constraint (3.5) is a constant that equals one when t aligns with period n and zero otherwise.

Constraints (3.7) – (3.9) describe the PV model's bounds. The PV capacity factor profile is determined by dividing the simulated PV array's generation output by its rated capacity. The PV array's generation output is determined using solution methods for solving the single-diode PV model; a detailed formulation of these solution methods are available in Section 2.3.4 of Chapter 2.

Constraints (3.10) – (3.18) describe the BES model. Constraint (3.10) restricts the charging power of the BES, while Constraints (3.11) – (3.13) restrict the discharging power. Constraints (3.14) and (3.15) define the state of charge at time t. Constraint (3.16) enforces upper and lower bounds on the state of charge. Constraint (3.17) ensures that the final state of charge (at $t = |\mathcal{T}|$) is no less than the initial state of charge, preventing perverse discharging schemes near the later time steps of the optimization horizon. Constraint (3.18) prevents the BES from charging from the grid, if specified by the scenario.

Constraints (3.19) – (3.22) describe the shiftable flexible demand model. Constraints (3.19) and (3.20) bound the amount demand deviates from the consumer's baseline demand profile. Constraint (3.21) ensures demand is balanced over the optimization horizon. Constraint (3.22) is a rolling window of size Δ in which demand deviations cannot result in a net decrease in demand.

3.3 Case Study I: Should Storage-Centric Tariffs be Extended to Commercial Flexible Demand?

3.3.1 Case Study Design

I consider two archetypal commercial consumers to assess the impact of extending the storage-centric tariff to consumers with flexible demand: a consumer with morning-and-evening-peaking (MEP) demand and a consumer with midday-peaking (MDP) demand. These consumers are modeled using the Department of Energy's large hotel and supermarket commercial prototype models, respectively, and typical meteorological year (TMY3) data from San Jose International Airport in San Jose, CA. The demand profiles are available from Ong and Clark [120] and have maximum demands of 430 kW and 321 kW for the MEP and MDP consumers, respectively. Each consumer is simulated alongside a solar PV system and a distributed flexible resource: either shiftable flexible demand or a BES system. Giving a consumer flexible demand allows the efficacy of extending the storage-centric tariff to other flexible resources to be tested, while giving consumers a BES system provides a baseline for results under the existing storage-centric tariff. The PV systems' rated capacities are sized according to each consumer's maximum demand. To determine the PV's capacity factor profile, I use TMY3 data from San Jose International Airport [121].

For flexible demand, I consider demand flexibility percentages ranging from 0% to 100% and load recovery periods of one, four, eight, twelve, and twenty-four hours. I define "demand flexibility percentage" as the percent of the consumer's base demand that can be curtailed or increased during a given time step, and I use it to populate the bounds placed on the demand deviations. As noted by Smith and Kirschen [93], potential bottlenecks during low-demand periods can cause this model to be conservative, but I ultimately believe it is a useful consideration for modeling technology-agnostic flexible demand that may experience intermittent availability from its assorted assets.

For the BES system, rated power capacity is set to values between 0% and 150% of the consumers' maximum demand, with durations of one, two, and four hours being considered. In this case study, BES are allowed to charge from the grid (in addition to using generation produced by the onsite PV system), but are prohibited from providing grid exports. Such a policy is commonly allowed by NEM programs [122, 123] and enables consumers with BES to take advantage of price arbitrage opportunities offered by the time-varying tariff.

The modeled consumers are exposed to PG&E's Electric Schedule B-19, which is a TOU-based tariff offered to commercial consumers. One of the riders under the B-19 tariff is the "Option S for Storage" rate schedule, which is available to consumers with BES installations that have power ratings of at least ten percent of the consumer's maximum annual demand. The Option S rate schedule imposes low demand charges on maximum daily demand and maximum demand during the TOU periods. In return, the Option S rate schedule has higher TOU energy charges, particularly during peak times [115]. I consider consumer participation under the base TOU rate schedule (referred to as the "base" tariff) and the Option S rider (referred to as the "storage-centric" tariff). Additionally, consumers participate in NEM 2.0, which sets the export price signal equal to the TOU energy price minus a small non-bypassable charge of $0.02129/kWh [115, 122]. To understand the impact of consumers with flexible demand participating under the storage-centric tariff, I examine both the utility's perspective, through impacts on net demand ramp rates and net demand during peak hours, and the consumer's perspective, through impacts on the total electricity bill.

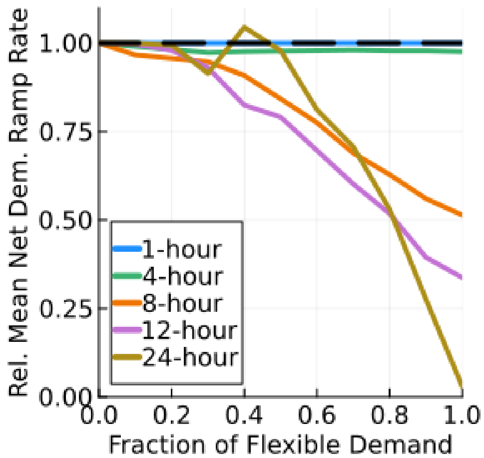
3.3.2 Results and Discussion

The model from Section 3.2 is implemented in DERIVE, which was introduced in Chapter 2 and is publicly available on GitHub [116]. The following subsections present results from these simulations and discuss how the specified storage-centric tariff affects asset operation and valuation.

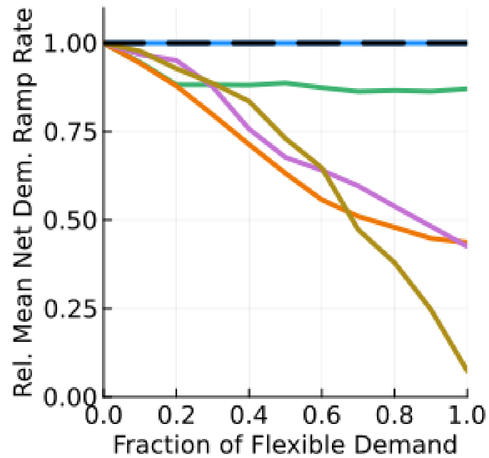
The Utility's Perspective

To examine the impact of consumers with flexible demand participating in the storage-centric tariff from the perspective of the utility, I compare net demand ramp rates and net demand realized under the base and storage-centric tariffs for different flexible demand configurations. The peak-period hours of 4pm to 9pm are of particular interest, as those are the hours when California's high penetration of solar generation drops off and gives way to high evening demand. The coincidence of these events results in sharp net demand ramp rates and high net demand, both of which necessitate the operation of expensive peaking generation [124]. Increased flexibility, including from flexible demand, can therefore be especially valuable to grid operators during these hours [5, 46, 124].

Figure 3.1 shows the consumers' mean net demand ramp rates during peak hours under the storage-centric tariff relative to the consumers' mean net demand ramp rates during peak hours under the base tariff. Sensitivity analyses are conducted for different load recovery periods (ranging from one to twenty-four hours) and different demand flexibility percentages



(a)

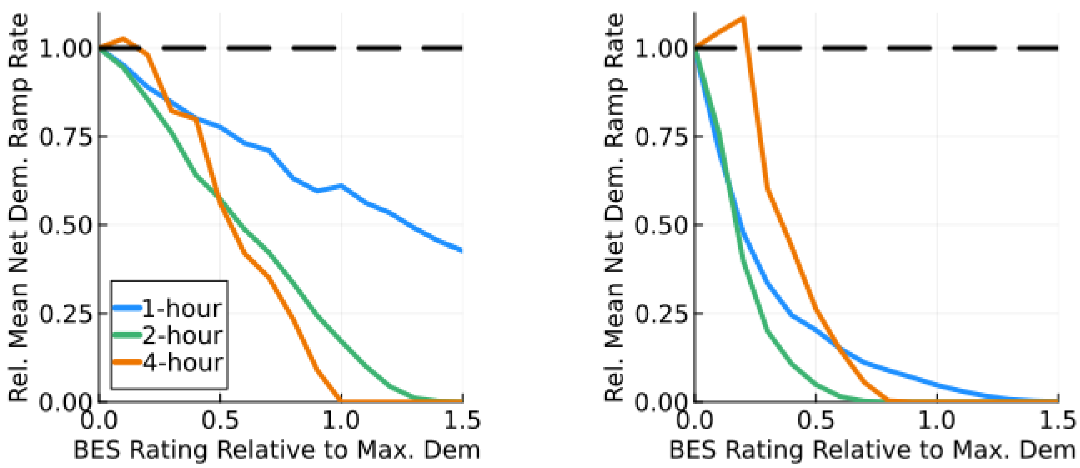


(b)

Figure 3.1: Mean net demand ramp rate under the storage-centric tariff relative to that under the base tariff during peak hours for a consumer with flexible demand. (a) depicts the relative mean net demand ramp rate for the MEP consumer and (b) shows the same for the MDP consumer. Different load recovery periods are compared over the range of demand flexibility percentages.

(ranging from 0% to 100%). As a comparison, Figure 3.2 shows the same relative mean net demand ramp rate plots, but for consumers with BES rather than flexible demand. Sensitivity analyses are conducted for different battery power ratings (ranging from 0% to 150% of the consumers' maximum demand) and battery durations (ranging from one to four hours).

As can be seen in Figures 3.1 and 3.2, taking service under the storage-centric tariff produces mean net demand ramp rates that are routinely lower than those observed under the base tariff. For consumers with flexible demand, net demand ramp rates under the storage-centric tariff improve relative to the base tariff as demand flexibility percentage increases. A similar result is observed for consumers with BES, where greater power ratings yield lower



(a)

(b)

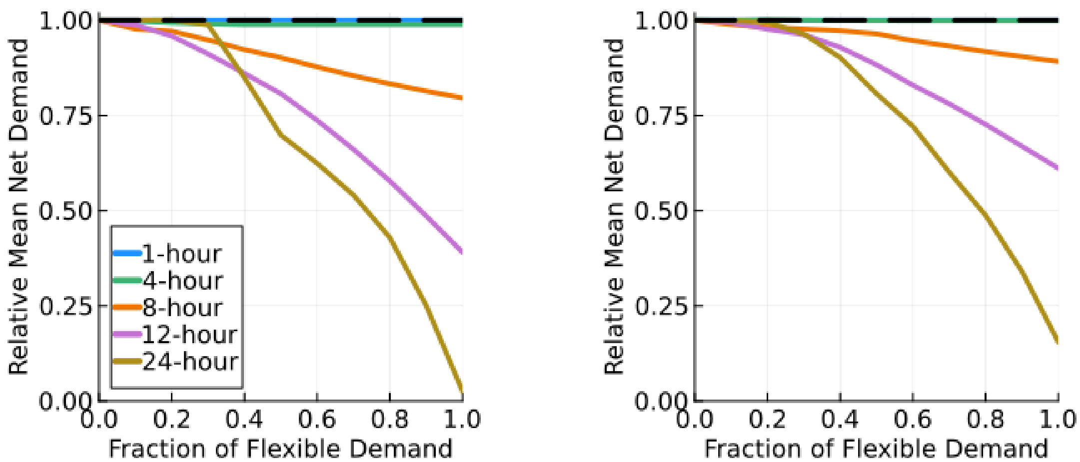
Figure 3.2: Mean net demand ramp rate under the storage-centric tariff relative to that under the base tariff during peak hours for a consumer with BES. (a) depicts the relative mean net demand ramp rate for the MEP consumer and (b) shows the same for the MDP consumer. Different battery durations are compared over the range of battery power ratings (relative to consumers' maximum demand).

net demand ramp rates under the storage-centric tariff. Higher peak-period energy charges, along with daily peak-period maximum demand charges, implemented by the storage-centric tariff, encourage a flatter net demand profile during peak hours [125]. The storage-centric tariff features starker differences in peak- and non-peak-period price signals than the base tariff, resulting in an optimal peak-period net demand profile that is as minimal and flat as possible.

Of note in Figures 3.1 and 3.2 is the apparent variability and general non-monotonicity of the relative mean net demand ramp rate curves. This is best explained by a couple characteristics intrinsic to the electric tariffs and the asset models. First, the electric tariffs implement discrete pricing periods, with the peak pricing period lasting five hours. If a resource is unable to sufficiently shift demand outside of the peak pricing period, due to a shorter demand recovery period (in the case of flexible demand) or battery duration (in the case of BES), the net demand profile will not change significantly from the base net demand profile, no matter the tariff. This results in net demand ramp rates that are more similar across the explored tariffs, as is seen for the smaller demand flexibility percentages in Figure 3.1. Conversely, when a resource becomes so flexible that most peak-period net demand can be shifted outside peak hours, the resultant net demand profile becomes increasingly similar under both tariffs. This behavior can be observed for the flexible demand with a twenty-four-hour recovery period and the four-hour BES, both of which produce smaller relative net demand ramp rates compared to some of the less-flexible configurations, particularly when the flexible demand has a lower demand flexibility percentage and the BES has a lower power rating.

Figure 3.3 shows the consumers' mean net demand during peak hours under the storage-centric tariff relative to the consumers' mean net demand during peak hours under the base tariff. Sensitivity analyses are conducted for different load recovery periods and different demand flexibility percentages. Figure 3.4 shows the same relative mean net demand plots, but for consumers with BES rather than flexible demand. Sensitivity analyses are conducted for different battery power ratings and battery durations.

Figures 3.3 and 3.4 exhibit similar trends, with mean net demand being similar between the two tariffs for assets that feature lower levels of flexibility. Flexible demand with lower demand recovery periods and BES systems with shorter durations cannot shift enough demand outside of the peak-pricing period, resulting in peak-period net demand profiles that do not drastically differ between the tariffs. Only when assets can shift a large amount of demand over a period that is sufficiently longer than the discrete peak pricing period do greater differences begin to arise between the peak-period net demand profiles under the two tariffs. This is apparent in Figure 3.3, where only the scenarios with larger demand recovery periods have a significant effect on the peak-period net demand profiles.



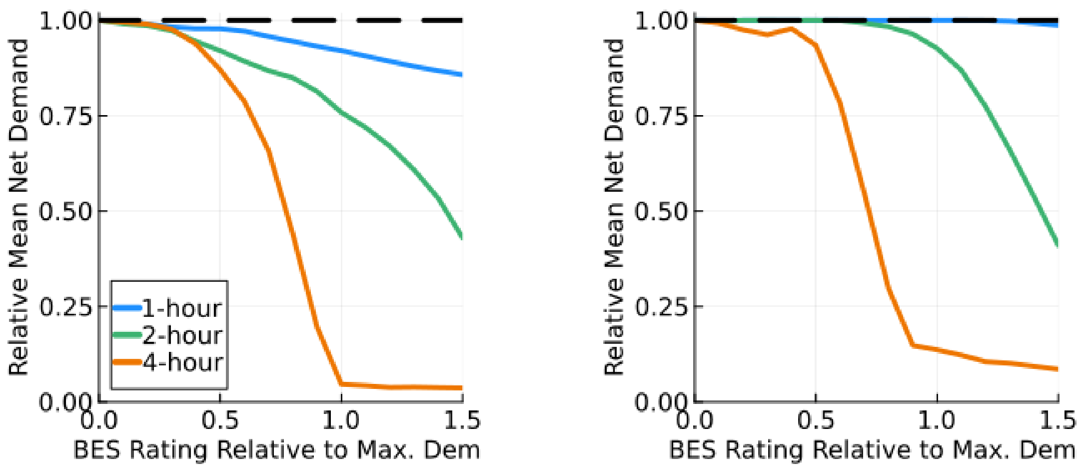
(a) (b)

Figure 3.3: Mean net demand under the storage-centric tariff relative to that under the base tariff during peak hours for a consumer with flexible demand. (a) depicts the relative mean net demand for the MEP consumer and (b) shows the same for the MDP consumer. Different load recovery periods are compared over the range of demand flexibility percentages.

The Consumer's Perspective

To assess the storage-centric tariff from the perspective of the consumers, I compare their total annual electric bills under the base and storage-centric tariffs for different configurations of flexible demand. While the previous subsection indicated that there can be a benefit to the utility if consumers with flexible demand adopt the storage-centric tariff, it is obvious that consumers will not voluntarily adopt a rate schedule if it is more expensive.

Figure 3.5 shows the consumers' total electric bill under the storage-centric tariff relative to the consumers' total electric bill under the base tariff. Sensitivity analyses are conducted for different load recovery periods and different demand flexibility percentages. Figure 3.6 shows the same relative total electric bill plots, but for consumers with BES rather than flexible demand. Sensitivity analyses are conducted for different battery power ratings and

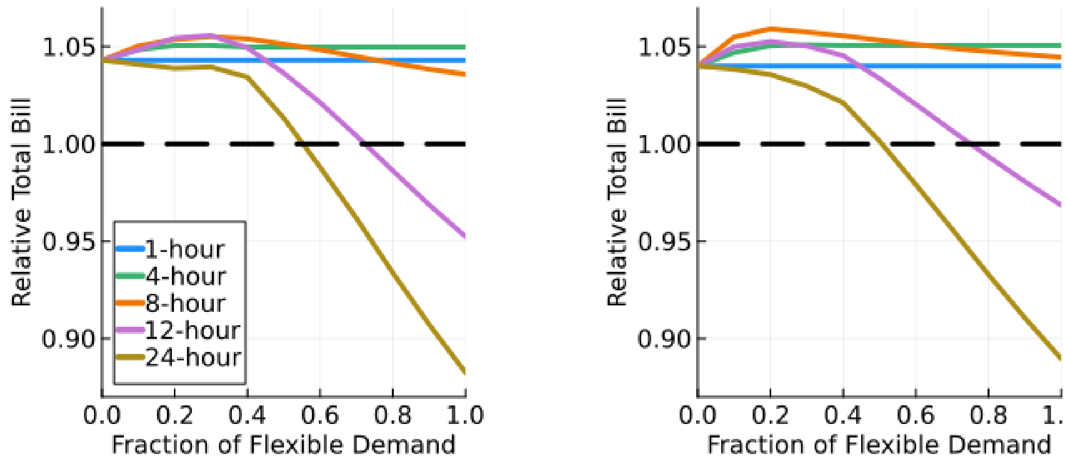


(a) (b)

Figure 3.4: Mean net demand under the storage-centric tariff relative to that under the base tariff during peak hours for a consumer with BES. (a) depicts the relative mean net demand for the MEP consumer and (b) shows the same for the MDP consumer. Different battery durations are compared over the range of battery power ratings (relative to consumers' maximum demand).

battery durations.

As is shown in Figures 3.5 and 3.6, consumer participation under the storage-centric tariff only benefits consumers that are highly flexible. In particular, the shiftable flexible demand must have at least a twelve-hour recovery duration and be no less than about fifty-percent flexible for the storage-centric tariff to be the cheaper option. As was discussed in the previous subsection, less-flexible consumers are unable to shift demand outside the peak pricing period, where the storage-centric tariff features greater energy charges than the base tariff. Such operational requirements would almost certainly preclude most consumers with flexible demand from taking service under the storage-centric tariff, at least with current technologies and use cases.



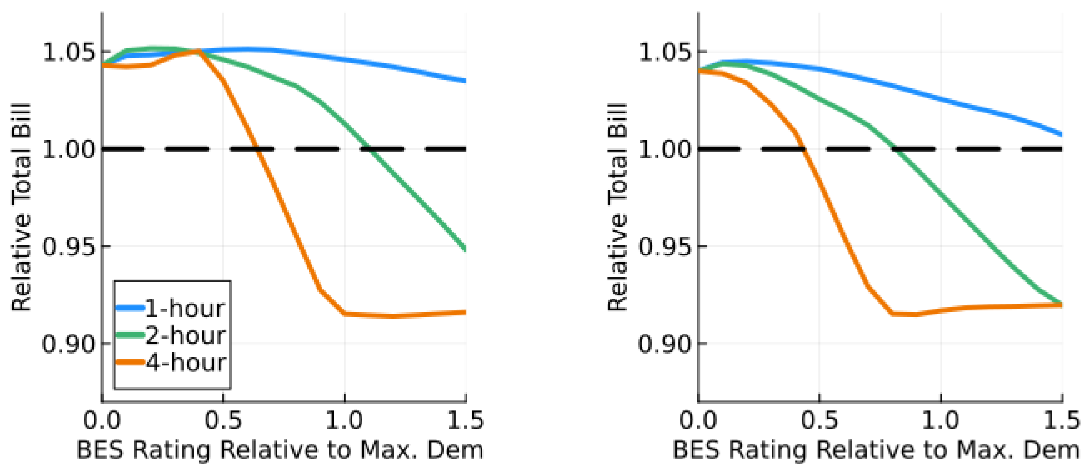
(a) (b)

Figure 3.5: Total electricity bill under the storage-centric tariff relative to that under the base tariff for a consumer with flexible demand. (a) depicts the relative total bill for the MEP consumer and (b) shows the same for the MDP consumer. Different load recovery periods are compared over the range of demand flexibility percentages.

3.4 Case Study II: Effects of Net Metering Policies on Distributed Energy Resource Valuation and Operation

3.4.1 Case Study Design

I again consider two archetypal commercial consumers to assess the impacts of different NEM policies: a consumer with morning-and-evening-peaking (MEP) demand and a consumer with midday-peaking (MDP) demand. These consumers are modeled using the Department of Energy's large hotel and supermarket commercial prototype models, respectively, and TMY3 data from Fresno Yosemite International Airport in Fresno, CA. The demand profiles are available from Ong and Clark [120] and have maximum demands of 444 kW and 358 kW for the MEP and MDP consumers, respectively.



(a) (b)

Figure 3.6: Total electricity bill under the storage-centric tariff relative to that under the base tariff for a consumer with BES. (a) depicts the relative total bill for the MEP consumer and (b) shows the same for the MDP consumer. Different battery durations are compared over the range of battery power ratings (relative to consumers' maximum demand).

With a source of renewable energy generation required for participation under NEM programs, each scenario models the consumers alongside a simulated solar PV system [126]. When testing the impact of different NEM policies on solar-only consumers, the PV's rated capacity is set to values between 0% and 150% of the consumers' maximum demand. When included alongside BES or flexible demand, the PV's rated capacity is sized according to the consumers' maximum demand. To determine the PV's capacity factor profile, I use TMY3 data from Fresno Yosemite International Airport [121].

To explore the impact of different NEM policies on consumers with flexible resources, I consider two configurations: PVs paired with either BES or shiftable flexible demand. The BES's rated power capacity is set to values between 0% and 150% of the consumers' maximum demand, with durations of two and six hours being considered. I model three BES management schemes for the solar-plus-storage consumers. The first allows BES to charge from the grid, but prohibits BES from producing grid exports. The second allows BES to charge only from paired PVs, but allows BES to export to the grid. Both designs are commonly allowed in NEM programs [126, 123]. The third, which is atypical for NEM, allows BES to charge from and export to the grid. This third management scheme is included to understand a best-case scenario for the BES in the event it were unrestricted. For flexible demand, I consider demand flexibility percentages ranging from 0% to 100% and load recovery periods of two, six, twelve, and twenty-four hours.

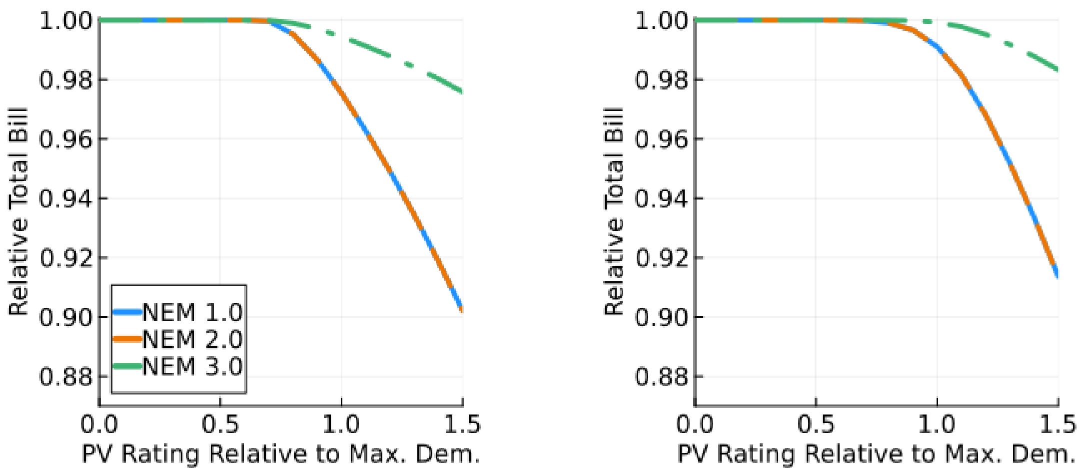
The modeled consumers are exposed to PG&E's Electric Schedule B-19 rate, a TOU tariff offered to commercial consumers [127]. I consider four NEM policies: NEM 1.0, NEM 2.0, NEM 3.0, and no NEM. NEM 1.0 sets the export price signal equal to the TOU energy prices. NEM 2.0 sets the export price signal equal to the TOU energy prices minus a small non-bypassable charge, which is set to \$0.02977/kWh [126, 127]. NEM 3.0 mimics the CPUC's Net Billing Tariff, which stipulates that export prices are set equal to outputs from E3's Avoided Cost Calculator [104] that are averaged by month, weekdays versus weekends and holidays, and hour of the day [96]. The NEM 3.0 export price signal is also reduced by the same non-bypassable charge of \$0.02977/kWh used in the NEM 2.0 export price signal [105]. Scenarios without NEM prohibit exports, causing PV generation to be consumed or curtailed.

3.4.2 Results and Discussion

The model from Section 3.2 is implemented in DERIVE, which was introduced in Chapter 2 and is publicly available on GitHub [116]. The following subsections present results from these simulations and discuss how different NEM policies affect asset valuation.

Impacts on Consumers with Only Solar PVs

To understand the impact of different NEM policies on PV systems, I first examine participation by solar-only consumers with different-sized systems. Numerical results can be seen



(a)

(b)

Figure 3.7: Total electricity bill under different NEM policies relative to that under no NEM for different consumers with only PVs. (a) depicts the MEP consumer's relative bills and (b) depicts the same for the MDP consumer.

in Figure 3.7, which shows the total electricity bill under NEM 1.0, 2.0, and 3.0 relative to the total electricity bill under no NEM participation for solar-only consumers.

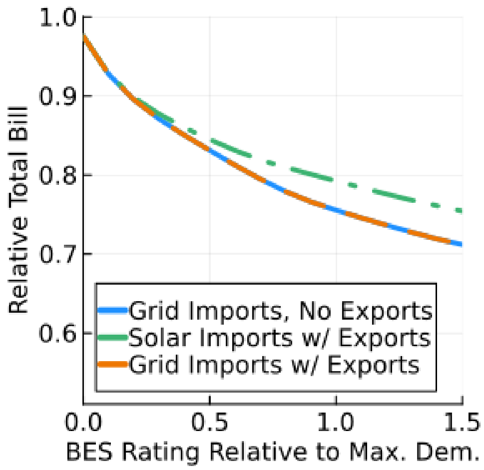
For PV systems that are not large enough to produce excess generation, all generation is self-consumed. From Figure 3.7, it can be seen that the MEP consumer requires a smaller relative PV capacity compared to the MDP consumer before excess generation can be exported. This is due in large part to the consumers' load shapes, with the MEP consumer having a smaller relative demand that coincides with PV generation compared to that of the MDP consumer.

Once the PV systems are relatively large enough to produce exports, it is clear that NEM 1.0 and NEM 2.0 provide consumers with the greatest export compensation while NEM 3.0 provides the worst; had the consumers' PV systems produced a greater amount of generation, there is a chance that NEM 2.0 could have proven less valuable than NEM 1.0 due to the non-bypassable charges that cannot be offset under NEM 2.0. Though NEM 3.0 offers export prices that can vastly exceed those offered under NEM 1.0 and NEM 2.0 (a maximum export price of \$2.96644/kWh versus a maximum export price of \$0.21585/kWh), such prices typically occur during the late afternoon and early evening when PV generation is waning or unavailable. With no flexible resources to take advantage of the heightened export prices, NEM 1.0 and NEM 2.0 can offer consumers better value during solar-generating hours, as NEM 1.0 and NEM 2.0 provide a greater export price than NEM 3.0 nearly 95% of the time during those hours.

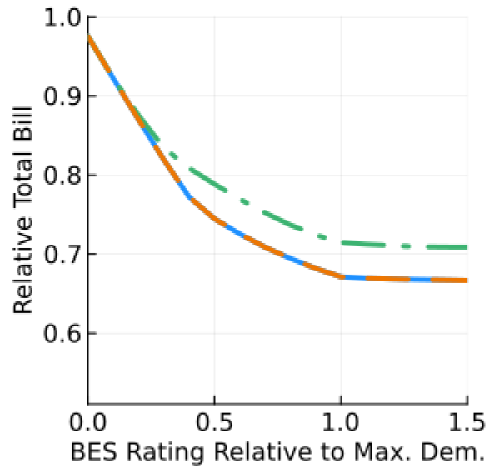
The Value of Battery Energy Storage Systems

As was discussed in the previous subsection, the inclusion of distributed flexible resources can better help consumers take advantage of the export prices offered under NEM policies, with an emphasis on those offered by NEM 3.0. To better understand the value of distributed flexibility, I first look at BES systems of different capacities and durations paired with a PV system rated to meet the consumers' maximum demand. Results from this analysis are shown in Figures 3.8 and 3.9, which show the total electricity bill for MEP consumers and MDP consumers, respectively, with BES and PVs under different NEM policies and different BES management schemes relative to the total electricity bill under no NEM participation for solar-only consumers.

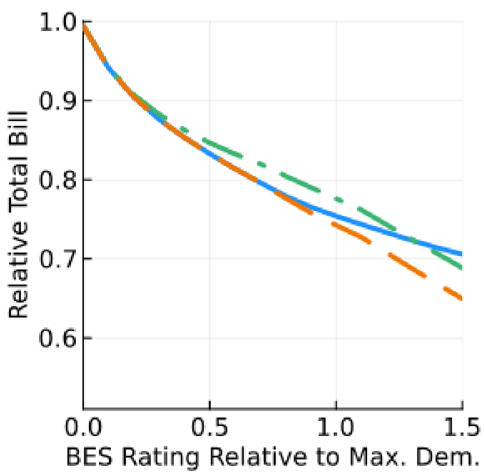
From Figures 3.8a, 3.8b, 3.9a, and 3.9b, the value of adding BES to a PV system when participating under NEM 2.0 can be observed. Under a NEM policy with export prices equal to or less than the TOU energy price, there is no value in exporting energy to the grid (unless the consumer lacks sufficient flexibility to make use of the generated solar energy). With the flexibility of BES, energy that would otherwise be exported can be shifted to a later, more expensive TOU period. As such, despite the ability of BES to charge from and export to the grid in one of the modeled management schemes, I observe an identical relative total electricity bill in the scenario where BES can charge from but cannot export to the grid. Both of these scenarios also result in lower relative total bills than the scenario in which



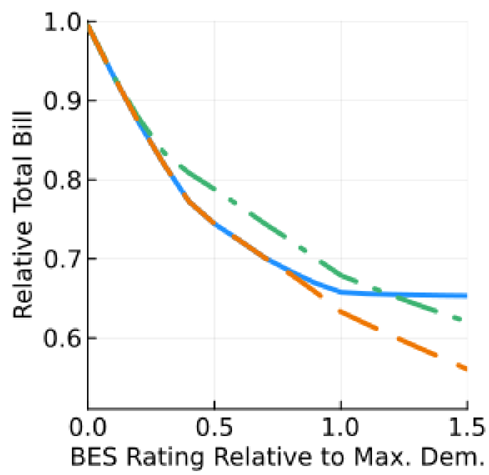
(a)



(b)



(c)



(d)

Figure 3.8: Total electricity bill under different NEM policies and BES management schemes for the MEP consumer with PVs and BES relative to that for the MEP consumer under no NEM with only PVs. (a) and (b) show consumer participation under NEM 2.0 and (c) and (d) show participation under NEM 3.0. (a) and (c) depict results obtained using a two-hour BES and (b) and (d) depict those with a six-hour BES. Each figure shows a range of BES power ratings (relative to the consumer's maximum demand).

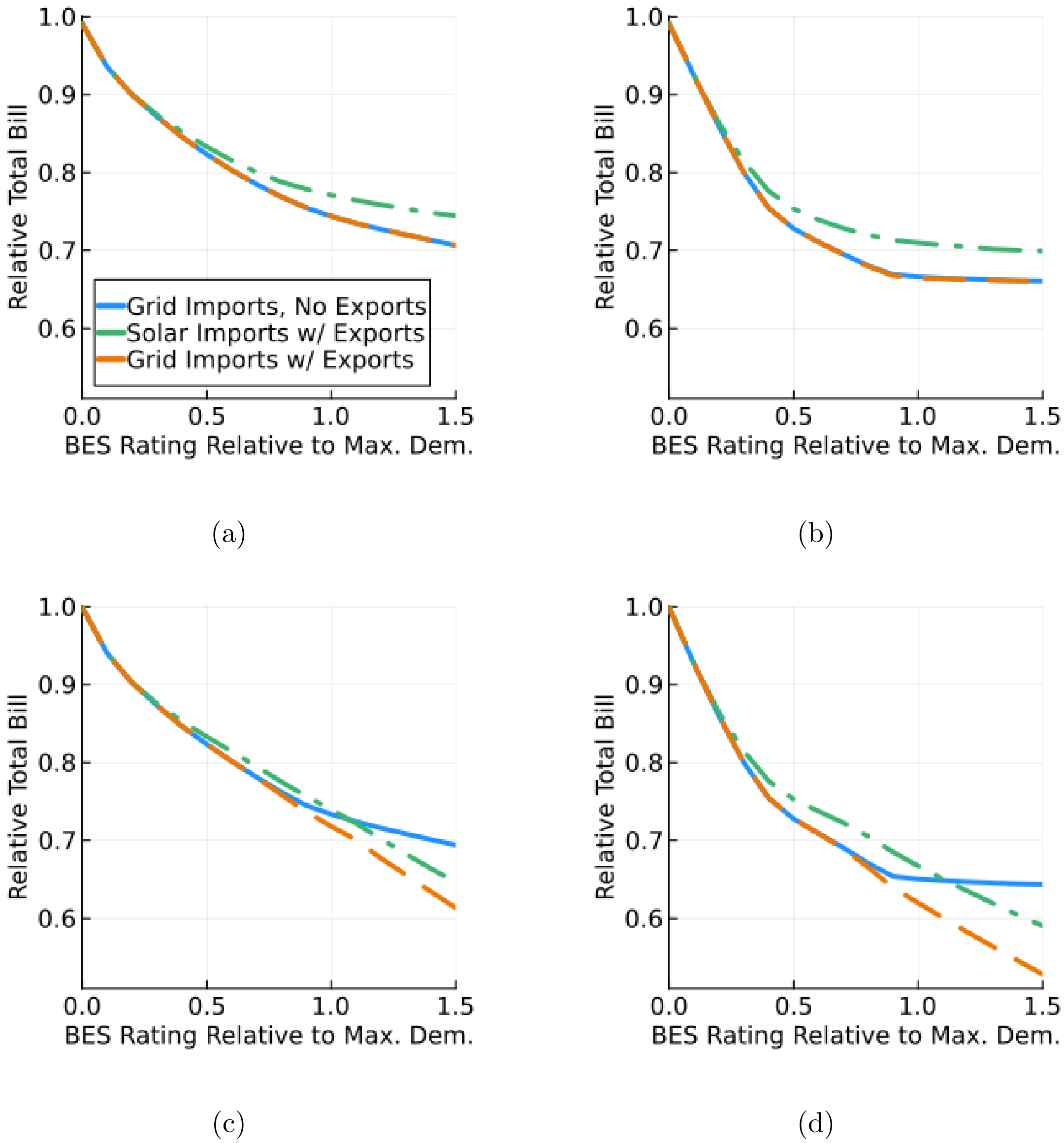


Figure 3.9: Total electricity bill under different NEM policies and BES management schemes for the MDP consumer with PVs and BES relative to that for the MDP consumer under no NEM with only PVs. (a) and (b) show consumer participation under NEM 2.0 and (c) and (d) show participation under NEM 3.0. (a) and (c) depict results obtained using a two-hour BES and (b) and (d) depict those with a six-hour BES. Each figure shows a range of BES power ratings (relative to the consumer's maximum demand).

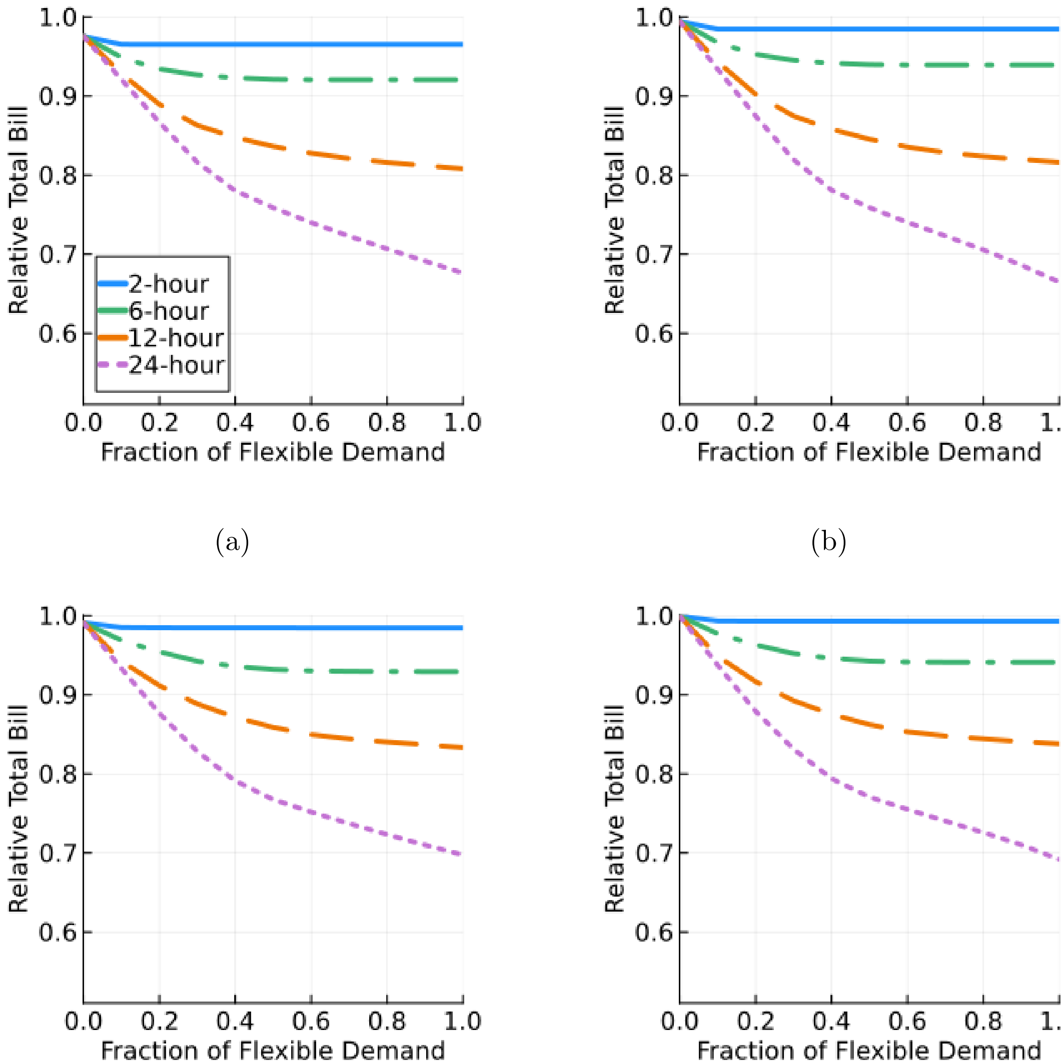
the BES can only charge from its PVs, but is allowed to export to the grid. This latter scenario loses out on valuable arbitrage opportunities afforded to the consumers with the other two BES management schemes. However, as can be seen in the figures, the value of the BES plateaus as its power rating increases, indicating that there is limited arbitrage and peak-shaving value available.

Under NEM 3.0, which influences the responses shown in Figures 3.8c, 3.8d, 3.9c, and 3.9d, high export prices provide an additional value stream to what was considered in the NEM 2.0 case. For smaller relative BES ratings, it is most valuable to participate in arbitrage and peak shaving, as evidenced by the identical relative total bills obtained using the two grid-imports-oriented management schemes. However, as the relative BES rating increases, the ability for the BES to export to the grid becomes increasingly valuable, especially as the value from arbitrage and peak shaving becomes exhausted. While charging from the grid and being able to export allows for the lowest relative total bill, the two more realistic management schemes each can provide consumers with valuable electricity bill savings depending on the rating of BES system.

Limited Value for Non-Storage Flexible Resources

Though flexible demand, through its inability to provide exports, is less suited for NEM programs compared to BES, the ability to shift demand can enable the PV system to export excess generation during times with high export prices. I examine pairing PVs and shiftable flexible demand with different demand flexibility percentages and recovery durations to understand the value provided by another source of flexibility. Figure 3.10 shows the total electricity bill for consumers with flexible demand and PVs under different NEM policies relative to that under no NEM participation for a solar-only consumer.

From Figure 3.10, it can be seen that the relative total bills for each consumer are similar regardless of participation under NEM 2.0 or NEM 3.0. This indicates that most of the value is not derived from the export prices, which would be difficult to take advantage of due to the time at which the most-profitable export prices occur, but rather from price differentials in



(a) (b)

(c) (d)

Figure 3.10: Total electricity bill under different NEM policies for consumers with PVs and flexible demand relative to that for consumers under no NEM with only PVs. (a) and (b) depict the MEP consumer's relative bills and (c) and (d) depict the same for the MDP consumer. (a) and (c) show consumer participation under NEM 2.0 and (b) and (d) show participation under NEM 3.0. Each figure shows various recovery periods and a range of demand flexibility percentages.

the underlying TOU rate. Only at its most flexible (i.e., a demand flexibility percentage near 100% and a recovery duration near twenty-four hours) does it appear that shiftable flexible demand is able to extract excess value by participating under NEM 3.0 when compared to NEM 2.0. This is in stark contrast to BES, which saw benefits under each management scheme with the shift from NEM 2.0 to NEM 3.0.

3.5 Conclusions

This chapter presents two case studies that explore the impacts that discriminatory technology-specific policies can have on consumers with different asset mixes. This first case study examines the impacts that PG&E's storage-centric electric tariff, the B-19 Option S for Storage rate schedule, has on consumers with BES and consumers with shiftable flexible demand, if such consumers were allowed to take service under the tariff. From the utility's perspective, consumers with flexible demand participating under the storage-centric tariff consistently reduced their net demand ramp rates during peak hours when compared to their participation under the base tariff. For higher levels of demand flexibility, consumers are also able to reduce their net demand during peak hours. Moreover, consumers with flexible demand produced similar relative changes to their peak-period net demand profiles when compared to consumers with BES, indicating that, under the current requirements, the storage-centric tariff could likely be technology-agnostic without changing the expected impact on the utility. From the consumer's perspective, participation in the storage-centric tariff is only beneficial for consumers with the highest levels of demand flexibility, making consumer participation under the currently constructed tariff a largely unappealing prospect if it was an option.

The second case study explores the impacts that different NEM policies have on consumers with different load shapes and DER mixes. The transition from NEM 2.0 to NEM 3.0, modeled after the CPUC's Net Billing Tariff, negatively impacts consumers with only solar PVs. The inclusion of large, but limited, export prices in NEM 3.0 necessitates that consumers have a specific source of distributed flexibility at their disposal. BES, under any of the three explored management schemes, can provide increased value to consumers under

NEM 3.0 compared to NEM 2.0. However, consumers with shiftable flexible demand are unable to see the same value gains between NEM 2.0 and NEM 3.0, even if flexible demand is at its most flexible. While the first case study highlights the programmatic restrictions that discriminate against broader flexible demand participation, the second case study reveals a tariff design that restricts participation through structural limitations, as flexible demand is unable to export power to the grid.

Both of these case studies highlight the need for sound, cost-reflective rate design. Both policies explored in this chapter are centered around rate components that are generally deemed to be inefficient by the literature. The storage-centric tariff examined in the first case study employed multiple non-coincident demand charges, which seek to suppress consumer demand during times in which the grid is not necessarily constrained, while the NEM 3.0 export prices explored in the second case study were unsymmetrical, only allowing resources that can produce grid exports to realize the additional value stream. Instead of implementing multiple inefficient technology-specific rates, regulators should be focusing on rates that are efficient, cost-reflective, and symmetrical, allowing multiple different DERs to participate in a way that is mutually beneficial to consumers and the grid [68, 71, 117, 41].

Chapter 4

COMPLEMENTARITY OF BEHIND-THE-METER SOLAR AND STORAGE RESOURCES UNDER CONTEMPORARY MECHANISMS

4.1 Introduction

Over the last few decades, export compensation mechanisms for behind-the-meter solar owners, such as net energy metering (NEM), have undergone some changes. NEM has been a largely successful policy aimed at increasing the penetration of behind-the-meter solar generation and helping reduce the costs of solar photovoltaic (PV) systems for consumers. However, as solar PVs have become more mature and have decreased in cost, public utilities commissions have begun to update their NEM programs. The original iteration, "NEM 1.0," compensated consumers by paying them the same amount as their electricity rate for any excess generation that was exported. As concerns over cost shifts arose, "NEM 2.0" was introduced, resulting in consumers receiving the same export compensation as they did under NEM 1.0 up to a cap. This cap was determined by a consumer's total annual energy charge minus some non-bypassable charges, which are determined by multiplying a small volumetric rate (e.g., \$0.02/kWh to \$0.03/kWh in the Pacific Gas and Electric Company (PG&E) service territory) by the annual energy a consumer purchases from the grid [103]. With further concerns over cost shifts [128], California recently changed NEM again to a third iteration, "NEM 3.0," or as the California Public Utilities Commission (CPUC) calls it, the "Net Billing Tariff" (NBT). NEM 3.0 aims to better align export prices with value that can be provided to the system [96].

While NEM programs were originally established to help incorporate behind-the-meter solar generation, NEM 3.0 proposals like the CPUC's NBT seem to indicate there has been a shift in the technology of interest. Though a renewable energy generating facility, such as a solar PV system, is still a necessary component for NEM participation, the focus on export values that do not align well with solar-generating times suggest there is a push to enable more distributed flexible resources, such as battery energy storage [96]. Solar-plus-storage systems are not novel, but previous NEM policies did little more than encourage storage to partake in arbitrage and peak shaving. New export prices that consider the system-level value could make exports an additional value stream for properly configured battery energy storage (BES) systems.

Hanging over this transition between compensation mechanisms is a concern for what might come of the distributed solar industry. Though much has been written on the negative effects that adopting NEM 3.0 has had on behind-the-meter solar PV installations [129, 130, 131, 132], others argue that this transition helps remove a disproportionate subsidy for distributed solar [128], which often comes at the expense lower-income consumers who are less likely to have solar PVs [133] and must cover for NEM programs through regressive electricity tariffs [69, 70]. Though NEM 3.0 may not offer as strong of a price signal to distributed solar, the need for a consumer to have a renewable energy generating facility to participate ties the viability of NEM 3.0 to the ability of consumers to afford solar PVs in addition to BES systems, which appear to be NEM 3.0's subsidized technology of choice.

As such, it is important to understand the ability of current mechanisms to support consumer adoption of behind-the-meter solar and storage resources. Many previous studies have examined the role of traditional NEM paradigms (e.g., NEM 1.0 and NEM 2.0) in supporting distributed solar adoption [73, 118, 119, 133]. In general, those studies find that combining traditional NEM offerings with typically available electric tariffs and other common solar PV subsidies is an effective way to help grow distributed solar growth. Bollinger et al. [134] examines the effects of outages and rebates on solar and storage co-adoption, but does not appear to consider the impacts of electricity rate structures. There have been fewer studies considering the implications of NEM 3.0 on behind-the-meter solar PVs. In its NBT decision [96], the CPUC included modeling results of consumers with solar PVs and BES from California's three different investor-owned utilities taking service under the NBT. CPUC reported simple payback periods ranging from six to nine years with first-year bill savings ranging from around $1000 to $3000, but omitted necessary context and did not provide the model used to produce their results. In Section 3.4 of this Dissertation, I present results showing that NEM 3.0 results in greater relative bills for consumers with only solar PVs than for those same consumers under previous NEM policies. I also show that consumers with solar and storage participating under NEM 3.0 can achieve relative total bills near or lower than those attained for the same consumer under the previously offered NEM 2.0, depending on storage capacity and storage participation scheme. Borenstein [135] finds that the increase in electricity prices makes the incentive to install distributed solar in the PG&E service territory slightly higher in 2024 to what it was in 2019, though that analysis does not consider the impact of distributed storage. Alahmed and Tong [95] show that NEM 1.0 successor programs based on social marginal costs or capacity-based charges could result in longer payback periods for DERs, but could lead to greater social welfare compared to NEM 1.0 and NEM 2.0 as more consumers participate. Finally, Ybarra et al. [136] explored the impacts of an early iteration of the CPUC NEM 3.0 proposal, one that included prohibitive fixed consumer costs in addition to what has already been discussed. Under those assumptions, they found that solar and storage adoption would not make financial sense for consumers.

This chapter explores the conditions under which consumers are incentivized to deploy solar PVs and BES with the current mix of value streams. Using consumers in the PG&E service territory as a case study, I examine the impacts that project asset costs, electricity rate components, and distributed resource participation schemes have on consumers who are making investment decisions. This work provides insights to the complementarity between behind-the-meter solar and storage resources, not only from a technical perspective, a topic that has been explored in depth in the literature, but from a financial perspective as well. Furthermore, the work presented in this chapter is a timely addition to the policy- and regulatory-relevant discourse surrounding electricity affordability in California. Namely, these insights help understand how distributed resources can aid consumers in the presence of ever-rising electricity prices and show the extent to which the CPUC's NBT can drive resource adoption. That latter point could be of particular interest considering the recent bill introduced in the California State Legislature to make CPUC reevaluate the solar-related benefits accounted for in the NBT [137].

This chapter is organized as follows. Section 4.2 describes the mathematical model used to minimize the total bill, including operational and investment costs, of a consumer considering the deployment of PV and BES resources. Section 4.3 introduces the case study design. Section 4.4 presents the results obtained through the simulation and discusses observations pertaining to asset investment and consumer affordability under different conditions. Section 4.5 concludes the chapter. Due to the volume of results obtained through the simulation of the described case study, Appendix A contains supplementary results and analysis.

4.2 Mathematical Formulation

I define a mixed-integer linear program (MILP) to determine the minimum electricity-related bill, comprised of costs associated with time-of-use (TOU) rates, revenues associated with net energy metering (NEM), and DER investment costs, for a consumer considering the deployment of a combination of PV and BES resources. Within the MILP, asset operation is optimized to achieve the minimum bill, while simulated demand and the PV capacity factor profile are provided as parameters. The MILP is formulated as follows:

$$\begin{aligned}\min.\quad & \sum_{n\in\mathcal{N}} \pi_{dem}(n)\cdot d_{max}(n) + \sum_{t\in\mathcal{T}} \pi_{en}(t)\cdot d_{net}(t) - \sum_{t\in\mathcal{T}} \pi_{exp}(t)\cdot \left[p_{pv}^{exp}(t) + p_{dis}^{exp}(t)\right] \\ & + \sum_{a\in\mathcal{A}} \left[\frac{r\cdot(1+r)^{L_a}}{(1+r)^{L_a}-1}\cdot\left[1-I_{ITC}^{a}\right]\cdot C_{cap}^{a}\cdot P_a + C_{O\&M}^{a}\cdot P_a \right]\end{aligned} \tag{4.1}$$

subject to:

$$\sum_{t\in\mathcal{T}} \pi_{en}(t)\cdot d_{net}(t) - \sum_{t\in\mathcal{T}} \pi_{exp}(t)\cdot\left[p_{pv}^{exp}(t)+p_{dis}^{exp}(t)\right] \geq \pi_{nbc}\cdot\sum_{t\in\mathcal{T}} d_{net}(t) \tag{4.2}$$

$$d_{net}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{4.3}$$

$$\zeta_{net}(s) = 1 \Rightarrow d_{net}(s) \leq 0, \qquad \forall s \in \mathcal{S} \tag{4.4}$$

$$p_{pv}^{exp}(s) + p_{dis}^{exp}(s) \leq \zeta_{net}(s) \cdot \left(\overline{P}_{pv} + \overline{P}_{bes}\right), \quad \forall s \in \mathcal{S} \subseteq \mathcal{T} \tag{4.5}$$

$$\delta(t,n) \cdot d_{net}(t) \leq d_{max}(n), \quad \forall t \in \mathcal{T}, \quad \forall n \in \mathcal{N} \tag{4.6}$$

$$d_{max}(n) \geq 0, \quad \forall n \in \mathcal{N} \tag{4.7}$$

$$p_{pv}^{btm}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{4.8}$$

$$p_{pv}^{exp}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{4.9}$$

$$p_{pv}^{btm}(t) + p_{pv}^{exp}(t) \leq \eta_{inv} \cdot P_{pv} \cdot CF_{pv}(t), \quad \forall t \in \mathcal{T} \tag{4.10}$$

$$0 \leq P_{pv} \leq \overline{P}_{pv} \tag{4.11}$$

$$0 \leq p_{cha}(t) \leq P_{bes}, \quad \forall t \in \mathcal{T} \tag{4.12}$$

$$p_{dis}^{btm}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{4.13}$$

$$p_{dis}^{exp}(t) \geq 0, \quad \forall t \in \mathcal{T} \tag{4.14}$$

$$p_{dis}^{btm}(t) + p_{dis}^{exp}(t) \leq P_{bes}, \quad \forall t \in \mathcal{T} \tag{4.15}$$

$$p_{dis}^{exp}(s) \leq P_{bes} - \left[d(s) - p_{pv}^{btm}(s)\right], \quad \forall s \in \mathcal{S} \tag{4.16}$$

$$J(t) = J(t-1) + \eta_{bes}^{rte} \cdot p_{cha}(t) - p_{dis}^{btm}(t) - p_{dis}^{exp}(t), \quad \forall t \in \mathcal{T} > 0 \tag{4.17}$$

$$J(t) = J_{init} + \eta_{bes}^{rte} \cdot p_{cha}(t) - p_{dis}^{btm}(t) - p_{dis}^{exp}(t), \quad t = 0 \tag{4.18}$$

$$\underline{J} \leq J(t) \leq \overline{J}, \quad \forall t \in \mathcal{T} \tag{4.19}$$

$$J(|\mathcal{T}|) \geq J_{init} \tag{4.20}$$

$$p_{cha}(t) \leq p_{pv}^{btm}(t), \quad \forall t \in \mathcal{T} \tag{4.21}$$

$$0 \leq P_{bes} \leq \overline{P}_{bes} \tag{4.22}$$

where

$$d_{net}(t) = d(t) - p_{pv}^{btm}(t) + p_{cha}(t) - p_{dis}^{btm}(t), \ \forall t \in \mathcal{T} \tag{4.23}$$

$$r = \frac{i - f}{1 + f} \tag{4.24}$$

Equation (4.1) is the objective function that reflects the consumer's total electricity-related bill, including tariff-related charges and DER investment costs. In the first line, the first summation pertains to a tariff's demand charges, the second summation describes the tariff's energy charge, and the third summation represents the NEM revenue, where the value of the export price π_{exp} varies depending on the NEM version being considered. As is shown in Constraint (4.2), NEM revenue is constrained such that annual NEM credits can only be used to offset a consumer's annual energy charges minus their annual non-bypassable charges. Depending on the scenario, it is possible that BES exports p_{dis}^{exp} may be prohibited or the consumer may not be participating in NEM, with both cases requiring the portion of the objective function focusing on NEM revenues to be adjusted accordingly. In the second line of Equation (4.1), the first product in the summation models the net annualized capital cost (including annualized investment tax credits) and the second product provides the annual fixed operations and maintenance (O&M) costs.

Constraints (4.3) – (4.7) describe bounds placed on demand-related values and expressions. Constraint (4.3) prevents the consumer's net demand, which is defined in Equation (4.23) and does not include exports p_{pv}^{exp} and p_{dis}^{exp}, from being exported to the grid. Differing from [92] and [93], exports and behind-the-meter consumption are disaggregated to avoid the practical infeasibility that occurs when export prices are greater than energy prices (i.e., $\pi_{exp}(t) > \pi_{en}(t)$), as is possible under the CPUC's Net Billing Tariff (NBT). Constraints (4.4) and (4.5) ensure there are only exports if the consumer's assets have already met the net demand. Constraints (4.6) and (4.7) define the maximum demand during different periods. The δ in Constraint (4.6) is a constant that equals one when t aligns with period n and zero otherwise.

Constraints (4.8) – (4.11) describe the solar PV model. Constraints (4.8) – (4.10) provide bounds on the PV model's generation output, which is based in part on the PV capacity factor profile. The PV capacity factor profile is determined by dividing the simulated PV array's generation output by its rated capacity. The PV array's generation output is determined using solution methods for the single-diode PV model, with the detailed formulation available in Chapter 2. Constraint (4.11) places bounds on the size of the PV system that can be built.

Constraints (4.12) – (4.22) describe the BES model. Constraint (4.12) restricts the charging power of the BES, while Constraints (4.13) – (4.15) restrict the discharging power. When the integer variables and constraints (i.e., Constraints (4.4) and (4.5)) are relaxed, Constraint (4.16) sets a cap on the power the BES is able to export, where the upper bound is established such that the BES must reserve some of its capacity to help serve the net demand not met by the solar PV system. Constraints (4.17) and (4.18) define the state of charge at time t. Constraint (4.19) enforces upper and lower bounds on the state of charge. Constraint (4.20) ensures that the final state of charge (at $t = |\mathcal{T}|$) is no less than the initial state of charge, preventing perverse discharging schemes. Constraint (4.21) prevents the BES from charging from the grid, if enabled by the scenario. Constraint (4.22) places bounds on the size of the BES system that can be built.

4.3 Case Study Design

To assess the complementarity of behind-the-meter solar and storage assets, I expose simulated commercial consumers to relevant asset prices, electric utility tariffs, and incentive programs and allow those consumers to build an optimal mix of solar PVs and BES. The case study presented in this chapter conducts five different tests to better understand the circumstances under which solar PVs and BES get deployed. The purpose of the first two tests is to examine how changing asset prices can influence the adoption of distributed resources, with one test each being used to perform a sensitivity analysis on solar investment costs and storage investment costs. The remaining three tests seek to explore how changing electricity tariff prices affects the installation of solar PVs and BES. In particular, the tests perform sensitivity analyses on a uniform percentage change in electricity prices, a percentage change in only demand charges, and a percentage change in only energy charges. Each of these five tests is conducted on simulated commercial consumers that vary by their load profile shapes and climate zone locations.

I consider two archetypal commercial consumers: a consumer with morning-and-evening-peaking (MEP) demand and a consumer with midday-peaking (MDP) demand. To understand the impact of different climate zones on distributed resource adoption, each archetypal consumer was modeled in two different California cities: Fresno and San Francisco. Fresno is located in California Climate Zone 13, which is characterized by its high summer daytime temperatures, abundant sunshine during a long growing season, cold winter days. San Francisco is situated in California Climate Zone 3, which features moderate year-round temperatures, wintertime precipitation, and summertime fog [138]. All told, Fresno has a better solar resource and starker temperature extremes, which cause buildings to consume more energy, while San Francisco has a weaker solar resource and milder temperatures, which result in buildings consuming less energy. The MEP and MDP consumers are modeled using the Department of Energy's large hotel and supermarket commercial prototype models, respectively, and TMY3 data from Fresno Yosemite International Airport in Fresno, CA and San Francisco International Airport in San Francisco, CA. The electricity demand profiles are available from Ong and Clark [120] and have maximum demands of 444 kW (MEP consumer in Fresno), 358 kW (MDP consumer in Fresno), 423 kW (MEP consumer in San Francisco), and 309 kW (MDP consumer in San Francisco).

The modeled consumers are exposed to electricity tariffs and incentives offered by PG&E. A California-based utility such as PG&E makes sense for this case study because of the rapid increases in the state's electricity prices, due in part to costs associated with wildfires and infrastructure upgrades [61, 69, 70], that have caused resources such as solar PVs and BES to become key tools to improving consumers' electricity affordability. In this chapter, the modeled consumers take service under PG&E's Electric Schedule B-19 rate, a TOU tariff offered to commercial consumers [139]. Additionally, the consumers are exposed to the recently adopted Net Billing Tariff (NBT), a net energy metering successor policy that aims to compensate consumers for their grid exports in accordance with the values of an avoided cost calculator. The export price profile is created by taking the outputs of E3's Avoided Cost Calculator [104] and averaging them by month, weekdays versus weekends and holidays, and hour of the day [96, 105]. Due to the yearly variation in export prices, the export price profile is averaged over fifteen years to provide a better representation of the type of export prices a consumer may expect over a longer investment time frame.

To reduce their costs of procuring energy from the utility, consumers have the ability to build some combination of solar PVs and BES. The capital costs and annual operating and maintenance (O&M) costs associated with building either asset are sourced from the National Renewable Energy Laboratory's 2023 Annual Technology Baseline [80]. For the baseline costs, I select the 2023 Moderate costs and scale those costs, which are provided in 2021 U.S. dollars, to be in terms of 2024 U.S. dollars. Since the capital expenditures would otherwise be single lump-sum payments, they are amortized so as to not be distortionary when compared to the consumer's annual electricity bill. The annualized cost is determined through the calculation of the capital recovery factor, shown in part in Equation (4.1), where the amortization period L_a is selected to be over fifteen years and the real discount rate r is calculated with a nominal discount rate i of 0.1 and an expected inflation rate f of 0.025 [140]. The amortization period and nominal discount rate are selected to be within the range of current solar and storage financing options [141, 142].

In line with recent guidance from the Inflation Reduction Act of 2022, I also enable consumers to be eligible for the current thirty-percent investment tax credits available for solar and storage installations [10]. While these investment tax credits are popular for their uncoerciveness and automaticity [143], they are nonrefundable, meaning that consumers must have a large enough tax liability to realize the full incentive. Although this can prove exclusionary to lower-income consumers or consumers who are unable to own their solar and storage systems (e.g., renters), this chapter's focus on larger commercial consumers makes the assumption that consumers will be able to claim the full investment tax credit a reasonable one. Similar to the capital expenditures, I also amortize the total investment tax credits over the same period as the capital expenditures so as to prevent undue distortions.

Finally, this case study explores four different participation schemes for the consumer's prospective solar PVs and BES. The first participation scheme, "Self Consumption" (SC), restricts the consumer from producing any exports, only allowing them to self-consume their locally generated energy. While this scheme restricts the consumer from earning net energy metering credits from the NBT, it is still important to understand the role that electricity tariffs can play with regards to procuring behind-the-meter solar and storage resources. Furthermore, there are some utilities that prefer to prevent exports to their distribution systems so as to limit distribution violations and reduce the need for distribution system upgrades [144, 123]. The second participation scheme, "Grid Imports, No Exports" (GINE), allows the consumer's BES to charge from the grid, but prohibits the BES from producing grid exports; in this scheme, only the consumer's solar PVs are allowed to produce exports. The third participation scheme, "Solar Imports with Exports" (SIE), allows the consumer's BES to only charge from their paired solar PVs, though both the BES and the solar PVs are allowed to produce grid exports. Both the second and third participation schemes are traditional offerings in net energy metering programs, where exports are allowed so long as the energy being exported is produced from a renewable energy generating facility (e.g., solar PVs) [105, 123]. The fourth participation scheme, "Grid Imports with Exports" (GIE), removes restrictions on the consumer's BES, allowing it to both charge from the grid and export to the grid alongside the consumer's solar PVs. Such a participation scheme is atypical amongst net energy metering programs, as the BES would be able to participate in market-esque arbitrage irrespective of its impact on the grid's mix of clean energy sources. This final scheme is included not for its realism, but rather to understand the consumer's optimal policy if they were to be unrestricted. Table 4.1 summarizes the different participation schemes considered in this case study.

4.4 Results and Discussions

The model from Section 4.2 is implemented in DERIVE, which was introduced in Chapter 2 and is publicly available on GitHub [116]. The results presented in this chapter are from

Table 4.1: Participation schemes for the consumer's solar PV and BES resources. This table indicates whether each participation scheme allows the consumer to participate in the NBT and how the consumer's assets are able to interact with the grid.

Scheme Description	**Scheme ID**	**NBT?**	**BES Grid Imports?**	**BES Grid Exports?**	**PV Grid Exports?**
Self Consumption	SC	No	Yes	No	No
Grid Imports, No Exports	GINE	Yes	Yes	No	Yes
Solar Imports with Exports	SIE	Yes	No	Yes	Yes
Grid Imports with Exports	GIE	Yes	Yes	Yes	Yes

a relaxed version of the model presented in Section 4.2, where integer variables and constraints (i.e., Constraints (4.4) and (4.5)) are removed. Though the relaxation was initially implemented to improve computational speed and allow for increasingly granular sensitivity analyses to be conducted, the relaxed model was found to produce results similar to those obtained through the integer-based version. Perhaps most importantly though, the relaxed model was able to preserve many of the asset-investment and total-cost trajectories observed when using the integer-based model. Refer to Section A.4 of Appendix A for a comparison of the asset-adoption and total-cost trajectories obtained via the integer-based and relaxed models.

Before proceeding, I would like to make a couple additional notes. First, the plots in this chapter will present relative values to describe the amount of invested capacity or the consumer's total cost (i.e., the sum of electricity bill expenses and investment costs). Doing so allows for more meaningful comparisons to be made across scenarios, especially considering that not all simulated consumers have similar load profile characteristics (e.g., maximum demand, annual energy consumption). As such, plots pertaining to asset capacities will show deployed capacities (in kW) relative to the consumer's maximum annual demand (in kW). Plots pertaining to a consumer's total costs will show the total cost (in $) relative to the consumer's electricity bill in the base case (i.e., the scenario where the consumer makes no asset investments). Second, I would like to note that while the following two subsections focus on one of the pairs of locations and consumer load profiles (the Fresno MEP consumer), results obtained for the other pairings will still be addressed either later in this section or in Appendix A. While the different location-load pairs may exhibit slight deviations that give insights to the effects of load profile shapes (discussed in Section 4.4.3) or locations within a particular climate zone (discussed in Section 4.4.4), the following two subsections discuss trends that are common amongst all simulated pairings when considering changes in asset investment costs and electricity tariff prices, respectively.

The following subsections present results from these simulations and discuss the complementarity of behind-the-meter solar and storage systems in the presence of contemporary mechanisms and different cost trajectories. The following subsections also offer policy- and regulatory-relevant insights to the design of subsidies and electricity rates.

4.4.1 Impact of Changing Asset Investment Costs

To understand how behind-the-meter solar and storage resources complement one another, I begin by looking at how consumers' investment decisions in both asset types change when exposed to various prices for each asset. Figure 4.1 shows the amount of solar PV and two-hour BES capacity the Fresno MEP consumer deploys under each of the four participation schemes[1]. Figures 4.1a through 4.1d reveal how the consumer's investment decisions are

[1]While the solar and storage capacity sizes shown in this chapter's figures may seem large, asset deployments generally fall under the installation limits imposed by PG&E in their NBT rule. Per the NBT rule, solar PVs are allowed to be sized such that the annual production is no larger than 150 percent of the consumer's annual energy consumption. The allowable BES capacity depends on how the solar and storage systems are coupled, with DC-coupled systems having no BES capacity restriction and AC-coupled systems limiting BES to a capacity no larger than 150 percent of the solar PV system's capacity [105]. As can be seen in the following figures, the only time this capacity limitation is violated is for some BES installations when BES is its most subsidized. Still, those results are reported in this study, as I am more concerned with exploring the optimal investment trends under different circumstances.

affected when the consumer is exposed to solar investment prices that range from 25 percent of the base solar investment cost up to 150 percent of the base solar investment cost; Figures 4.1e through 4.1h examine the same investment decisions when exposed to storage investment prices that are modified using the same range of percentages. Figure 4.2 is configured similarly to Figure 4.1, though it shows investments in solar PVs and six-hour BES.

From Figures 4.1 and 4.2, it can be seen that the strategy for investing in solar and storage changes depending on the participation scheme that is being followed. Under the SC scheme, the consumer is not able to earn NBT credits, so they are investing in behind-the-meter assets to offset their electricity bills[2]. As either solar or storage gets cheaper, both assets are found to be installed in larger quantities, albeit at different deployment rates. These trends highlight the technical and financial complementarity of solar and storage under the SC scheme: as one asset type gets cheaper, it becomes increasingly viable to have BES shift the zero-marginal-cost energy produced from solar PVs to offset peak-period energy charges and demand charges.

These investment trends begin to differ under the other participation schemes that allow consumers to access NBT credits. Under the GINE scheme, solar and storage are found to still be largely complementary as either solar or storage investment costs are changed. Particularly when either asset investment cost is expensive (i.e., near or greater than the base investment costs), asset investments are complementary. With storage unable to provide grid exports, more solar gets built to obtain NBT credits and more storage gets built to use excess solar to help reduce peak-period energy charges and demand charges. Such a theme persists as storage costs continue to decrease, though the same cannot be said of investments exposed to solar cost decreases. As solar costs decrease, there reaches a point where solar PVs are cheap enough that they begin to be overbuilt to claim as many NBT credits as possible. This response results in BES capacity stagnating, if not slightly decreasing, as

[2]Note that there are other reasons consumers employing an SC scheme might invest in distributed resources, such as for providing their own back-up power in the event of a blackout. While such a value stream can be useful to consider, it is omitted from study and left for future work.

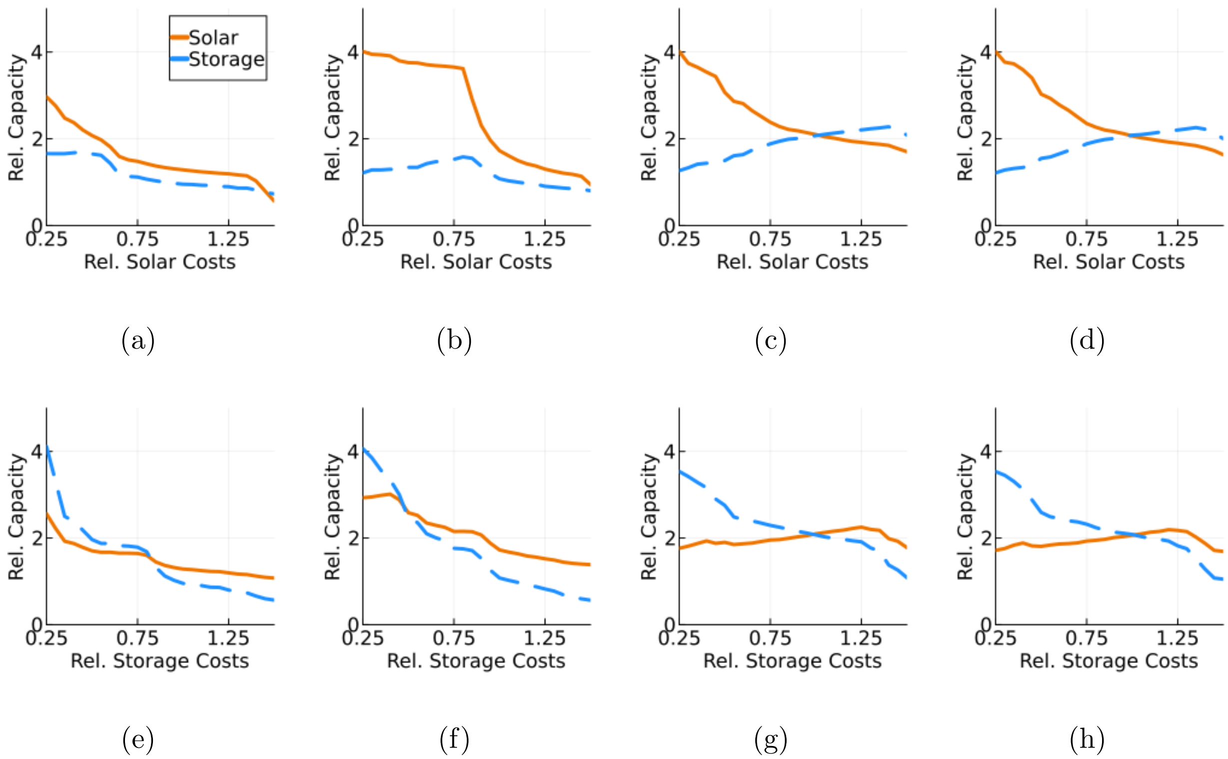


Figure 4.1: Installed solar PV and two-hour BES capacity for the Fresno MEP consumer, relative to the consumer's maximum demand, as asset-related costs are changed. (a) – (d) depict investments as solar investment costs change. (e) – (h) depict investments as storage investment costs change. (a) and (e) depict the SC scheme. (b) and (f) depict the GINE scheme. (c) and (g) depict the SIE scheme. (d) and (h) depict the GIE scheme.

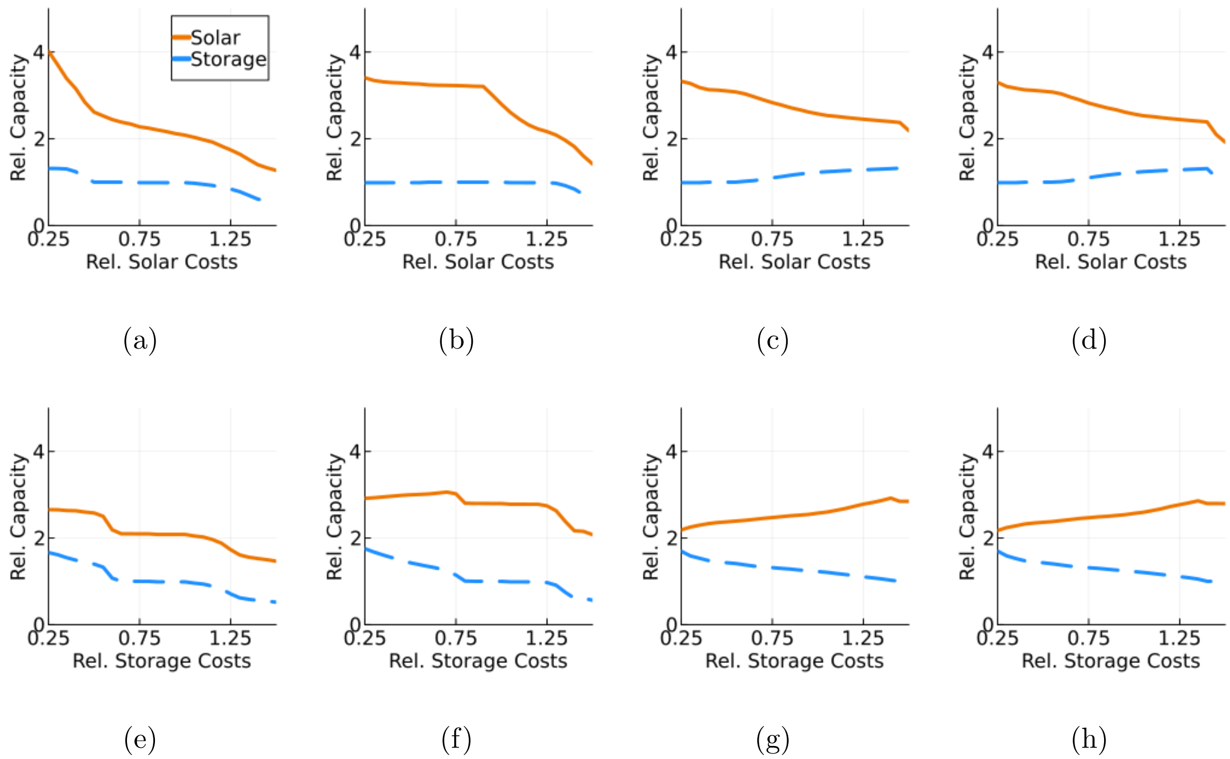


Figure 4.2: Installed solar PV and six-hour BES capacity for the Fresno MEP consumer, relative to the consumer's maximum demand, as asset-related costs are changed. (a) – (d) depict investments as solar investment costs change. (e) – (h) depict investments as storage investment costs change. (a) and (e) depict the SC scheme. (b) and (f) depict the GINE scheme. (c) and (g) depict the SIE scheme. (d) and (h) depict the GIE scheme.

solar investment costs continue to decrease. Of the participation schemes discussed thus far, this is the first example of solar PVs and BES behaving more like substitute resources, rather than complementary resources. Capacity of both is still built, but we begin to see that new solar capacity slightly offsets new storage capacity.

Under the SIE and GIE schemes, we continue to observe that solar PVs and BES act more like substitutes than they do complements. The difference here is that this behavior is observed for nearly the whole parameter sweep of investment costs, not just while solar investment costs are subsidized. Since both solar PVs and BES are able to provide grid exports under the SIE and GIE schemes (with the notable exception that BES cannot charge from the grid under SIE but can under GIE), consumers, in trying to produce NBT credits, are incentivized to build larger quantities of the asset that is being subsidized. Note that even at the extremes, when one asset type is at its most expensive or its cheapest, the other asset type is still built. This points to the interdependencies between solar and storage resources that were discussed in Section 4.1. Investments under the SIE scheme reinforce the idea that interdependencies enforced by the NBT require solar and storage resources to be built together. As BES gets cheaper, it is built in larger quantities, but BES, through the inability to charge from the grid, still requires solar PVs to be built to produce NBT credits. Similarly, as solar PVs get cheaper, they are also built in larger quantities, though BES is still required to produce exports during some of the highest-value export times and to help reduce peak-period energy charges and demand charges. Interestingly, investments under the GIE scheme point to the deeper interdependencies between solar and storage resources. Even with BES being able to both charge from and export to the grid, we see that solar PVs and BES are still built together, following near-identical trajectories to those observed under the SIE scheme. Under the GIE scheme, a consumer could conceivably only build BES and still have access to NBT credits. However, consumers are still found to build solar PVs, even when they are at their most expensive.

The latter schemes discussed above reveal an interesting interplay between the NBT and subsidies for assets that are allowed to produce exports. Rather than a more nuanced strategy, where multiple value streams aim to be tapped, subsidizing an asset that can produce exports for NBT credits appears to yield a dominant strategy of concentrating more capacity into the subsidized asset so as to maximize NBT credit accrual. Note that this strategy is not solely about amassing NBT credits, which are capped by the consumer's annual energy charges less the non-bypassable charges, but rather trying to capitalize on the most-valuable export times available through the NBT program. Recall that these are times that consumers would be aware of due to the prescribed nature of the NBT (e.g., PG&E publishes their export prices for the year [145], though savvy consumers could use the results from E3's Avoided Cost Calculator [104] to determine the prices multiple years out). Through this paradigm, maxing out the NBT credit allotment during the most-valuable export hours allows the assets to be used more during the less-valuable export hours in order to better capture the secondary value streams (e.g., offsetting costs related to the TOU electricity tariff).

Regardless of the participation scheme and the asset being subsidized, consumer deployment of solar PVs and BES is found to be cheaper for consumers on an annual basis than the alternative of not investing in distributed resources at all. Figure 4.3 compares the Fresno MEP consumer's total costs (including the annual electricity bill, annualized capital costs, and annualized tax credits) under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures 4.3a and 4.3b show the relative total costs when solar and storage investment costs are subsidized, respectively, for the consumer with solar and two-hour BES. Figures 4.3c and 4.3d show the same for the consumer with solar and six-hour BES.

The total cost trajectories shown in Figure 4.3 provide many insights to the impacts of the participation schemes on consumer affordability. Unsurprisingly, each of the three participation schemes that allow consumers to participate in the NBT produce lower bills than if the consumer were to just follow the SC scheme. However, the total costs under the SC scheme are still closer to those under the other schemes than they are to the base case, indicating that merely using solar PVs and BES to offset costs associated with the electricity

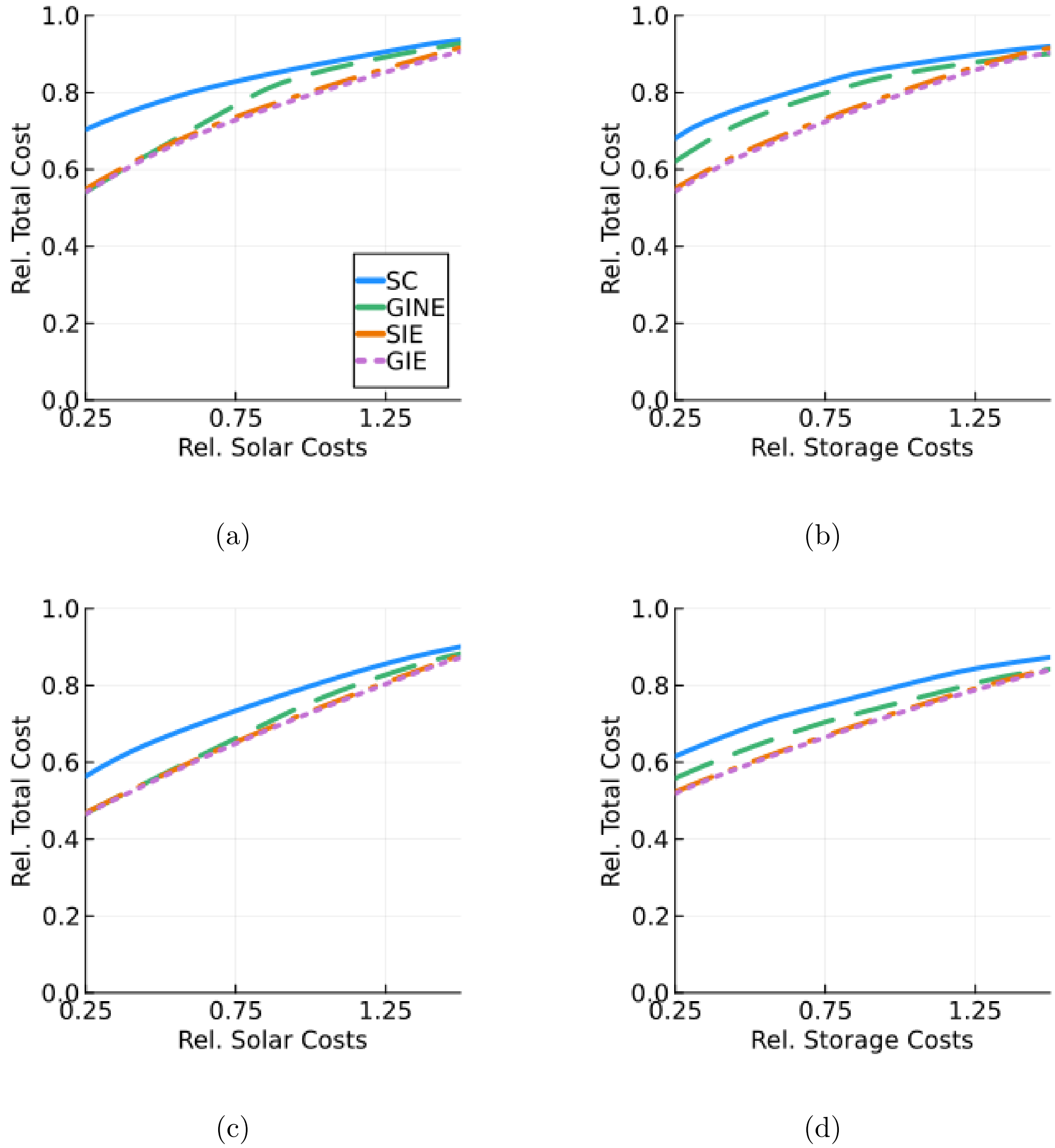


Figure 4.3: Total cost for the Fresno MEP consumer with solar PVs and BES, relative to the base case without investments, as asset-related costs are changed. (a) and (c) depict total costs as solar investment costs change. (b) and (d) depict total costs as storage investment costs change. (a) and (b) show the results for a consumer investing in two-hour BES. (c) and (d) show the results for a consumer investing in six-hour BES.

tariff is valuable. We can also see that the total costs under the SC and GIE schemes bound the trajectory space for the GINE and SIE schemes. Generally, the SIE scheme yields total costs that very nearly match those of the GIE scheme, which makes sense based on the similar asset investments shown in Figures 4.1 and 4.2 and the ability of both asset types to produce grid exports. The total costs under the GINE scheme are less predictable however. When solar investment costs are higher, the GINE scheme produces total costs closer to the SC trajectory. As solar investment costs decrease, total costs under the GINE scheme begin to converge towards the trajectory of the GIE scheme, which follows from the earlier observation that solar and storage investments become less complementary under the GINE scheme. As storage investment costs decrease, the GINE trajectory begins to diverge from the trajectory of the GIE scheme, pointing to the fact that storage is unable to export under the GINE scheme, thereby limiting the ability to acquire NBT credits.

From a policy perspective, Figure 4.3 also produces some interesting insights. As more subsidies are introduced to either asset (i.e., as asset investment costs decrease), we observe that the relative total costs under each participation scheme decrease sublinearly. This indicates that as subsidies increase, the benefit for consumer's affordability increases even more. If the ability to provide subsidies is limited, it appears that subsidizing solar PVs produces lower total costs for consumers. For consumers investing in solar PVs and two-hour BES, the difference in subsidizing either asset is less stark. However, as the BES duration increases, it becomes clear that subsidizing solar is more valuable. This is especially interesting considering the difference in each asset type's capital costs. While capital costs for solar PVs and BES are similar for lower duration BES (commercial solar PVs cost \$2143.63/kW and commercial two-hour BES costs \$1988.27/kW), the difference in each asset type's capital costs increases for longer duration BES (commercial six-hour BES costs \$3107.73/kW). Therefore, for consumers that invest in longer duration BES, subsidizing solar by some percentage amount is a cheaper subsidy than subsidizing storage by that same percentage amount, all while producing a greater benefit.

4.4.2 Impact of Changing Electricity Tariff Prices

Next, I look at how consumers' investment decisions in both asset types are impacted when exposed to changing electricity prices. Figure 4.4 shows the amount of solar PV and two-hour BES capacity the Fresno MEP consumer deploys under each of the four participation schemes. Figures 4.4a through 4.4d reveal how the consumer's investment decisions are affected when the consumer is exposed to electricity tariff prices that are uniformly scaled to be between 75 percent and 200 percent of the base electricity tariff prices. Figures 4.4e through 4.4h examine the same investment decisions when exposed to demand charges that are scaled to be between 75 percent and 200 percent of the base demand charges. Figures 4.4i through 4.4l examine the same investment decisions when exposed to energy charges that are scaled to be between 75 percent and 200 percent of the base energy charges. Figure 4.5 is configured similarly to Figure 4.4, though it shows investments in solar PVs and six-hour BES.

From Figures 4.4 and 4.5, it can be seen that the four participation schemes produce investment strategies that are fairly similar. Regardless of the scenario, solar and storage are complementary resources as electricity tariff price components increase. This is particularly true when tariff price components are uniformly increased and when energy charges are increased. In both cases, the increase in prices leads consumers to deploy larger quantities of solar and storage, something that makes sense on the surface. As prices go up, larger distributed resources will be needed to better help offset the consumers' electricity bills. However, the driver behind this growth in resource capacity differs based on the participation scheme. Under the SC scheme, more resource capacity gets built to help account for the increased electricity prices. The GINE scheme follows a similar strategy, but the fact that solar PVs can produce exports and earn NBT credits causes a deviation from the SC scheme. In the desire to obtain as many NBT credits as possible, solar ends up getting overbuilt. However, due to solar generation not being coincident with enough of the high-priced export hours, the consumer must also build more storage to use the extra solar generation to help

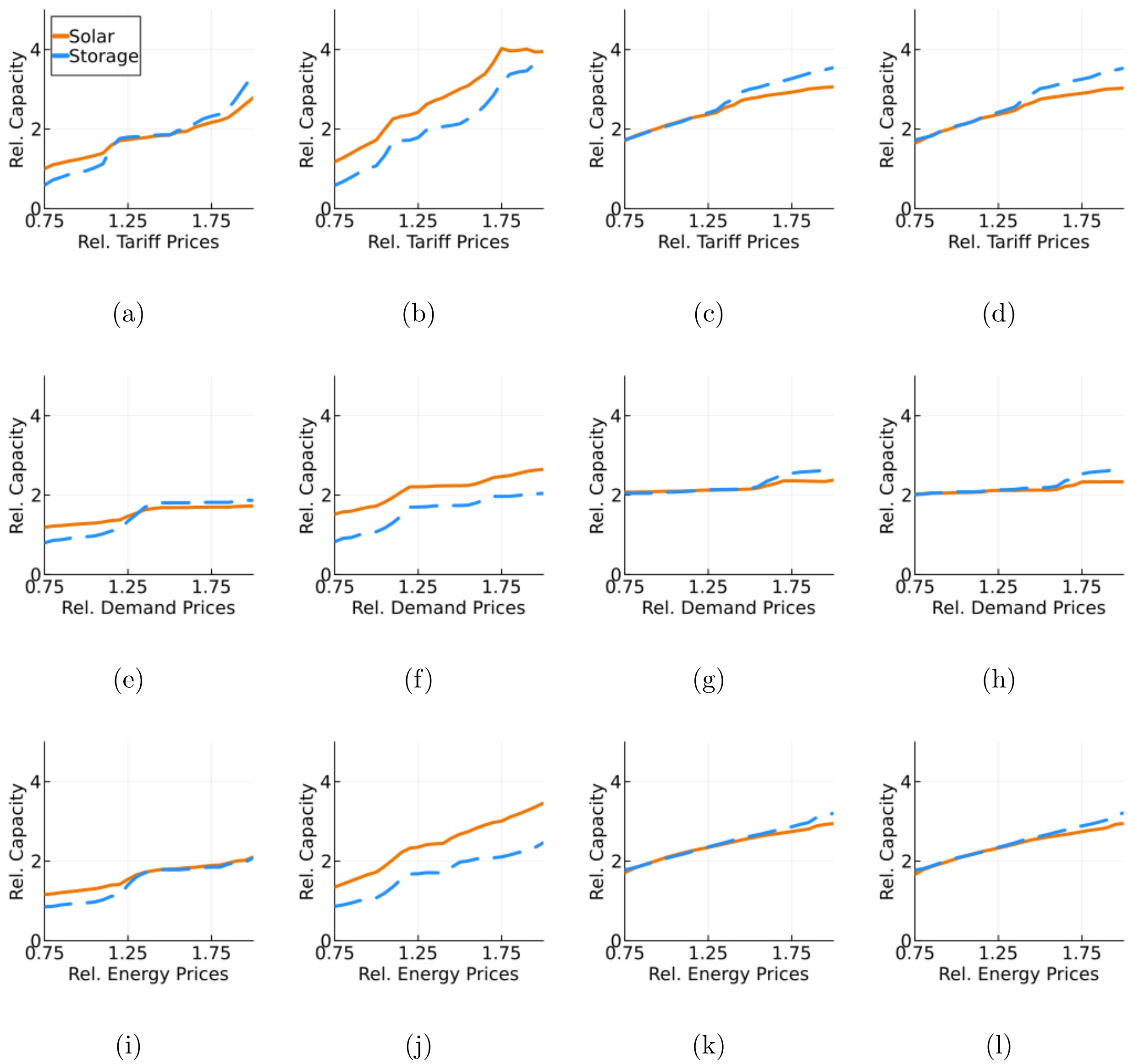


Figure 4.4: Installed solar PV and two-hour BES capacity for the Fresno MEP consumer, relative to the consumer's maximum demand, as tariff-related prices are changed. (a) – (d) depict investments as all tariff prices change. (e) – (h) depict investments as demand charges change. (i) – (l) depict investments as energy charges change. (a), (e), and (i) depict the SC scheme. (b), (f), and (j) depict the GINE scheme. (c), (g), and (k) depict the SIE scheme. (d), (h), and (l) depict the GIE scheme.

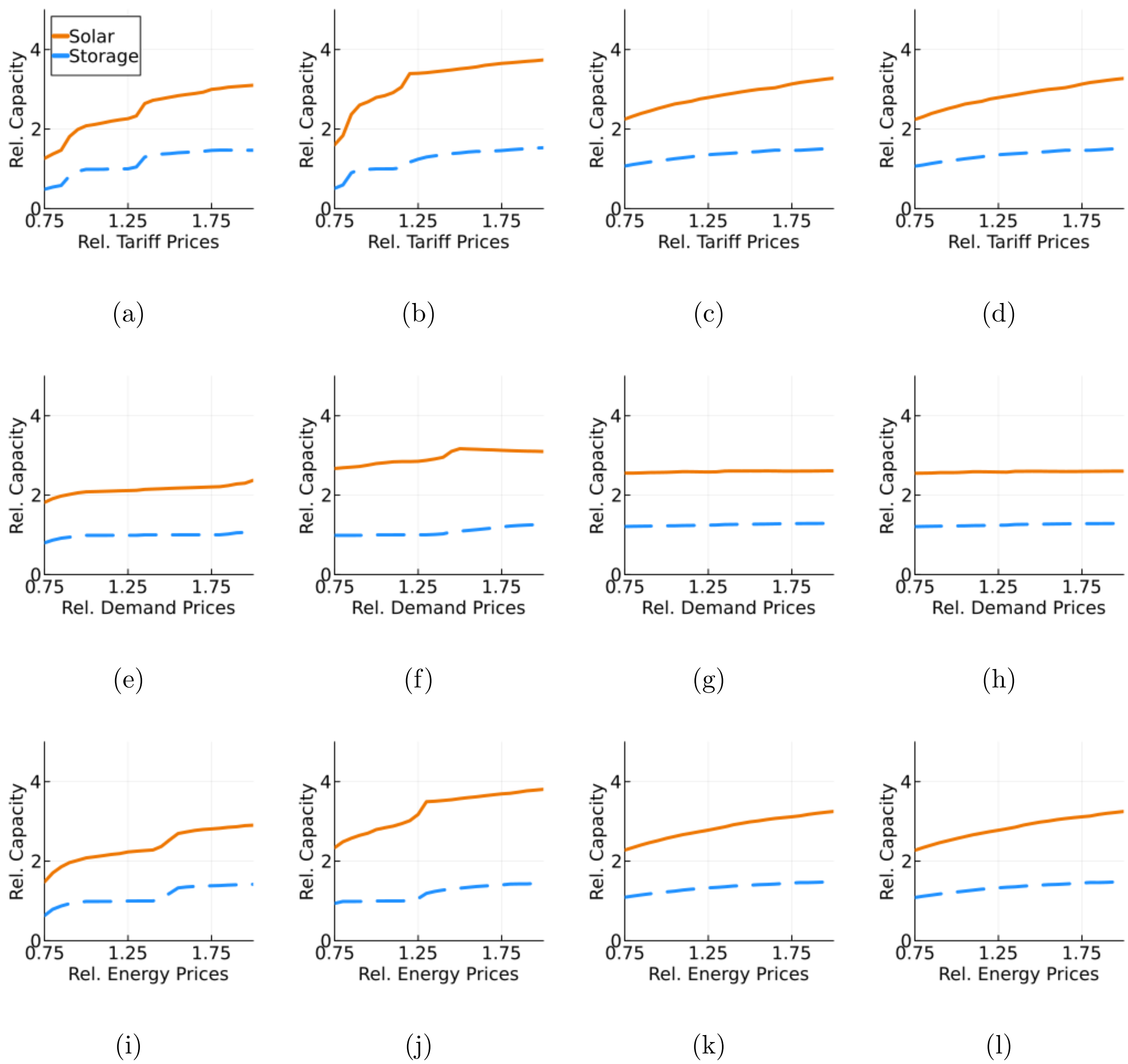


Figure 4.5: Installed solar PV and six-hour BES capacity for the Fresno MEP consumer, relative to the consumer's maximum demand, as tariff-related prices are changed. (a) – (d) depict investments as all tariff prices change. (e) – (h) depict investments as demand charges change. (i) – (l) depict investments as energy charges change. (a), (e), and (i) depict the SC scheme. (b), (f), and (j) depict the GINE scheme. (c), (g), and (k) depict the SIE scheme. (d), (h), and (l) depict the GIE scheme.

reduce the increased electricity bill. Under the SIE and GIE schemes, more solar PVs and BES get built because of the connection between the consumer's energy charges and the amount of NBT credits they can procure. As energy charges increase, consumers now have the ability to tap into a larger pool of NBT credits.

While increasing energy charges and all tariff price components (largely due to the fact that energy charges also get scaled in this test) causes consumers to build larger solar and storage resources, increasing demand charges does not necessarily have the same effect. The effect that increasing demand charges has on a consumer's solar PVs and BES depends on the consumer's participation scheme. Under the SC and GINE schemes, we see an increase in demand charges lead to an increase in solar and storage capacity, albeit at a much slower rate of change compared to what was observed for the increases in all tariff price components and the increase in energy charges. Increasing demand charges has an effect on resource sizing under those participation schemes because the NBT has little to no influence on either of those schemes. However, the influence of the NBT is apparent when considering the impact of demand charges on consumers employing the SIE and GIE schemes. With asset investments largely being driven by the acquisition of NBT credits in both of those participation schemes, it is of little surprise that investments in solar PVs and BES are largely insensitive to changes in demand charges. Only when consumers have limited flexibility (i.e., a shorter duration BES) and demand charges reach a point that their cost rivals the credits that can be earned through the NBT do we observe consumers beginning to build more solar and storage.

Similar to earlier observations, adopting solar PVs and BES is found to be cheaper for consumers on an annual basis than the alternative of not investing in distributed resources. Figure 4.6 compares the Fresno MEP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES[3]. Figures 4.6a through 4.6c show the relative total costs when all tariff price components are increased,

[3]Note that the base electricity bills are generated in a way that takes the relevant price change into account. For instance, the data point that corresponds to the consumer's total costs for a 150-percent increase in energy charges is related to a base case that increased its tariff's energy charges by 150 percent too.

when demand charges are increased, and when energy charges are increased, respectively, for the consumer with solar and two-hour BES. Figures 4.6d through 4.6f show the same for the consumer with solar and six-hour BES.

From Figure 4.6, we can see that, due to the presence of distributed resources, consumers' relative total costs decrease as electricity prices are increased. This is interesting from the perspective of consumer affordability, indicating that solar PVs and BES become increasingly valuable affordability solutions as electricity prices increase. As might be expected from the previous discussion on asset investments as electricity prices change, the consumer's total costs are more sensitive to changes in the entire tariff's price components and changes in the energy charges than they are to changes in the demand charges. Again, we can observe the trajectories associated with the SC and GIE participation schemes serving as an upper bound and lower bound, respectively, for the total cost trajectories of the other two participation schemes. Similar to before, the SIE total costs closely follow those obtained under the GIE scheme. The GINE scheme produces total costs that lie between the two bounds, with total costs for the consumer with solar PVs and two-hour BES trending closer to total costs under the SC scheme and total costs for the consumer with solar PVs and six-hour BES trending closer to total costs under the GIE scheme.

These results, coupled with those from the previous subsection, help highlight the perverse investment strategies that consumers adopt due to the presence of the NBT. No matter if asset-related subsidies are introduced or electricity prices are increased, the influence of the NBT looms large in consumers' decision making. Though the NBT provides consumers with a strong incentive to deploy distributed resources, that incentive is static and fails to take into account actual grid conditions. Per the NBT, consumers building new distributed resources and taking service under the NBT before early 2028 are able to lock in their export prices for nine years [96]. While this is surely helpful for the consumers investing in these resources, such a policy makes it difficult to leverage these new flexible resources moving forward. New value streams may be introduced to try to provide grid-relevant price signals, such as those offered by some existing virtual power plant (VPP) companies. However, those price signals

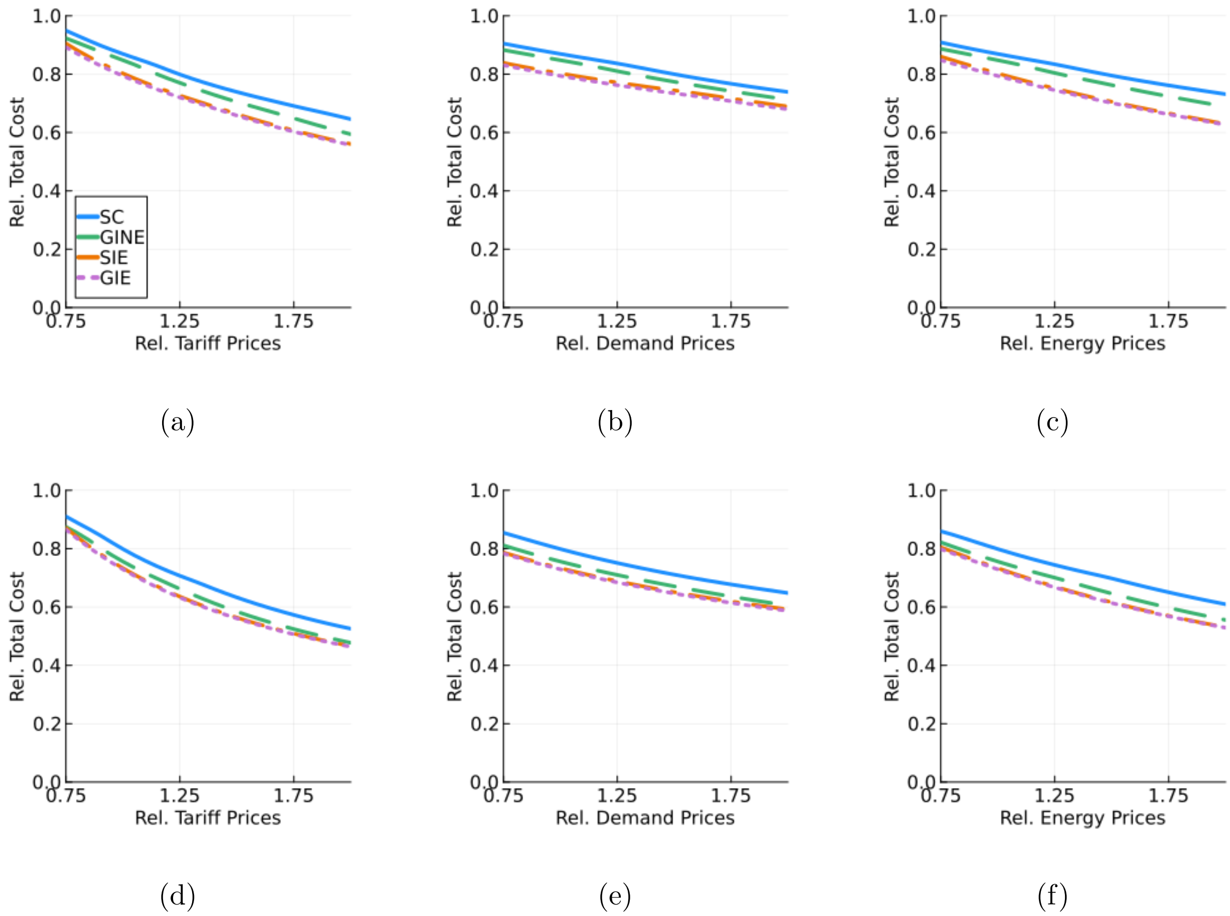


Figure 4.6: Total cost for the Fresno MEP consumer with solar PVs and BES, relative to the base case without investments, as tariff-related prices are changed. (a) and (d) depict total costs as all tariff prices change. (b) and (e) depict total costs as demand charges change. (c) and (f) depict total costs as energy charges change. (a) – (c) show the results for a consumer investing in two-hour BES. (d) – (f) show the results for a consumer investing in six-hour BES.

will need to be quite large to overcome the incentive offered by the NBT, which during its most lucrative hours already provides a price signal that is at least an order of magnitude larger than today's retail electricity prices. Without a more dynamic price signal, consumers may be investing in large solar and storage resources and operating them in a way that could be counterproductive for the grid years down the road, all due to the dominant investing strategy induced by this static policy.

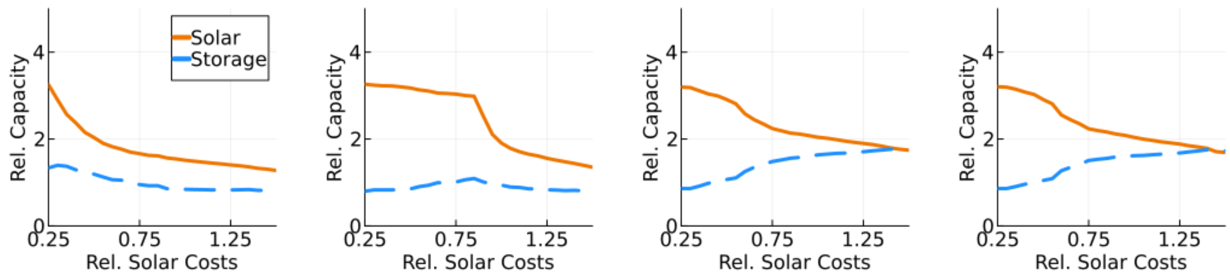
4.4.3 Effect of Load Profile Shape

Though all simulated consumers considered in this study exhibit similar investment trends when asset investment costs and electricity tariff prices are changed, it is important to understand how robust the observed results are to intrinsic consumer characteristics. As such, this subsection examines how consumers' load shapes influence their investment decisions when exposed to the same sensitivity analyses. Figure 4.7 shows the amount of solar PV and two-hour BES capacity the Fresno MDP consumer deploys under each of the four participation schemes. Figures 4.7a through 4.7d reveal how the consumer's investment decisions are affected when the consumer is exposed to solar investment prices that range from 25 percent of the base solar investment cost up to 150 percent of the base solar investment cost; Figures 4.7e through 4.7h examine the same investment decisions when exposed to storage investment prices that are modified using the same range of percentages. Figure 4.8 shows the amount of solar PV and two-hour BES capacity the Fresno MDP consumer deploys under each of the four participation schemes. Figures 4.8a through 4.8d reveal how the consumer's investment decisions are affected when the consumer is exposed to electricity tariff prices that are uniformly scaled to be between 75 percent to 200 percent of the base electricity tariff prices. Figures 4.8e through 4.8h examine the same investment decisions when exposed to demand charges that are scaled to be between 75 percent to 200 percent of the base demand charges. Figures 4.8i through 4.8l examine the same investment decisions when exposed to energy charges that are scaled to be between 75 percent to 200 percent of the base energy charges[4].

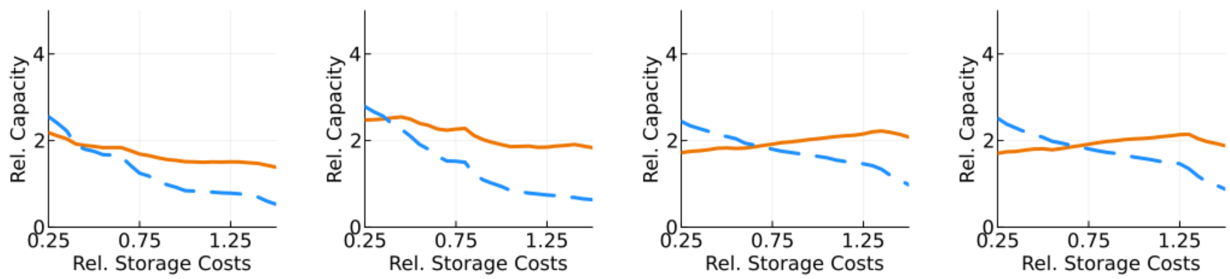
As can be seen in Figures 4.7 and 4.8, the MDP consumer and MEP consumer, whose comparable results can be revisited in Figures 4.1 and 4.4, respectively, produce similar investment trajectories across the four different participation schemes. As was seen for the MEP consumer, asset investments for the MDP consumer under the SC and GINE schemes are largely complementary, while the SIE and GIE schemes exhibit indications that solar PVs and BES act as substitutes when one resource is subsidized. As electricity prices increase, we see that solar and storage are complementary for the MDP consumer. Similar to what was observed for the MEP consumer, investments in solar PVs and BES are most sensitive to increases in all tariff price components and increases in energy charges. Once again, the MDP consumer is found to be insensitive to changes in demand charges for consumers under the SIE and GIE schemes, due in large part to the influence of the NBT.

The main difference between the investments coaxed by the MEP and MDP load shapes lies in the relative magnitude of the distributed resource capacity chosen to be installed. The MDP consumer, with its midday-peaking demand, has a load profile that is less coincident with the higher priced times in PG&E's TOU electricity tariff compared to that of the MEP consumer. Consumers with a profile similar to that of the MDP consumer have benefited from the TOU rate structure since 2021, when PG&E shifted its peak period back to be later in the day [92]. The lower electricity bills for the MDP consumer do not offer the same potential for solar and storage resources to offset costs. First, the MDP consumer's lower energy charges mean that there are fewer NBT credits that can be earned. Second, with large amounts of the MDP consumer's demand already occurring outside of peak-period hours, there is less value in shifting the consumer's demand to other TOU periods. This all results in relative installed solar PV and BES capacities that are routinely lower for the

[4]Note that this subsection only presents results for consumers investing in solar PVs and two-hour BES. While it is important to also understand the impact of investing in longer-duration BES, it was deemed that only presenting the results with the shorter-duration BES was sufficient for examining the impact that a consumer's load profile shape has on investments in this chapter. If interested, results that consider the six-hour BES can be found in Appendix A.



(a) (b) (c) (d)



(e) (f) (g) (h)

Figure 4.7: Installed solar PV and two-hour BES capacity for the Fresno MDP consumer, relative to the consumer's maximum demand, as asset-related costs are changed. (a) – (d) depict investments as solar investment costs change. (e) – (h) depict investments as storage investment costs change. (a) and (e) depict the SC scheme. (b) and (f) depict the GINE scheme. (c) and (g) depict the SIE scheme. (d) and (h) depict the GIE scheme.

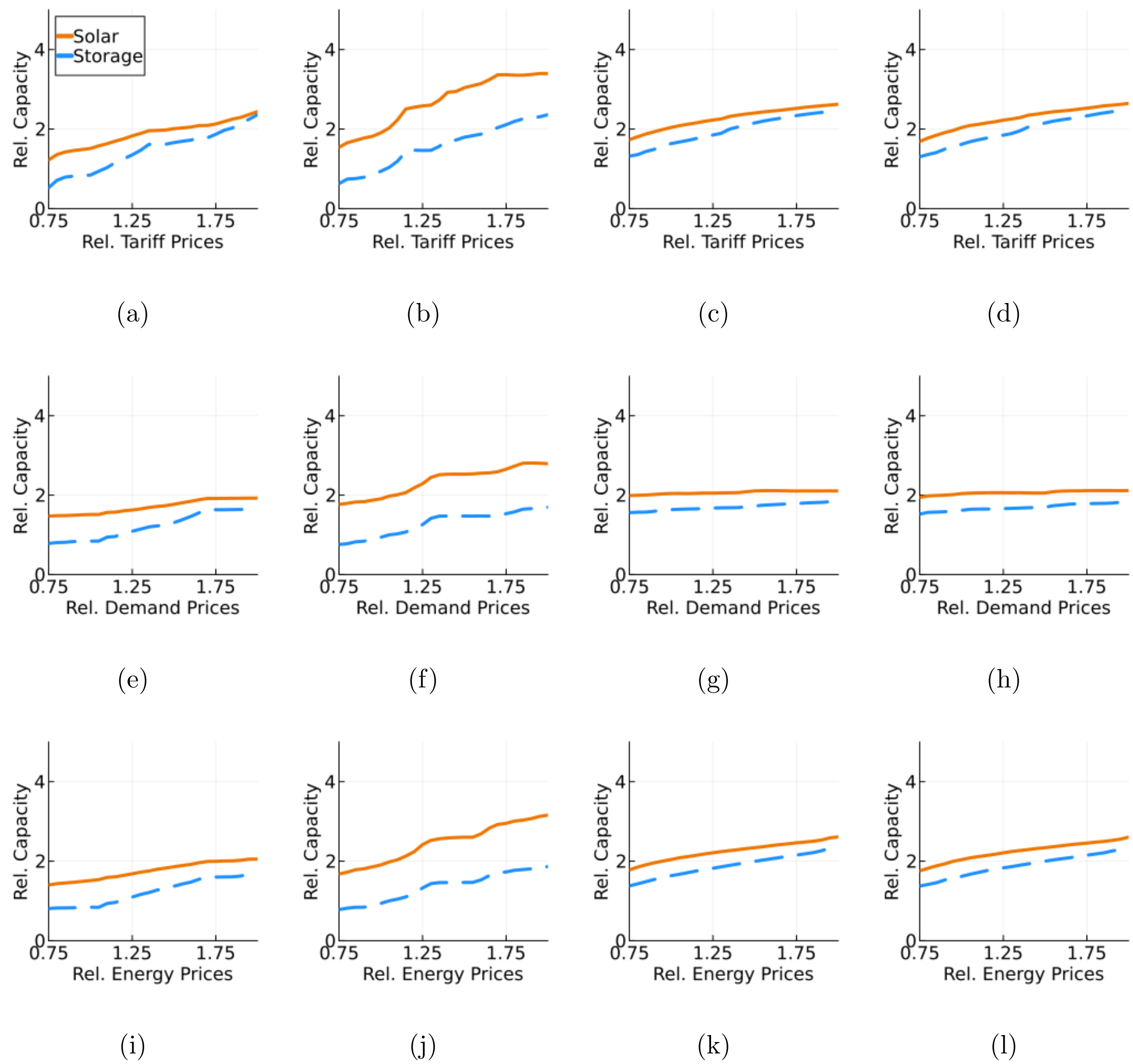
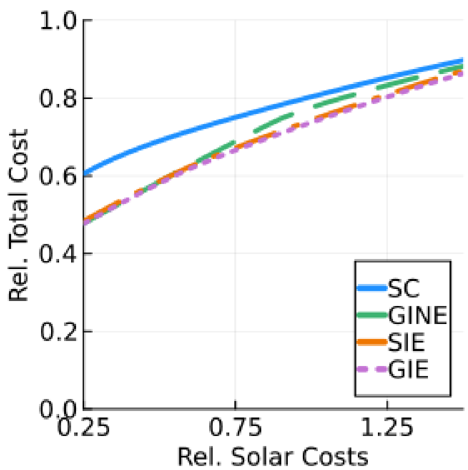


Figure 4.8: Installed solar PV and two-hour BES capacity for the Fresno MDP consumer, relative to the consumer's maximum demand, as tariff-related prices are changed. (a) – (d) depict investments as all tariff prices change. (e) – (h) depict investments as demand charges change. (i) – (l) depict investments as energy charges change. (a), (e), and (i) depict the SC scheme. (b), (f), and (j) depict the GINE scheme. (c), (g), and (k) depict the SIE scheme. (d), (h), and (l) depict the GIE scheme.

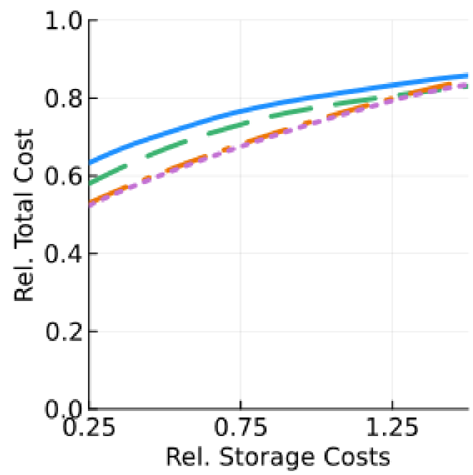
MDP consumer compared to those for the MEP consumer across each of the five sensitivity analyses considered.

The observations made for consumers' asset adoption also make sense in the context of the consumers' total costs. Figure 4.9 compares the Fresno MDP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures 4.9a and 4.9b show the relative total costs when solar and storage investment costs are subsidized, respectively, for the consumer with solar and two-hour BES. Figure 4.10 compares the Fresno MDP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures 4.10a through 4.10c show the relative total costs when all tariff price components are increased, when demand charges are increased, and when energy charges are increased, respectively, for the consumer with solar and two-hour BES.

As can be seen in Figures 4.9 and 4.10, the total cost trajectories for the MDP consumer under each participation scheme are similar to those for the MEP consumer, shown in Figures 4.3 and 4.6, respectively. The MDP consumer sees lower relative total costs as each asset becomes more subsidized. Once again, the trajectories associated with the SC and GIE schemes form the upper and lower bounds, respectively, of the total cost trajectories, with the GINE and SIE trajectories falling in between. As electricity prices increase, the MDP consumer has lower relative total costs, indicating that despite smaller relative asset investments, solar PVs and BES are an effective affordability solution for consumers. The MDP and MEP consumers differ in that the MDP consumers have lower relative total costs throughout each of the five sensitivity analyses. This indicates that MDP consumers are able to extract even more value from their investments, especially considering that they build smaller relative quantities of solar PV and BES capacity. Note that the MEP and MDP consumers have similar absolute reductions in total cost when compared to their respective baselines, but the fact that the MDP consumer has a much lower baseline total cost leads to a better relative cost reduction.



(a)



(b)

Figure 4.9: Total cost for the Fresno MDP consumer with solar PVs and two-hour BES, relative to the base case without investments, as asset-related costs are changed. (a) depicts total costs as solar investment costs change. (b) depicts total costs as storage investment costs change.

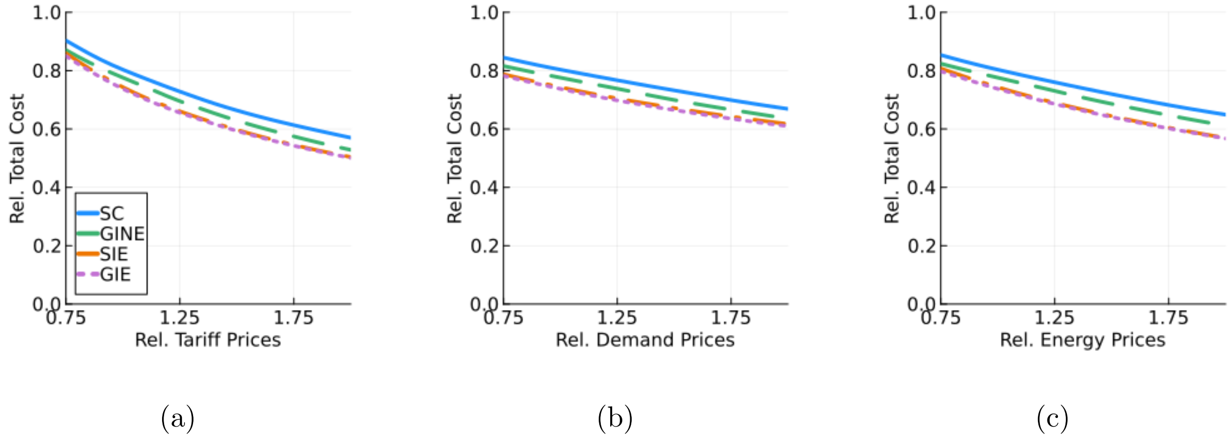


Figure 4.10: Total cost for the Fresno MDP consumer with solar PVs and two-hour BES, relative to the base case without investments, as tariff-related prices are changed. (a) depicts total costs as all tariff prices change. (b) depicts total costs as demand charges change. (c) depicts total costs as energy charges change.

4.4.4 Effect of Climate Zone Membership

For the final robustness check of this chapter, I consider the impact of a simulated consumer's climate zone membership on their asset-investment and total-cost trajectories. Figure 4.11 shows the amount of solar PV and two-hour BES capacity the San Francisco MEP consumer deploys under each of the four participation schemes. Figures 4.11a through 4.11d reveal how the consumer's investment decisions are affected when the consumer is exposed to solar investment prices that range from 25 percent of the base solar investment cost up to 150 percent of the base solar investment cost; Figures 4.11e through 4.11h examine the same investment decisions when exposed to storage investment prices that are modified using the same range of percentages. Figure 4.12 shows the amount of solar PV and two-hour BES capacity the San Francisco MEP consumer deploys under each of the four participation schemes. Figures 4.12a through 4.12d reveal how the consumer's investment decisions are affected when the consumer is exposed to electricity tariff prices that are uniformly scaled to be between 75 percent to 200 percent of the base electricity tariff prices. Figures 4.12e through 4.12h examine the same investment decisions when exposed to demand charges that are scaled to be between 75 percent to 200 percent of the base demand charges. Figures 4.12i through 4.12l examine the same investment decisions when exposed to energy charges that are scaled to be between 75 percent to 200 percent of the base energy charges

As can be seen in Figures 4.11 and 4.12, the San Francisco MEP consumer and Fresno MEP consumer, whose comparable results can be explored in Figures 4.1 and 4.4, respectively, produce similar investment trajectories across the four different participation schemes. As was seen for the Fresno MEP consumer, capacity investments for the San Francisco MEP consumer are largely complementary under the SC and GINE schemes. Under the SIE and GIE schemes, the San Francisco MEP consumer's investment trajectories indicate that solar PVs and BES act more like substitutes when one asset type is subsidized. As electricity prices increase, we see that solar and storage are complementary for the San Francisco MEP consumer. Similar to what was observed for the Fresno MEP consumer, solar PV and BES investments are most sensitive to increases in all tariff price components and increases in energy charges. As was previously indicated for the Fresno MEP consumer, the San Francisco MEP consumer is found to be largely insensitive to changes in demand charges for consumers under the SIE and GIE schemes, due in large part to the influence of the NBT.

There are limited differences between the asset-investment trajectories of the San Francisco MEP consumer and the Fresno MEP consumer, indicating that climate zone locations have a negligible effect on consumers' solar PV and BES deployments. The only noticeable difference is that the San Francisco MEP consumer builds larger quantities of solar PVs when they are unsubsidized compared to the Fresno MEP consumer. Considering that San Francisco has a weaker solar resource than Fresno, it is apparent that the San Francisco MEP consumer requires more solar to be built so that it can adequately claim its full allotment of NBT credits and help offset its peak-period energy charges and demand charges.

Regardless of the extra solar capacity that must be built to account for the weaker solar resource in San Francisco, it does not appear to impact the San Francisco MEP consumer's

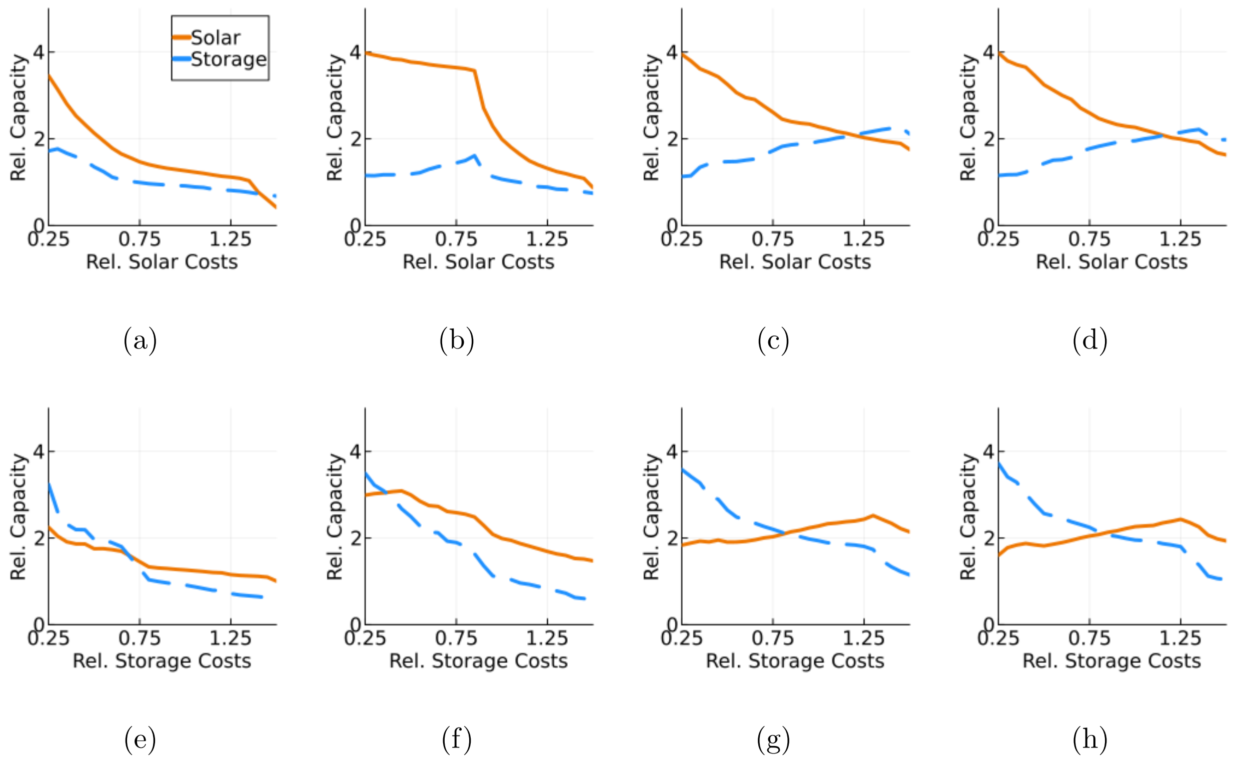


Figure 4.11: Installed solar PV and two-hour BES capacity for the San Francisco MEP consumer, relative to the consumer's maximum demand, as asset-related costs are changed. (a) – (d) depict investments as solar investment costs change. (e) – (h) depict investments as storage investment costs change. (a) and (e) depict the SC scheme. (b) and (f) depict the GINE scheme. (c) and (g) depict the SIE scheme. (d) and (h) depict the GIE scheme.

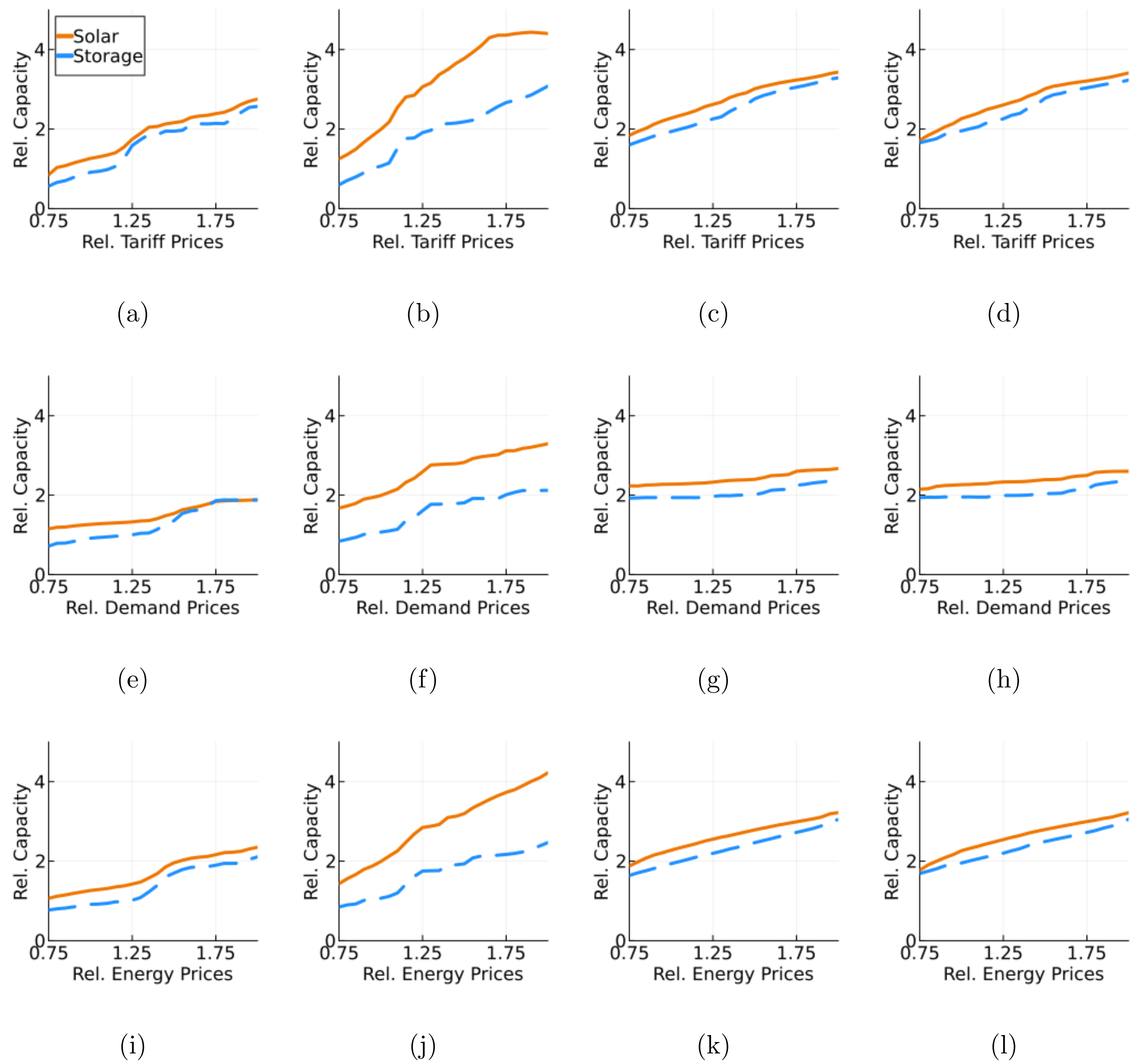
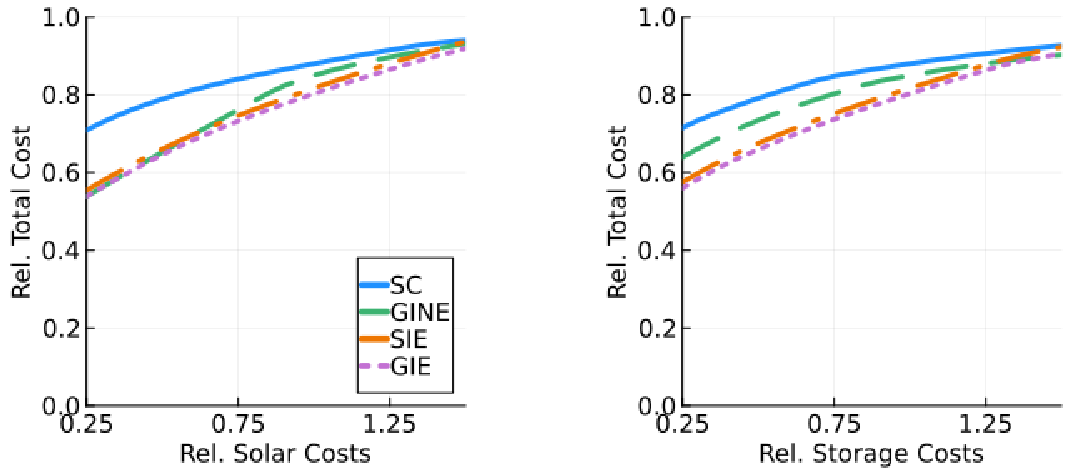


Figure 4.12: Installed solar PV and two-hour BES capacity for the San Francisco MEP consumer, relative to the consumer's maximum demand, as tariff-related prices are changed. (a) – (d) depict investments as all tariff prices change. (e) – (h) depict investments as demand charges change. (i) – (l) depict investments as energy charges change. (a), (e), and (i) depict the SC scheme. (b), (f), and (j) depict the GINE scheme. (c), (g), and (k) depict the SIE scheme. (d), (h), and (l) depict the GIE scheme.



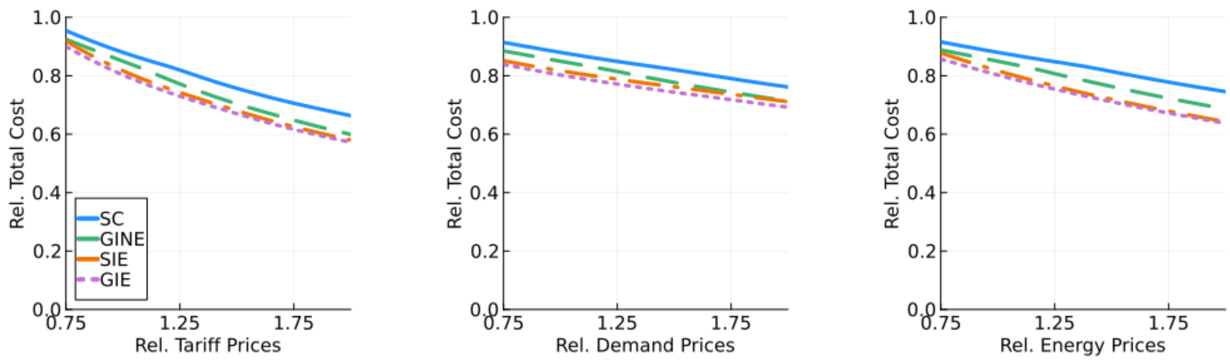
(a)

(b)

Figure 4.13: Total cost for the San Francisco MEP consumer with solar PVs and two-hour BES, relative to the base case without investments, as asset-related costs are changed. (a) depicts total costs as solar investment costs change. (b) depicts total costs as storage investment costs change.

total-cost trajectories relative to those of the Fresno MEP consumer. Figure 4.13 compares the San Francisco MEP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures 4.13a and 4.13b show the relative total costs when solar and storage investment costs are subsidized, respectively, for the consumer with solar and two-hour BES. Figure 4.14 compares the San Francisco MEP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures 4.14a through 4.14c show the relative total costs when all tariff price components are increased, when demand charges are increased, and when energy charges are increased, respectively, for the consumer with solar and two-hour BES.

As can be seen in Figures 4.13 and 4.14, the total-cost trajectories for the San Francisco



(a) (b) (c)

Figure 4.14: Total cost for the San Francisco MEP consumer with solar PVs and two-hour BES, relative to the base case without investments, as tariff-related prices are changed. (a) depicts total costs as all tariff prices change. (b) depicts total costs as demand charges change. (c) depicts total costs as energy charges change.

MEP consumer under each participation scheme are similar to those for the Fresno MEP consumer, shown in Figures 4.3 and 4.6, respectively. The near-identical total-cost trajectories supplement the earlier claim that climate zone membership has a limited affect on solar and storage investments. In addition to consumers investing in solar PVs and BES similarly across climate zones, those resources also have a similar impact on the consumers' total costs, regardless of the participation scheme.

4.5 Conclusions

This chapter examines the complementarity of behind-the-meter solar PVs and BES in the presence of contemporary asset investment costs and electricity tariffs. Across all explored scenarios, it was found to be optimal for consumers with different load profile shapes in different climate zones to build a combination of solar and storage resources, indicating that solar PVs and BES are indeed complementary resources. While the technical and programmatic interdependencies between these two asset types help ensure they be built together, the sensitivity analyses conducted in this chapter help reveal the extent to which solar and storage are complementary. As solar and storage investment costs decrease, it is only under certain participation schemes that consumers see both solar PVs and BES increasingly built together. Consumers that are either unable to or limited in their ability to provide grid exports generally see solar and storage resources be truly complementary as asset investment costs decrease. Conversely, consumers who are able to participate in the Net Billing Tariff (NBT) and have both solar PVs and BES produce grid exports exhibit substituting behavior, whereby the assets that decrease in their investment costs begin to replace some of the capacity that would otherwise be deployed by the other resource. Regardless of the participation scheme, solar PVs and BES are found to be complementary as electricity tariff prices increase. Consumers are found to be more sensitive to changes in energy charges than they are to changes in demand charges.

The results presented in this chapter have implications for electricity tariffs and solar PV and BES subsidies. As was shown throughout this chapter, the NBT has an outsized effect on consumers' investment strategies. Not only did the NBT heavily influence what proved to be the most effective participation schemes (i.e., any participation scheme that allows as many assets as possible to produce exports), but it also impacted consumers' investment strategies in the face of asset subsidies and rising electricity prices. It would be one thing if the NBT was a dynamic price signal that considered grid-level impacts or even if was updated on a regular basis to make necessary adjustments to its incentive structure. Instead, the NBT's static export price profiles and nine-year lock-in could unduly influence consumers' asset investments and operations for many years to come. Considering that the U.S. electric grid could look very different a decade from now [3, 4, 5, 6], policymakers and regulators should be ensuring that incentives and rules put in place today have the ability to be adjusted or retired in order to limit detrimental side effects in the future.

Chapter 5
CONCLUSIONS

5.1 Summary of Contributions

This dissertation is intended to further the understanding of the impacts that electricity tariffs and relevant policies have on the deployment and operation of consumers' distributed energy resources (DERs). As retail electricity prices continue to increase and the cost of technologies like behind-the-meter solar and storage continue to decrease, DERs will only become more popular amongst consumers for affordability and resiliency purposes and amongst regulators for potential system cost savings and progress towards clean energy goals. To help avoid detrimental outcomes and negative long-term effects, it is imperative to have tools that can better reveal the impacts of proposed electricity rates, policies, and rules. Moreover, it is vital to critically examine the current policy landscape to uncover concerning trends that can become more deeply ingrained as we progress through this energy transition. Each of the chapters contained herein work to advance a combination of (1) the modeling of electricity tariffs and their ability to influence consumers' DER-related operational and investment decisions and (2) the analysis of established and proposed electricity rates and policies to provide novel insights relevant to decision makers.

Chapter 2 introduces the Distributed Energy Resource Investment and Valuation Engine (DERIVE), an open-source software tool that helps explore the impacts that different value streams, including various electricity rate structures, have on DER investments and operations. Through its design, DERIVE allows stakeholders to thoroughly model multiple different types of electric tariffs, a unique capability at a timely juncture. The capabilities of DERIVE are displayed in analyses conducted in Chapter 3 and Chapter 4. The former showcases DERIVE's production cost modeling capabilities while the latter features DERIVE's capacity expansion functionality.

Chapter 3 presents two case studies that explore the impacts of discriminatory technology-specific electric tariffs implemented in California. The first case study examines the impacts that Pacific Gas and Electric Company's storage-centric electric tariff, the Option S for Storage rider from the B-19 tariff, has on consumers with battery energy storage and consumers with flexible demand. Though not actually offered to flexible demand resources, I find that flexible demand provides similar grid benefits to the utility as battery energy storage, indicating that the utility should engage a wider class of consumers in the storage-centric tariff. Unfortunately, only the most flexible consumers benefit from the Option S rider, so the utility and regulator would need to leverage the same rate structure components while reducing the cost burden if they wanted to entice more consumers to take service under the tariff rider. The second case study explores the impacts that the California Public Utilities Commission's successor to net energy metering, the Net Billing Tariff, has on consumers with different DER mixes. The adoption of the Net Billing Tariff negatively affects consumers with only distributed solar, but benefits consumers who can pair their behind-the-meter solar with battery energy storage, which is able to take advantage of the greater, but limited, export prices. With the export prices being unsymmetrical from the energy price, consumers with flexible demand are not able to benefit. Both case studies highlight the inefficient rate design decisions made in the service of supporting specific technologies.

Chapter 4 examines the complementarity of behind-the-meter solar photovoltaics and battery energy storage when exposed to contemporary asset investment costs and electricity tariffs. For the explored scenarios, it was optimal for consumers to build both solar and storage resources, regardless of the assets' investment prices or the cost of purchasing electricity from the utility. This finding indicates that solar photovoltaics and battery energy storage are indeed complementary resources, dispelling the widespread notion that the California Public Utility Commission's Net Billing Tariff is entirely adversarial to the distributed solar industry. The sensitivity analyses conducted in Chapter 4 help reveal the extent to which the solar and storage resources are complementary. For consumers whose solar photovoltaics and battery energy storage can both provide exports and be compensated through the Net Billing Tariff, the assets exhibit substituting behavior as asset investment prices decrease. That is, as the investment cost of one asset type decreases, that asset type increases in capacity while the other decreases in capacity. For consumers that are unable to provide grid exports in the same way, solar and storage resources are more complementary as asset investment costs decrease, where building more capacity of one asset type leads to building more of the other as well. Regardless of the participation scheme, all simulated consumers were found to have complementary solar photovoltaic and battery energy storage investments as electricity tariff prices increase. In addition to insights about the investment dynamics between behind-the-meter solar and storage resources, Chapter 4 discusses the larger implications of electricity tariffs and asset subsidies. In particular, the Net Billing Tariff is found to heavily influence consumers' investment strategies, which is concerning considering its static export price profiles and near-decade price lock-in.

5.2 Opportunities for Future Work

There are ample research topics that could look to build on the models and analyses presented in this dissertation. This section discusses some of those topics alongside additional commentary.

The first topic of future work is to find ways to incorporate more sources of uncertainty into the simulations presented in this dissertation. Though the analyses conducted in Chapter 3 and Chapter 4 considered some forms of uncertainty, such as differences in asset sizes, investment costs, electricity price magnitudes, load profile shapes, and consumer locations, the results presented herein could be more generalizable if a larger sample of consumers were to be considered. While the analyses conducted in those two chapters were generally aided by the ability to make direct comparisons between different standard load shapes, running simulations on a larger sample of consumers could make the conclusions stronger from a policy perspective, especially if conclusions are able to be made about a representative sample population.

A second topic of future work could expand on this dissertation by considering the impacts of different electricity tariffs and policies on residential consumers. All of the simulations included in this dissertation were run on simulated commercial consumers, though that was a scenario design choice rather than a limitation of DERIVE. Commercial consumers were solely considered for a couple reasons. First, the load profiles used throughout this dissertation, which are sourced from Ong and Clark [120], offer more variation in their commercial load profiles than they do in their residential load profiles. This allows for consumers with different load shapes to more easily be examined, as is done in Chapter 3 and Chapter 4. Second, electricity tariffs offered to commercial consumers are more involved than those offered to residential consumers. The main difference in the electric tariffs offered to commercial consumers is that they also have demand charges, which makes both the operation and investment decision making more complicated. However, while the rates offered to residential consumers may not pose the most complex optimization problem, this is still an interesting problem within the energy policy space. For example, concerns over consumer affordability, especially for low-income consumers, are prominent in states with high electricity prices, such as California. As such, understanding drivers of the high electricity prices or potential solutions that can help lower consumers' bills are arguably of greater public importance.

Looking to build more broadly upon the topics discussed in this dissertation, a third topic of future work is to design and simulate electricity rates that are more cost-reflective. As was discussed in Chapter 1, the price signals provided by contemporary electricity tariffs are prone to producing inefficient consumer responses and fail to recover costs in a manner that is reflective of the way the costs were originally incurred. With the wave of distributed flexible resources that are being and plan to be deployed by consumers, inadequate electricity tariffs can pose a threat to the energy transition, as inefficient signals to invest in and operate DERs can make grid operations more challenging. As such, it is crucial to design rates that are more cost-reflective and more capable of eliciting efficient consumer responses. Chapter 1, as well as other literature [67, 68, 71], give an idea of the form that efficient and cost-reflective electric tariffs may take, so I will not reiterate those ideas here. What is worth mentioning is the need to robustly model and simulate future electricity tariff designs, both in how they affect consumers and in how they work alongside the electric grid. While this dissertation has shown how impacts on individual consumers can be modeled and analyzed, it does not provide insights to how grid impacts may be examined. A methodology like what is used in Pacific Northwest National Laboratory's Distribution System Operator with Transactive (DSO+T) Study [117, 146, 147, 148, 149] could be expanded upon for such analyses, where the Transactive Energy Simulation Platform (TESP) [150] was used to coordinate models for electricity markets, grid operations, and consumer load behavior. Unlike the DSO+T Study, which only considered two limited electricity tariffs, a broader family of electricity tariffs will need to be explored.

Building upon the third topic of future work that was just discussed, a fourth topic of future work should look more into a pathway for implementing electricity tariffs that are found to be more cost-reflective. The components of some of the "optimal" or "best-case" proposed electricity tariffs can be challenging to implement at scale, both technically and administratively. For instance, the implementation of many efficient and cost-reflective tariffs hinges on implementing a dynamic time-varying price that is meant to track, if not equal, the marginal cost of electricity in the system. However, passing such a price to consumers is no easy feat. On the technical side, most consumers would need to have enabling technologies, such as a home energy management system, to allow them to sufficiently operate their flexible resources. Even if each consumer were able to get the proper enabling technologies, seamlessly coordinating each consumer would be challenging, especially due to the high-resolution, low-latency, high-reliability communication network that would also need to be built and supported. Separate from the technical side, there are also regulatory and political concerns that must be considered. Depending on the underlying electricity market construct, real-time pricing is likely to carry some sort of risk that consumers have been largely insulated against in the past. This can cause the regulator or other decision-making entity to either take preemptive measures to shield consumers or risk the fallout if consumers are exposed to prohibitively high prices for an extended period of time. The latter is similar to what happened in Texas in February 2021. A Texas electricity retailer, Griddy, whose primary rate structure passed real-time wholesale electricity prices directly to consumers, had sustained electricity prices of \$9/kWh (corresponding to the wholesale market price cap of \$9000/MWh) due to generator outages caused by a winter storm [44]. In the aftermath, where some inflexible and unaware consumers were stuck with electricity bills that cost tens of thousands of dollars, Texas lawmakers passed a law that banned real-time electricity prices from being passed to residential electricity consumers [151]. Since not all "optimal" electricity tariffs will be able to be implemented, "near-optimal" electricity tariffs should be designed that incorporate components more likely to be adopted by regulators and utilities. Additionally, plans to implement such rates should be examined, as regulators and utilities will be more likely to incrementally update their rate structures rather than going directly from flat rates to market-based transactive rates.

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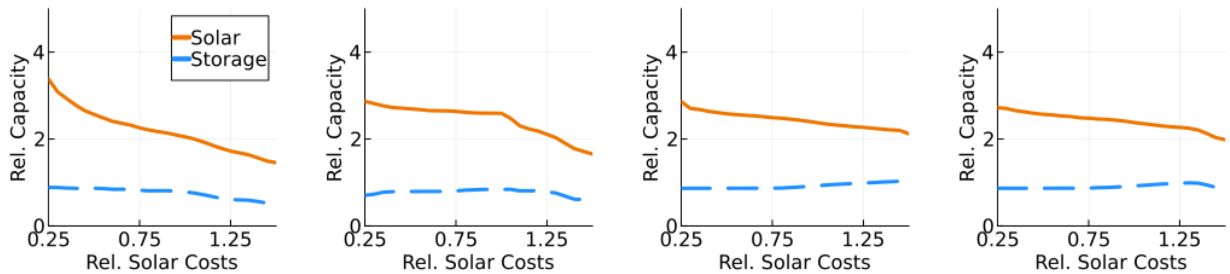
Appendix A

SUPPLEMENTARY INFORMATION FOR CHAPTER 4

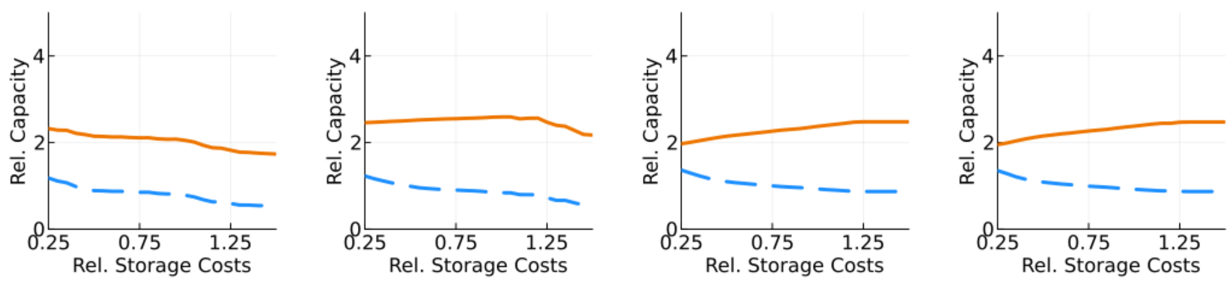
A.1 Additional Results for Consumer with Midday-Peaking Demand from Fresno

Figure A.1 shows the amount of solar PV and six-hour BES capacity the Fresno MDP consumer deploys under each of the four participation schemes. Figures A.1a through A.1d reveal how the consumer's investment decisions are affected when the consumer is exposed to solar investment prices that range from 25 percent of the base solar investment cost up to 150 percent of the base solar investment cost; Figures A.1e through A.1h examine the same investment decisions when exposed to storage investment prices that are modified using the same range of percentages. Figure A.2 shows the amount of solar PV and six-hour BES capacity the Fresno MDP consumer deploys under each of the four participation schemes. Figures A.2a through A.2d reveal how the consumer's investment decisions are affected when the consumer is exposed to electricity tariff prices that are uniformly scaled to be between 75 percent to 200 percent of the base electricity tariff prices. Figures A.2e through A.2h examine the same investment decisions when exposed to demand charges that are scaled to be between 75 percent to 200 percent of the base demand charges. Figures A.2i through A.2l examine the same investment decisions when exposed to energy charges that are scaled to be between 75 percent to 200 percent of the base energy charges

Figure A.3 compares the Fresno MDP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures A.3a and A.3b show the relative total costs when solar and storage investment costs are subsidized, respectively, for the consumer with solar and six-hour BES. Figure A.4 compares the Fresno MDP consumer's total costs under each participation scheme, relative to the



(a) (b) (c) (d)



(e) (f) (g) (h)

Figure A.1: Installed solar PV and six-hour BES capacity for the Fresno MDP consumer, relative to the consumer's maximum demand, as asset-related costs are changed. (a) – (d) depict investments as solar investment costs change. (e) – (h) depict investments as storage investment costs change. (a) and (e) depict the SC scheme. (b) and (f) depict the GINE scheme. (c) and (g) depict the SIE scheme. (d) and (h) depict the GIE scheme.

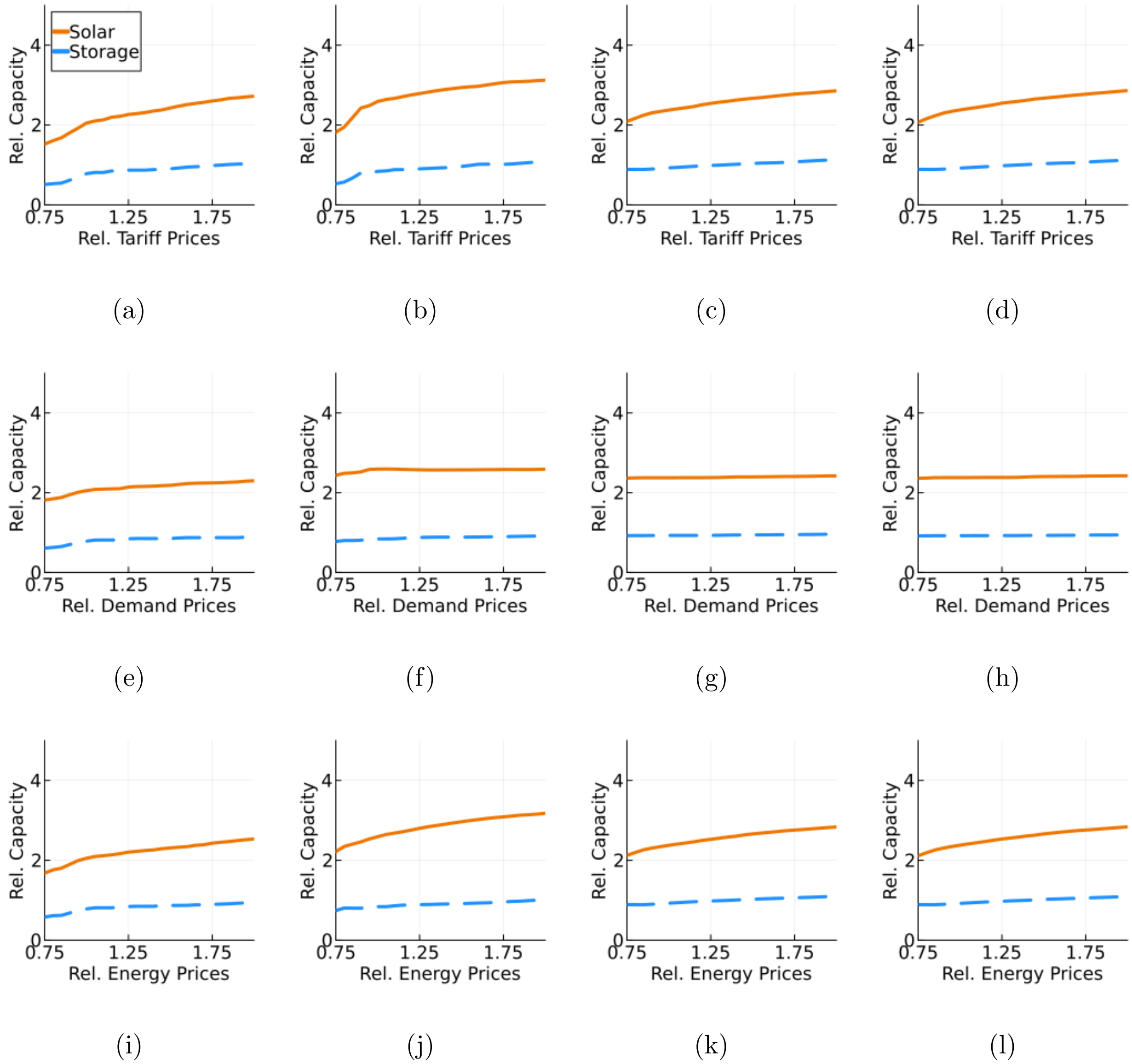
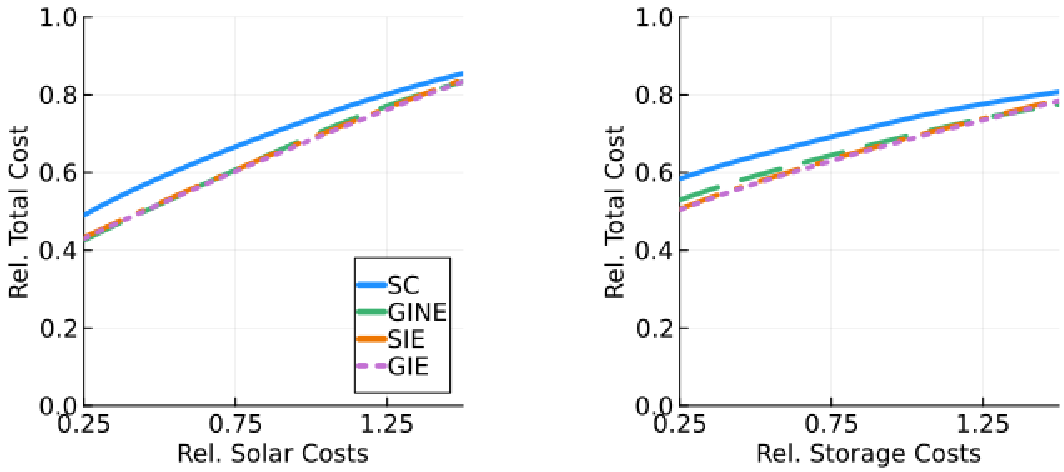


Figure A.2: Installed solar PV and six-hour BES capacity for the Fresno MDP consumer, relative to the consumer's maximum demand, as tariff-related prices are changed. (a) – (d) depict investments as all tariff prices change. (e) – (h) depict investments as demand charges change. (i) – (l) depict investments as energy charges change. (a), (e), and (i) depict the SC scheme. (b), (f), and (j) depict the GINE scheme. (c), (g), and (k) depict the SIE scheme. (d), (h), and (l) depict the GIE scheme.



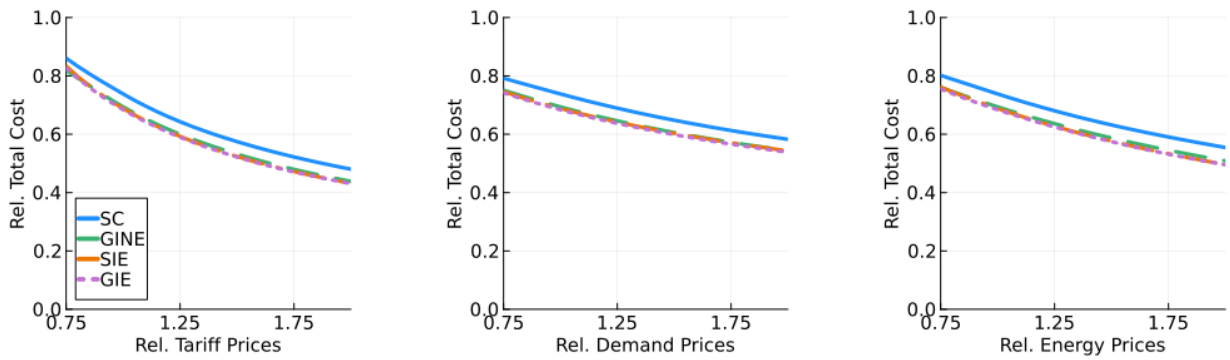
(a) (b)

Figure A.3: Total cost for the Fresno MDP consumer with solar PVs and six-hour BES, relative to the base case without investments, as asset-related costs are changed. (a) depicts total costs as solar investment costs change. (b) depicts total costs as storage investment costs change.

electricity bill without the influence of solar PVs and BES. Figures A.4a through A.4c show the relative total costs when all tariff price components are increased, when demand charges are increased, and when energy charges are increased, respectively, for the consumer with solar and six-hour BES.

A.2 Additional Results for Consumer with Morning-and-Evening-Peaking Demand from San Francisco

Figure A.5 shows the amount of solar PV and six-hour BES capacity the San Francisco MEP consumer deploys under each of the four participation schemes. Figures A.5a through A.5d reveal how the consumer's investment decisions are affected when the consumer is exposed to solar investment prices that range from 25 percent of the base solar investment cost up to



(a) (b) (c)

Figure A.4: Total cost for the Fresno MDP consumer with solar PVs and six-hour BES, relative to the base case without investments, as tariff-related prices are changed. (a) depicts total costs as all tariff prices change. (b) depicts total costs as demand charges change. (c) depicts total costs as energy charges change.

150 percent of the base solar investment cost; Figures A.5e through A.5h examine the same investment decisions when exposed to storage investment prices that are modified using the same range of percentages. Figure A.6 shows the amount of solar PV and six-hour BES capacity the San Francisco MEP consumer deploys under each of the four participation schemes. Figures A.6a through A.6d reveal how the consumer's investment decisions are affected when the consumer is exposed to electricity tariff prices that are uniformly scaled to be between 75 percent to 200 percent of the base electricity tariff prices. Figures A.6e through A.6h examine the same investment decisions when exposed to demand charges that are scaled to be between 75 percent to 200 percent of the base demand charges. Figures A.6i through A.6l examine the same investment decisions when exposed to energy charges that are scaled to be between 75 percent to 200 percent of the base energy charges

Figure A.7 compares the San Francisco MEP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES.

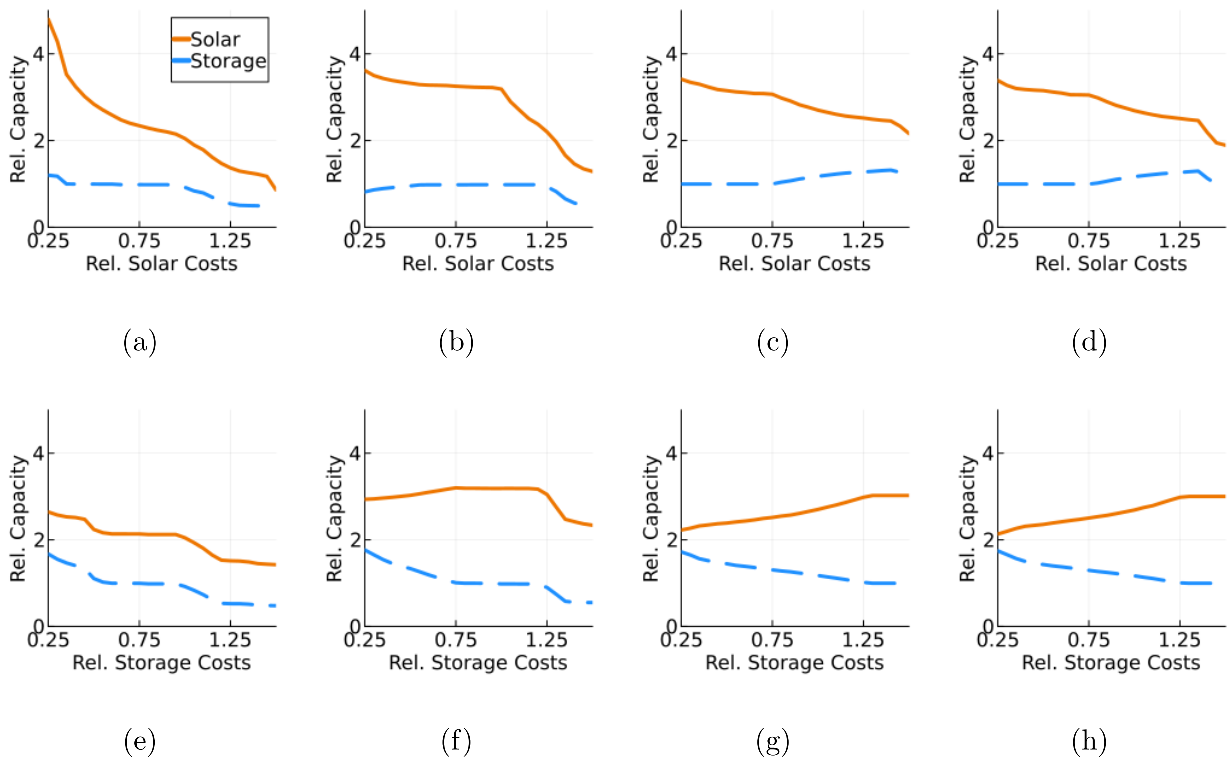


Figure A.5: Installed solar PV and six-hour BES capacity for the San Francisco MEP consumer, relative to the consumer's maximum demand, as asset-related costs are changed. (a) – (d) depict investments as solar investment costs change. (e) – (h) depict investments as storage investment costs change. (a) and (e) depict the SC scheme. (b) and (f) depict the GINE scheme. (c) and (g) depict the SIE scheme. (d) and (h) depict the GIE scheme.

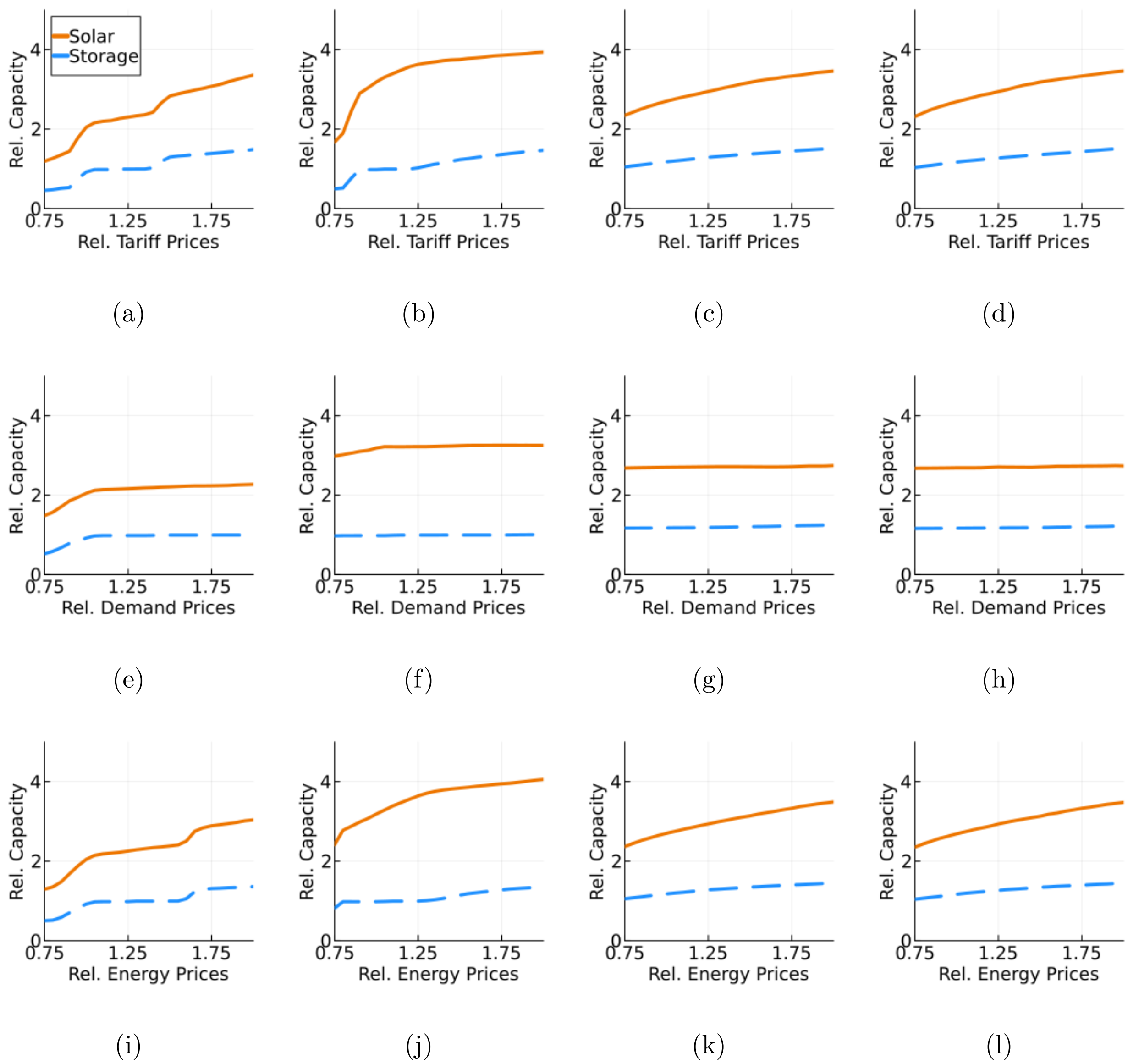
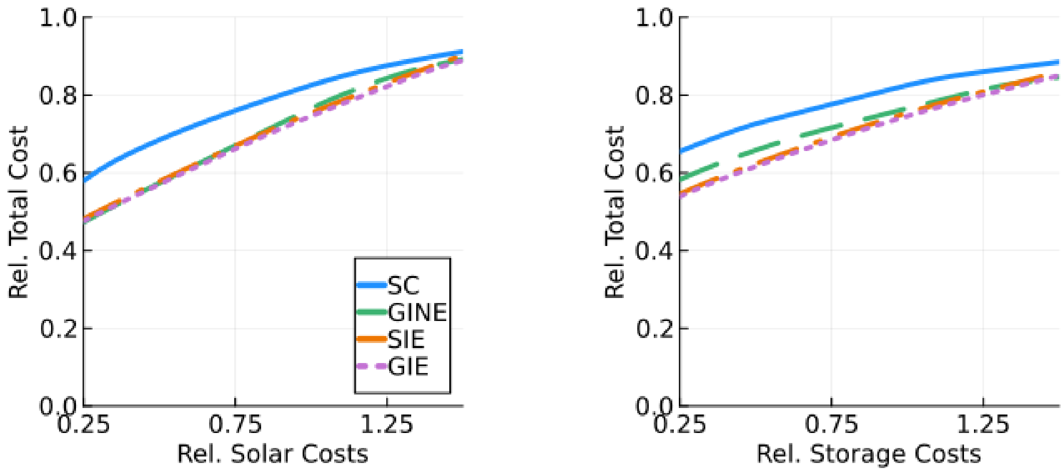


Figure A.6: Installed solar PV and six-hour BES capacity for the San Francisco MEP consumer, relative to the consumer's maximum demand, as tariff-related prices are changed. (a) – (d) depict investments as all tariff prices change. (e) – (h) depict investments as demand charges change. (i) – (l) depict investments as energy charges change. (a), (e), and (i) depict the SC scheme. (b), (f), and (j) depict the GINE scheme. (c), (g), and (k) depict the SIE scheme. (d), (h), and (l) depict the GIE scheme.



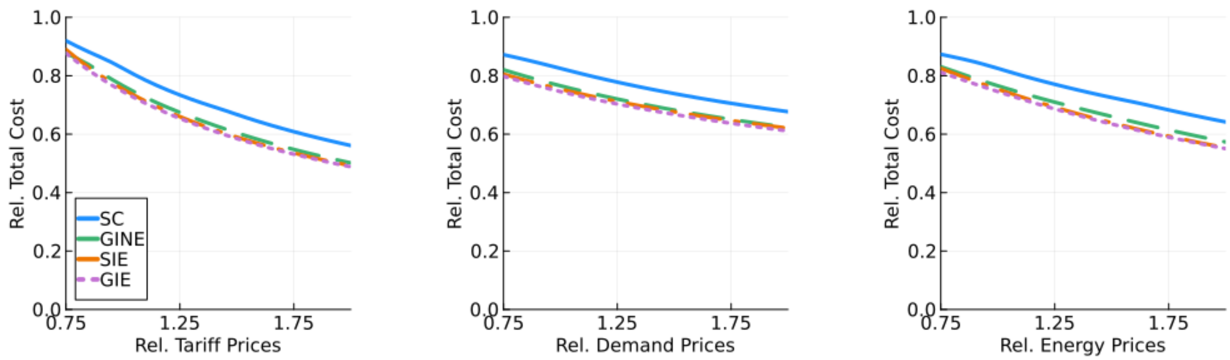
(a) (b)

Figure A.7: Total cost for the San Francisco MEP consumer with solar PVs and six-hour BES, relative to the base case without investments, as asset-related costs are changed. (a) depicts total costs as solar investment costs change. (b) depicts total costs as storage investment costs change.

Figures A.7a and A.7b show the relative total costs when solar and storage investment costs are subsidized, respectively, for the consumer with solar and six-hour BES. Figure A.8 compares the San Francisco MEP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures A.8a through A.8c show the relative total costs when all tariff price components are increased, when demand charges are increased, and when energy charges are increased, respectively, for the consumer with solar and six-hour BES.

A.3 Results for Consumer with Midday-Peaking Demand from San Francisco

Figure A.9 shows the amount of solar PV and two-hour BES capacity the San Francisco MDP consumer deploys under each of the four participation schemes. Figures A.9a through A.9d



(a) (b) (c)

Figure A.8: Total cost for the San Francisco MEP consumer with solar PVs and six-hour BES, relative to the base case without investments, as tariff-related prices are changed. (a) depicts total costs as all tariff prices change. (b) depicts total costs as demand charges change. (c) depicts total costs as energy charges change.

reveal how the consumer's investment decisions are affected when the consumer is exposed to solar investment prices that range from 25 percent of the base solar investment cost up to 150 percent of the base solar investment cost; Figures A.9e through A.9h examine the same investment decisions when exposed to storage investment prices that are modified using the same range of percentages. Figure A.10 is configured similarly to Figure A.9, though it shows investments in solar PVs and six-hour BES.

Figure A.11 shows the amount of solar PV and two-hour BES capacity the San Francisco MDP consumer deploys under each of the four participation schemes. Figures A.11a through A.11d reveal how the consumer's investment decisions are affected when the consumer is exposed to electricity tariff prices that are uniformly scaled to be between 75 percent and 200 percent of the base electricity tariff prices. Figures A.11e through A.11h examine the same investment decisions when exposed to demand charges that are scaled to be between 75 percent and 200 percent of the base demand charges. Figures A.11i through A.11l examine

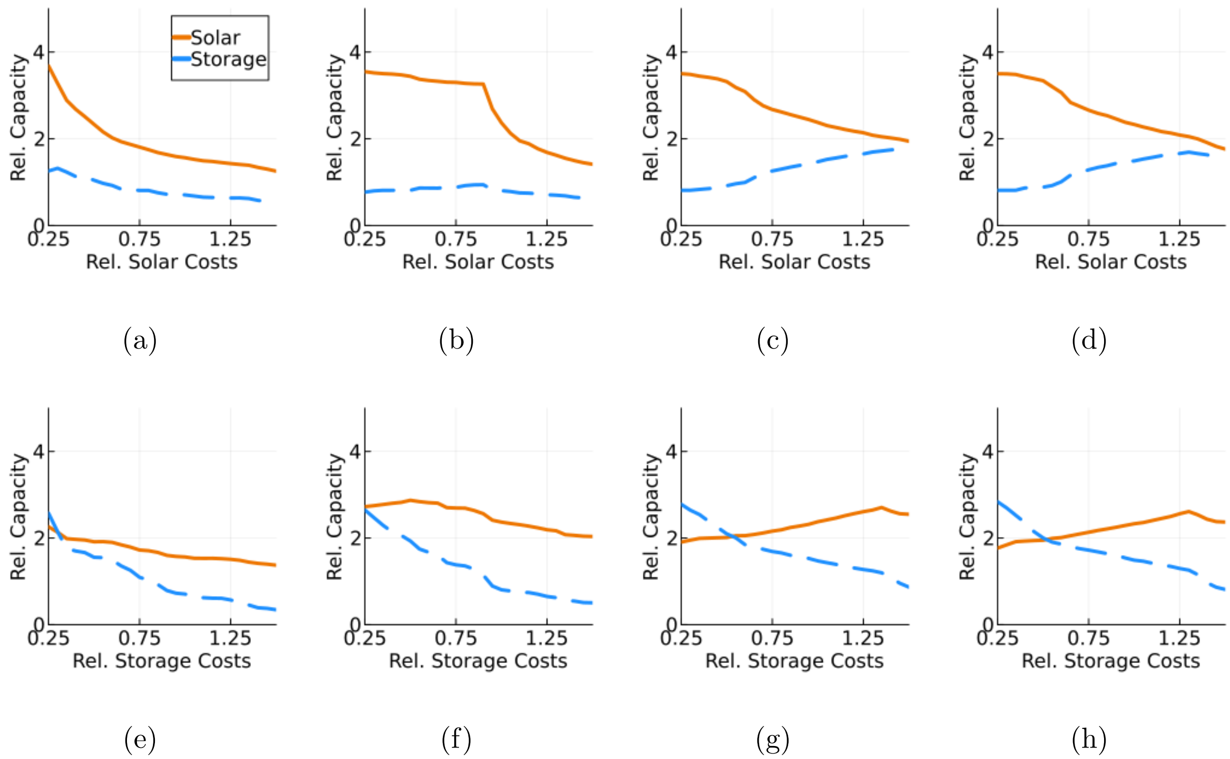


Figure A.9: Installed solar PV and two-hour BES capacity for the San Francisco MDP consumer, relative to the consumer's maximum demand, as asset-related costs are changed. (a) – (d) depict investments as solar investment costs change. (e) – (h) depict investments as storage investment costs change. (a) and (e) depict the SC scheme. (b) and (f) depict the GINE scheme. (c) and (g) depict the SIE scheme. (d) and (h) depict the GIE scheme.

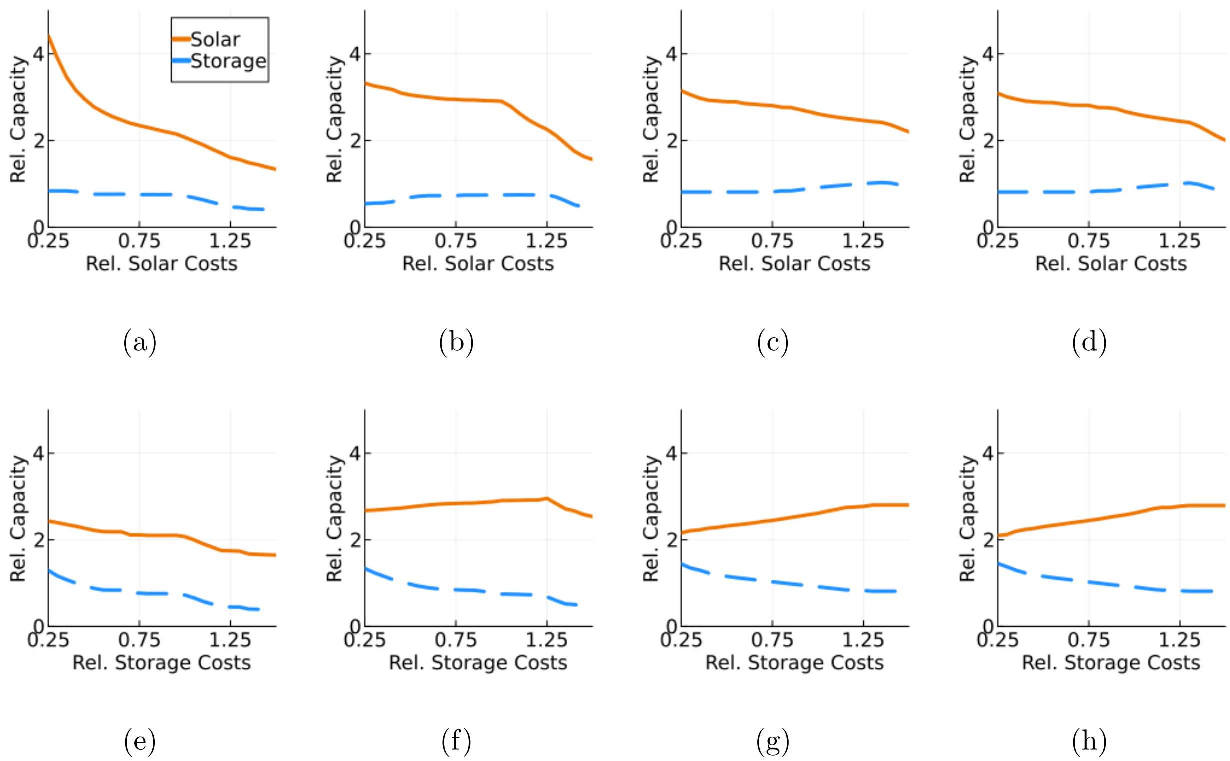


Figure A.10: Installed solar PV and six-hour BES capacity for the San Francisco MDP consumer, relative to the consumer's maximum demand, as asset-related costs are changed. (a) – (d) depict investments as solar investment costs change. (e) – (h) depict investments as storage investment costs change. (a) and (e) depict the SC scheme. (b) and (f) depict the GINE scheme. (c) and (g) depict the SIE scheme. (d) and (h) depict the GIE scheme.

the same investment decisions when exposed to energy charges that are scaled to be between 75 percent and 200 percent of the base energy charges. Figure A.12 is configured similarly to Figure A.11, though it shows investments in solar PVs and six-hour BES.

Figure A.13 compares the San Francisco MDP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures A.13a and A.13b show the relative total costs when solar and storage investment costs are subsidized, respectively, for the consumer with solar and two-hour BES. Figures A.13c and A.13d show the same for the consumer with solar and six-hour BES.

Figure A.14 compares the San Francisco MDP consumer's total costs under each participation scheme, relative to the electricity bill without the influence of solar PVs and BES. Figures A.14a through A.14c show the relative total costs when all tariff price components are increased, when demand charges are increased, and when energy charges are increased, respectively, for the consumer with solar and two-hour BES. Figures A.14d through A.14f show the same for the consumer with solar and six-hour BES.

A.4 Comparison of Integer-Based Model and Relaxed Model

This subsection compares the performance of the integer-based model, which is introduced in Section 4.2 of Chapter 4, and the relaxed version of that model (referred to as the "relaxed model" throughout the rest of this subsection), which removes the integer variables and constraints. Results from the relaxed model ended up being used in Chapter 4 due to their similarity with the results from the integer-based model and their ability to preserve many of the asset-investment and total-cost trajectories. Additionally, the relaxed model also has the benefit of improving computation speed and allowing for increasingly granular sensitivity analyses to be conducted.

The tests presented in this subsection are of the sensitivity analysis conducted on the solar investment costs. These tests consider two of the participation schemes described in Section 4.4 of Chapter 4: the "Grid Imports, No Exports" (GINE) scheme and the "Solar Imports with Exports" (SIE) scheme. The "Self Consumption" (SC) scheme was excluded

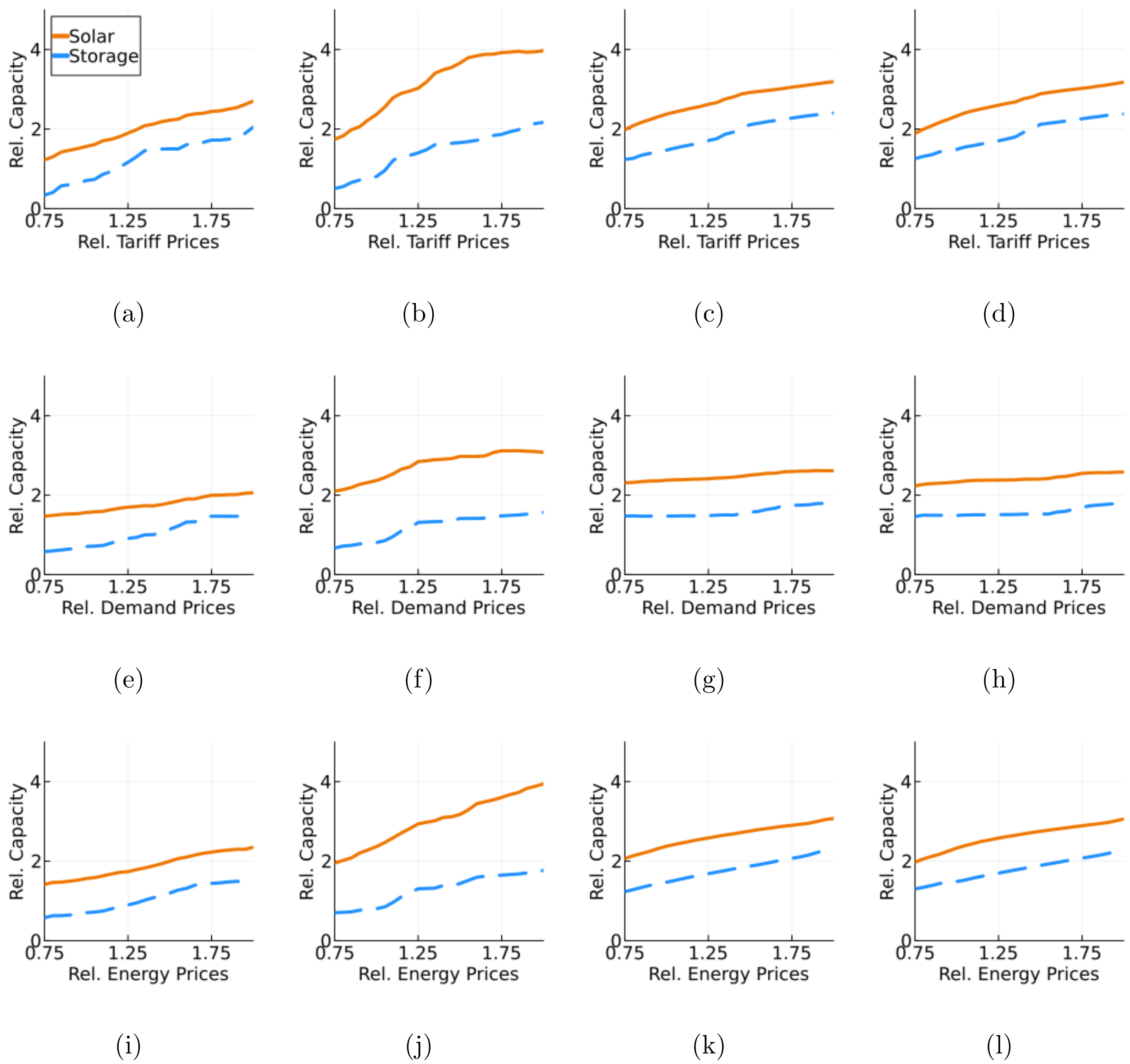


Figure A.11: Installed solar PV and two-hour BES capacity for the San Francisco MDP consumer, relative to the consumer's maximum demand, as tariff-related prices are changed. (a) – (d) depict investments as all tariff prices change. (e) – (h) depict investments as demand charges change. (i) – (l) depict investments as energy charges change. (a), (e), and (i) depict the SC scheme. (b), (f), and (j) depict the GINE scheme. (c), (g), and (k) depict the SIE scheme. (d), (h), and (l) depict the GIE scheme.

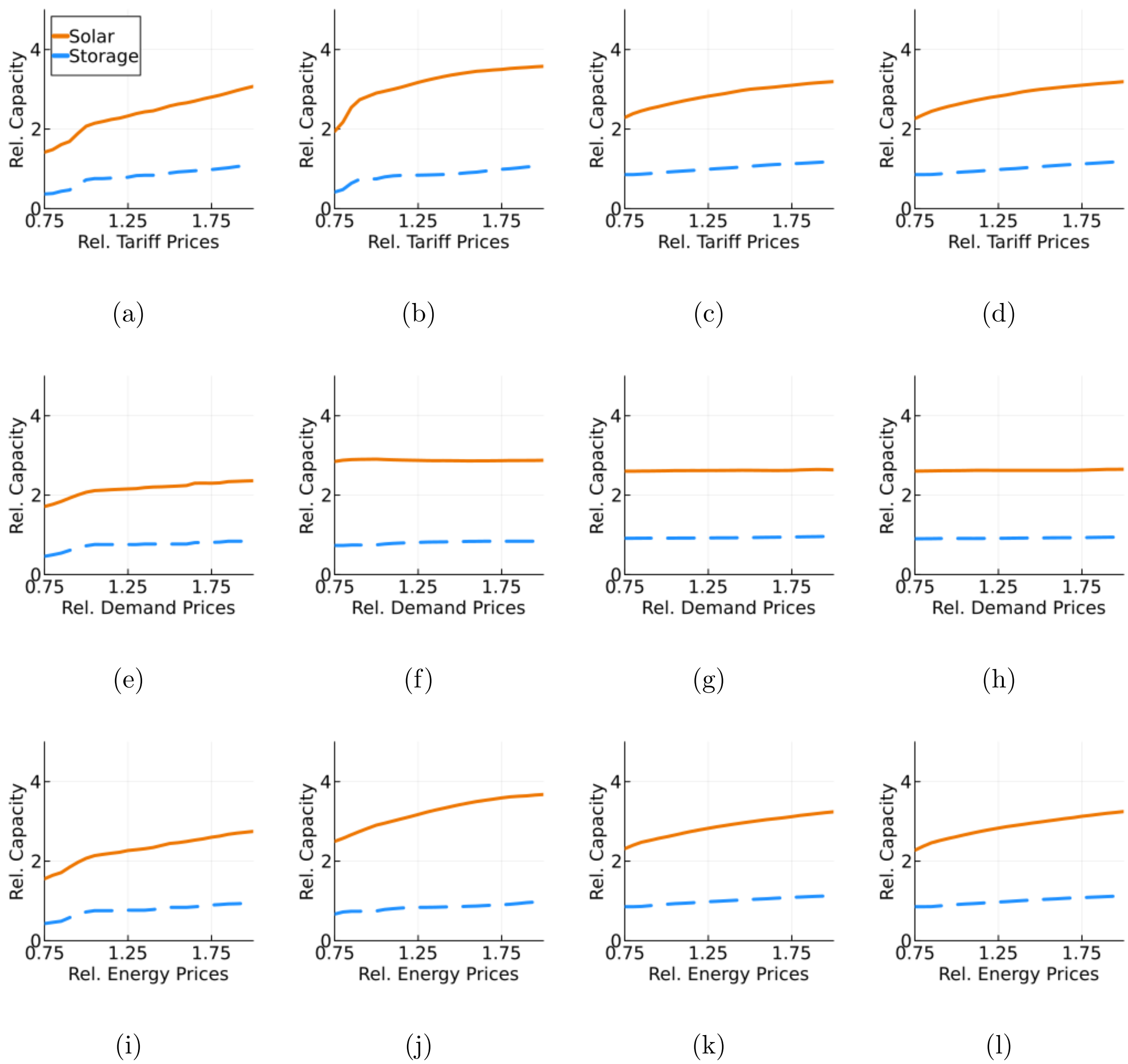


Figure A.12: Installed solar PV and six-hour BES capacity for the San Francisco MDP consumer, relative to the consumer's maximum demand, as tariff-related prices are changed. (a) – (d) depict investments as all tariff prices change. (e) – (h) depict investments as demand charges change. (i) – (l) depict investments as energy charges change. (a), (e), and (i) depict the SC scheme. (b), (f), and (j) depict the GINE scheme. (c), (g), and (k) depict the SIE scheme. (d), (h), and (l) depict the GIE scheme.

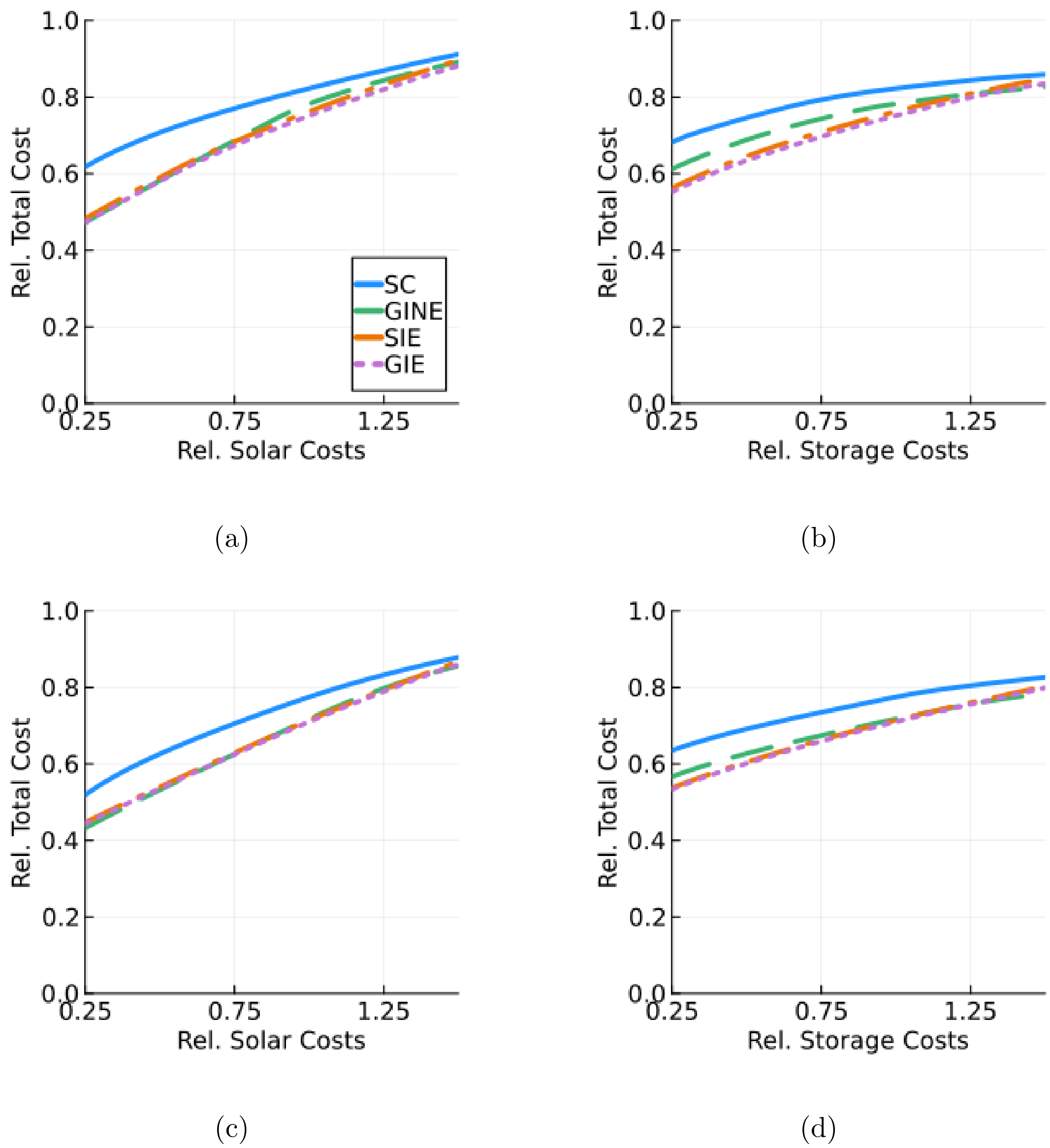


Figure A.13: Total cost for the San Francisco MDP consumer with solar PVs and BES, relative to the base case without investments, as asset-related costs are changed. (a) and (c) depict total costs as solar investment costs change. (b) and (d) depict total costs as storage investment costs change. (a) and (b) show the results for a consumer investing in two-hour BES. (c) and (d) show the results for a consumer investing in six-hour BES.

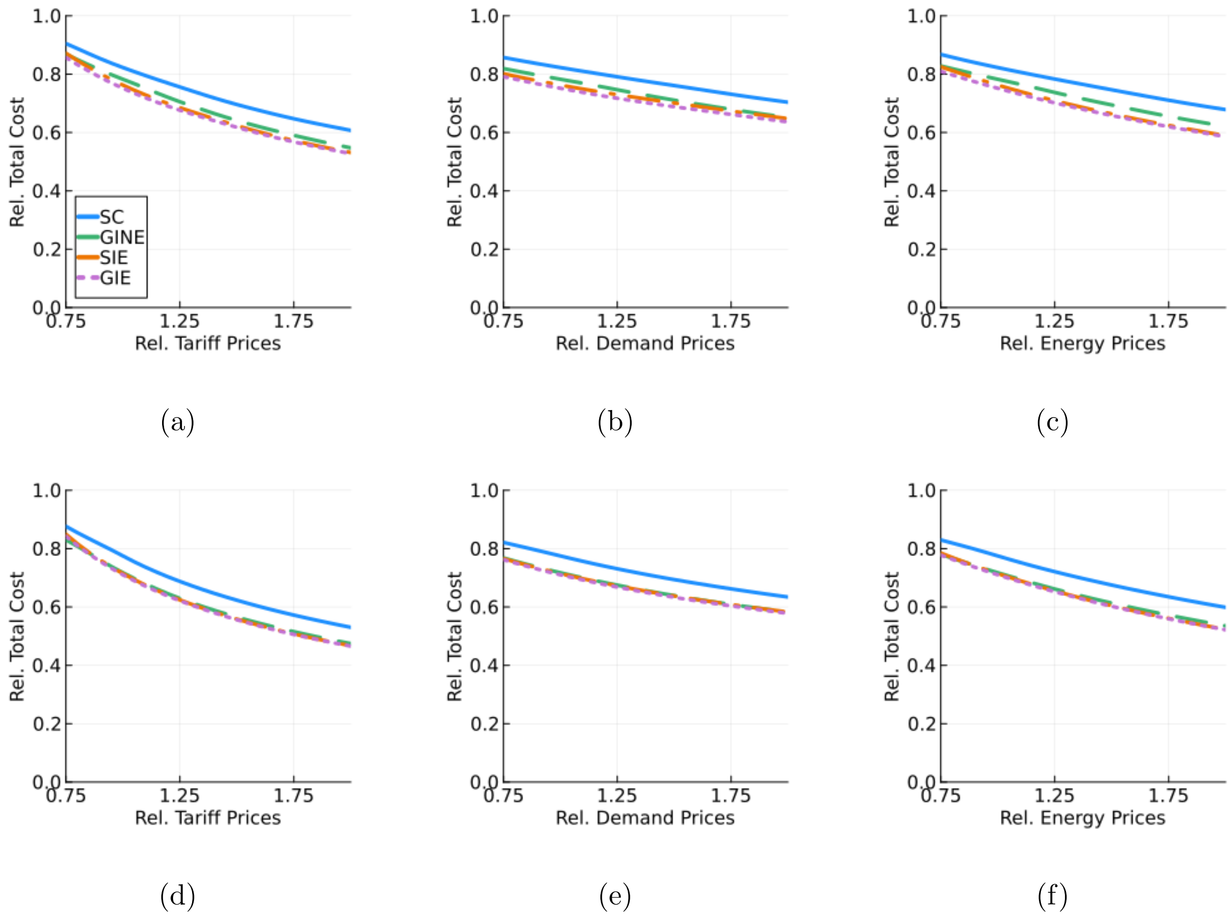


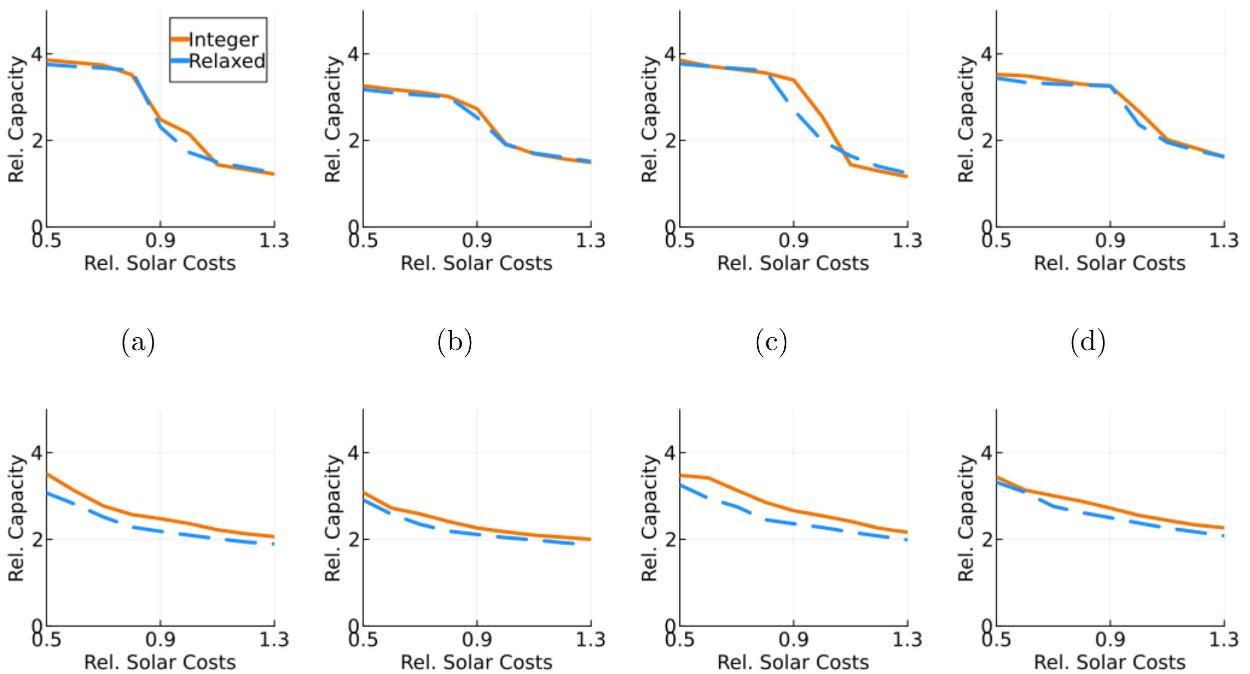
Figure A.14: Total cost for the San Francisco MDP consumer with solar PVs and BES, relative to the base case without investments, as tariff-related prices are changed. (a) and (d) depict total costs as all tariff prices change. (b) and (e) depict total costs as demand charges change. (c) and (f) depict total costs as energy charges change. (a) – (c) show the results for a consumer investing in two-hour BES. (d) – (f) show the results for a consumer investing in six-hour BES.

from the tests because only simulations that include the Net Billing Tariff (NBT) have integer components and consumers under the SC scheme do not participate in the NBT. The "Grid Imports with Exports" (GIE) scheme was also excluded due to the fact that the SIE scheme so closely matched its asset-investment and total-cost trajectories. The tests were run for both load profile shapes (i.e., the MEP consumer and the MDP consumer) and both locations (i.e., Fresno, CA and San Francisco, CA).

All simulations were run on an Apple MacBook Pro with an Apple M1 Pro chip (eight-core CPU with six performance cores and two efficiency cores) and 32 GB of RAM. Gurobi version 10.0.1 [152] was used as the optimization solver within DERIVE, which, as was discussed in Chapter 2, is written in Julia and uses JuMP to help formulate the optimization problem formulation. To help with the computation speed of the integer-based model, two stopping criteria were set within Gurobi's settings. First, the relative mixed-integer program (MIP) optimality gap ("MIPGap") was set to be be one percent. Second, a time limit ("TimeLimit") of twenty minutes was set, which serves as the stopping criterion if the relative MIP optimality gap is not reached before then.

Figure A.15 shows the installed solar PV capacity using the integer-based model and the relaxed model, relative to each consumer's maximum demand, when the consumer is investing in solar PVs and two-hour BES. Figures A.15a through A.15d show the installed solar PV capacity under the GINE scheme and Figures A.15e through A.15h show the installed solar capacity under the SIE scheme. Figures A.15a and A.15e show the installed solar PV capacity for the Fresno MEP consumer, Figures A.15b and A.15f show the installed solar PV capacity for the Fresno MDP consumer, Figures A.15c and A.15g show the installed solar PV capacity for the San Francisco MEP consumer, and Figures A.15d and A.15h show the installed solar PV capacity for the San Francisco MDP consumer. Figure A.16, which has a similar structure to Figure A.15, shows the installed solar PV capacity using the integer-based model and the relaxed model, relative to each consumer's maximum demand, when the consumer is investing in solar PVs and six-hour BES.

As can be seen from Figure A.15, the solar investments observed using the integer-based



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure A.15: Installed solar PV capacity using the integer-based model and the relaxed model, relative to the consumer's maximum demand, as solar-related investment costs are changed. The solar PV system is installed alongside a two-hour BES system. (a) – (d) depict investments under the GINE scheme. (e) – (h) depict investments under the SIE scheme. (a) and (e) depict the Fresno MEP consumer. (b) and (f) depict the Fresno MDP consumer. (c) and (g) depict the San Francisco MEP consumer. (d) and (h) depict the San Francisco MDP consumer.

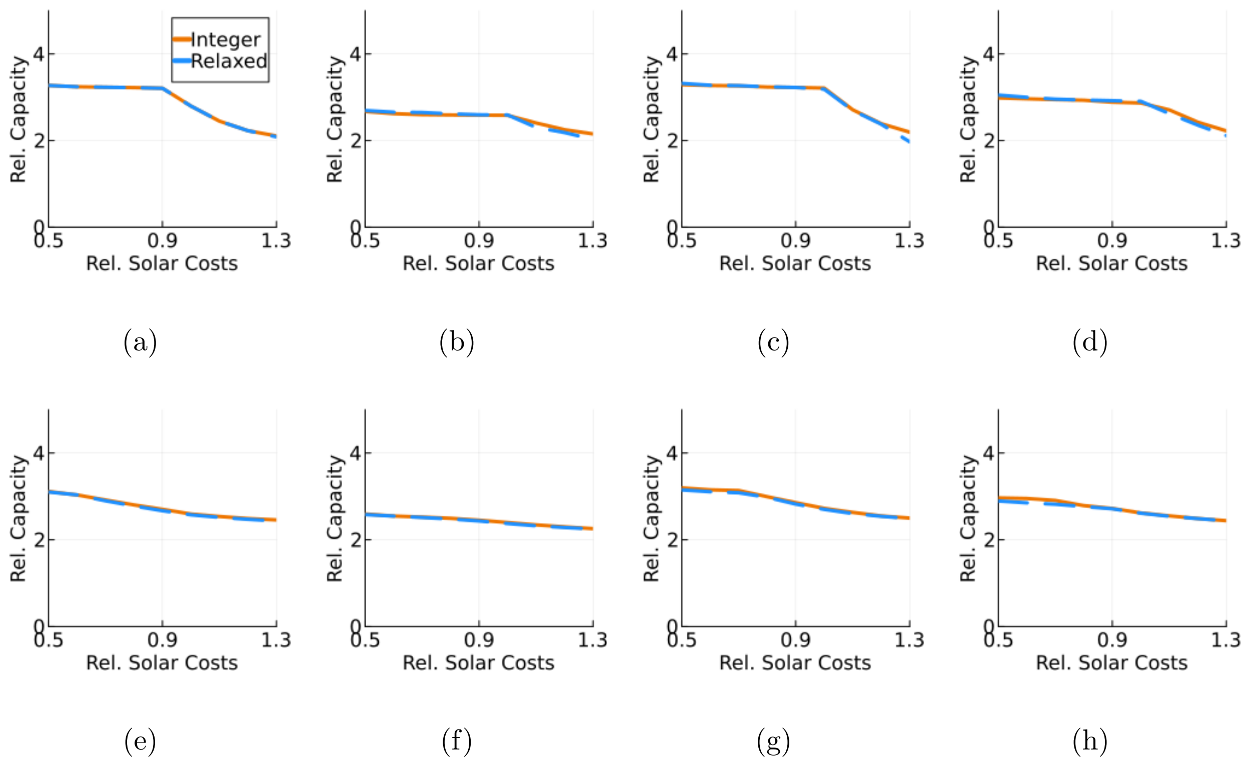
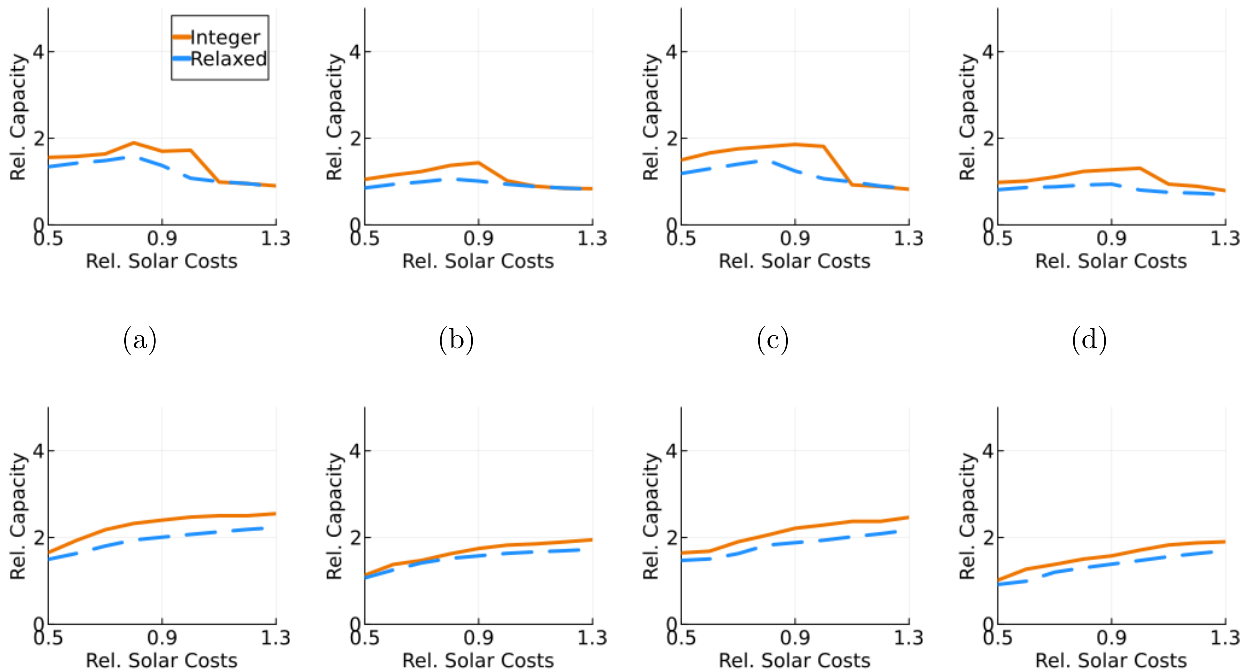


Figure A.16: Installed solar PV capacity using the integer-based model and the relaxed model, relative to the consumer's maximum demand, as solar-related investment costs are changed. The solar PV system is installed alongside a six-hour BES system. (a) – (d) depict investments under the GINE scheme. (e) – (h) depict investments under the SIE scheme. (a) and (e) depict the Fresno MEP consumer. (b) and (f) depict the Fresno MDP consumer. (c) and (g) depict the San Francisco MEP consumer. (d) and (h) depict the San Francisco MDP consumer.

model and the relaxed model are of similar magnitudes and follow similar trajectories for consumers investing in solar PVs and two-hour BES. Under the GINE scheme, solar PV investments using the relaxed model closely follow those from the integer-based model. For solar investment costs of around 80 to 100 percent of the base solar investment cost, some of the consumers build slightly smaller amounts of solar PVs using the relaxed model. Under the SIE scheme, solar capacity from the relaxed model slightly underestimates that from the integer-based model, though it does still track the trajectory. Figure A.16, which shows the solar investment results for consumers investing in solar PVs and six-hour BES, indicates that the relaxed model is a very good approximation of the integer-based model when the consumer is investing in longer duration BES.

Figure A.17, which has a similar structure to Figure A.15, shows the installed two-hour BES capacity using the integer-based model and the relaxed model, relative to each consumer's maximum demand, when the consumer is investing in solar PVs and two-hour BES. Figure A.18, which has a similar structure to Figure A.15, shows the installed six-hour BES capacity using the integer-based model and the relaxed model, relative to each consumer's maximum demand, when the consumer is investing in solar PVs and six-hour BES.

As can be seen from Figure A.17, the storage investments observed using the integer-based model and the relaxed model are of similar magnitudes and follow similar trajectories for consumers investing in solar PVs and two-hour BES. Under the GINE scheme, storage investments using the relaxed model are similar to those observed under the integer-based model. For storage investment costs under 120 percent of the base storage investment cost, consumers are found to build less BES capacity using the relaxed model than they do using the integer-based model. Still though, the relaxed model produces a trajectory that is similar to that produced by the integer-based model. Under the SIE scheme, storage capacity from the relaxed model slightly underestimates that from the integer-based model, though it does still track the trajectory. Figure A.18, which shows the storage investment results for consumers investing in solar PVs and six-hour BES, indicates that the relaxed model is a



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure A.17: Installed two-hour BES capacity using the integer-based model and the relaxed model, relative to the consumer's maximum demand, as solar-related investment costs are changed. The two-hour BES system is installed alongside a solar PV system. (a) – (d) depict investments under the GINE scheme. (e) – (h) depict investments under the SIE scheme. (a) and (e) depict the Fresno MEP consumer. (b) and (f) depict the Fresno MDP consumer. (c) and (g) depict the San Francisco MEP consumer. (d) and (h) depict the San Francisco MDP consumer.

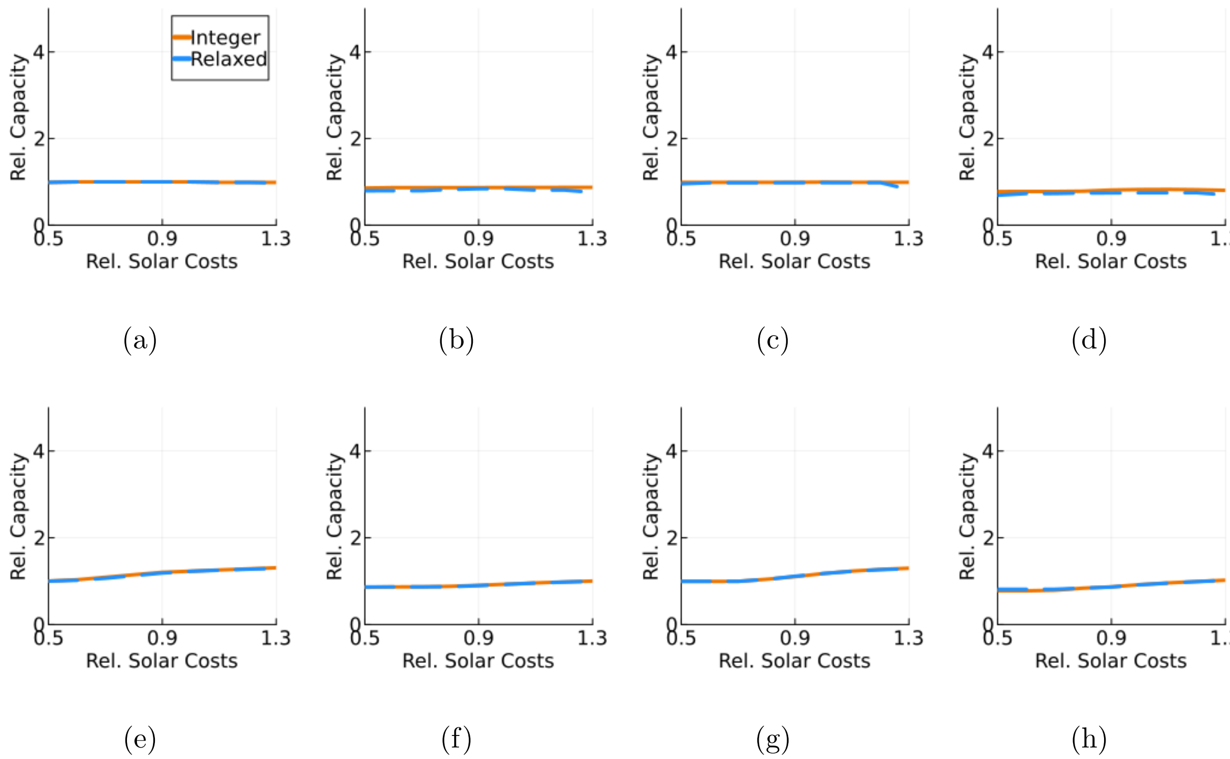


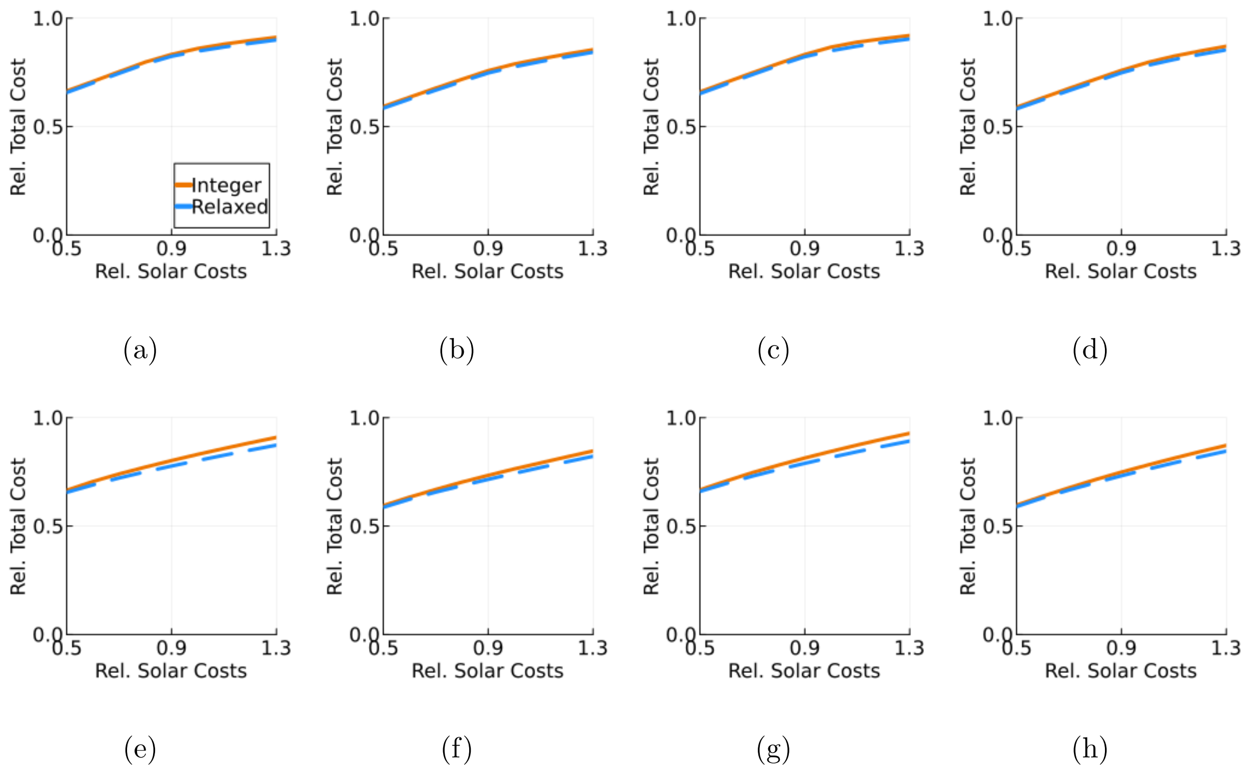
Figure A.18: Installed six-hour BES capacity using the integer-based model and the relaxed model, relative to the consumer's maximum demand, as solar-related investment costs are changed. The six-hour BES system is installed alongside a solar PV system. (a) – (d) depict investments under the GINE scheme. (e) – (h) depict investments under the SIE scheme. (a) and (e) depict the Fresno MEP consumer. (b) and (f) depict the Fresno MDP consumer. (c) and (g) depict the San Francisco MEP consumer. (d) and (h) depict the San Francisco MDP consumer.

very good approximation of the integer-based model when the consumer is investing in longer duration BES.

Figure A.19, which has a similar structure to Figure A.15, shows the consumers' total costs using the integer-based model and the relaxed model, relative to each consumer's base case costs without investments, when the consumer is investing in solar PVs and two-hour BES. Figure A.20, which has a similar structure to Figure A.15, shows the consumers' total costs using the integer-based model and the relaxed model, relative to each consumer's base case costs without investments, when the consumer is investing in solar PVs and six-hour BES.

As can be seen in Figures A.19 and A.20, the total costs discovered using the relaxed model very closely match those found using the integer-based model. For consumers investing in solar PVs and two-hour BES, the relaxed model produces total costs that slightly underestimate the integer-based model's total costs for higher relative solar investment costs. For consumers investing in solar PVs and six-hour BES, the total costs obtained under both models appear to be nearly identical.

Figure A.21 shows a comparison of the computation times (in seconds) that were needed to produce results for each sensitivity analysis conducted in this subsection. Each key in the y-axis of Figure A.21 refers to a location, load profile, participation scheme, and BES duration combination. As can be seen, the relaxed model regularly outperforms the integer-based model by multiple orders of magnitude.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure A.19: Total cost using the integer-based model and the relaxed model, relative to the base case without investments, as solar-related investment costs are changed. The consumer has solar PVs and two-hour BES. (a) – (d) depict investments under the GINE scheme. (e) – (h) depict investments under the SIE scheme. (a) and (e) depict the Fresno MEP consumer. (b) and (f) depict the Fresno MDP consumer. (c) and (g) depict the San Francisco MEP consumer. (d) and (h) depict the San Francisco MDP consumer.

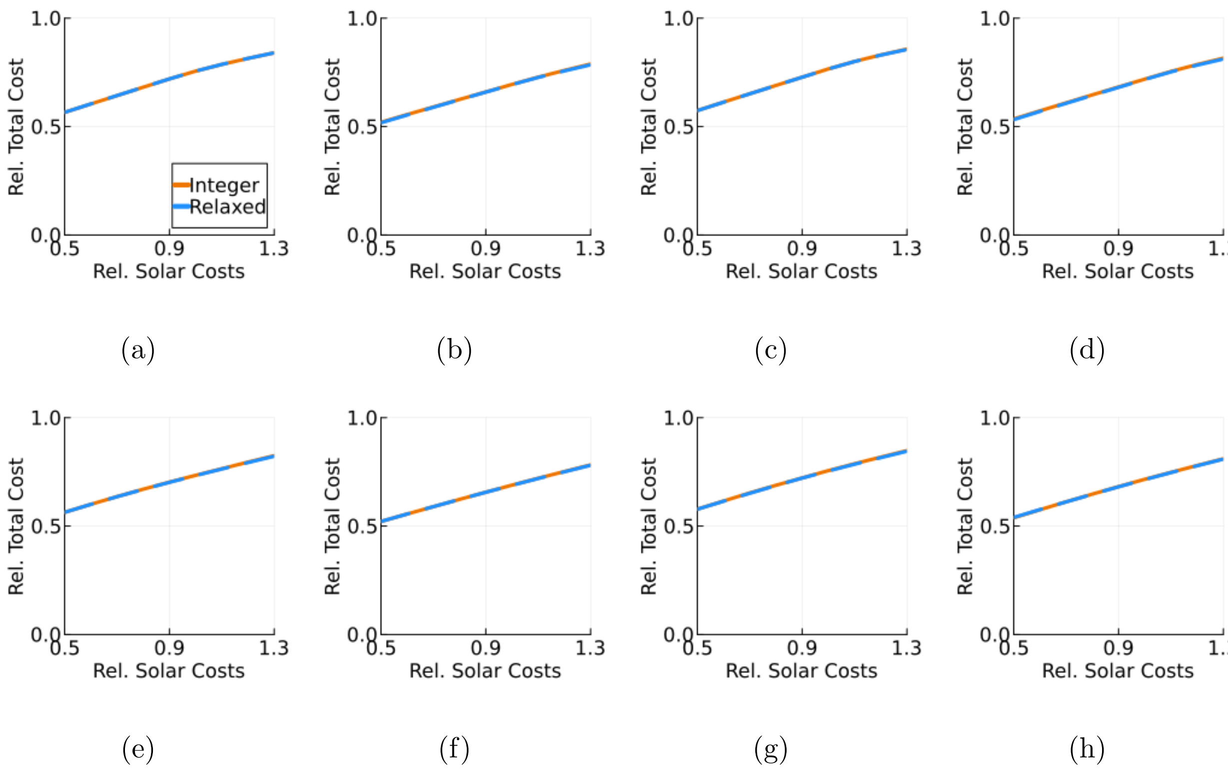


Figure A.20: Total cost using the integer-based model and the relaxed model, relative to the base case without investments, as solar-related investment costs are changed. The consumer has solar PVs and six-hour BES. (a) – (d) depict investments under the GINE scheme. (e) – (h) depict investments under the SIE scheme. (a) and (e) depict the Fresno MEP consumer. (b) and (f) depict the Fresno MDP consumer. (c) and (g) depict the San Francisco MEP consumer. (d) and (h) depict the San Francisco MDP consumer.

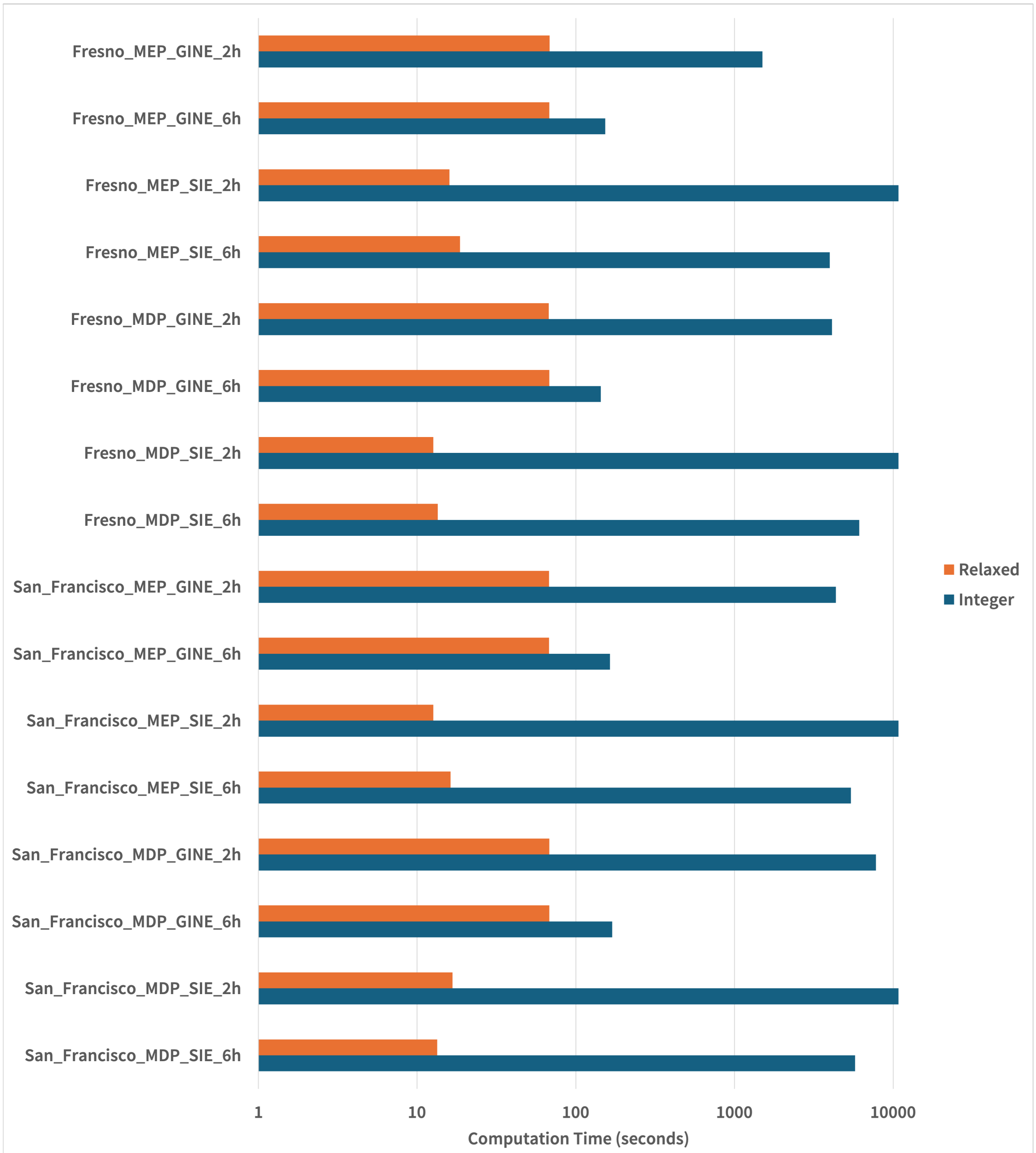


Figure A.21: Comparison of the computation times (in seconds) necessary to solve the sensitivity analyses that examine the effect of changing solar investment costs under the relaxed and integer-based models. Each key on the y-axis refers to a tested city, load profile, participation scheme, and BES duration combination.