ADAPTING ENERGY OPTIMIZATION MODELS TO BETTER INFORM REALISTIC ENERGY DECISIONS

by

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A thesis proposal submitted to the Faculty and the Board of Trustees of the Colorado School of Mines in partial fulfillment of the requirements for the degree of Doctor of Philosophy (Advanced Energy Systems).

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ABSTRACT

Energy models are widely used to evaluate the technical and economic feasibility of energy efficiency, renewable energy, and sustainable transportation, and to guide the economic deployment of clean energy technologies. However, a gap exists between theoretical recommendations, and what individuals, businesses, or utilities choose to deploy. This research explores why these gaps exist, and how adaptations to technical modeling capabilities and the way in which results are communicated can increase clean energy deployment. We first develop and document an energy decision model that optimizes technology size and dispatch strategy with the objective of minimizing lifecycle cost of energy for a building or campus. We then exercise the model with a view to improving implementation and adoption of clean energy technologies by creating diverse solutions that can help the decision maker select a solution that works best in practice. Finally, we consider methods to quantify metrics not traditionally considered, such as resilience and social-behavioral factors. The work presented here may enable building owners and campus energy managers to make more effective and efficient decisions that will, in turn, increase the speed and scale of clean energy deployment.

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CHAPTER 1

INTRODUCTION

The global energy system is rapidly changing. In the US, electricity generation from renewable energy sources has doubled in the past ten years, and currently accounts for about 18% of total generation [1]. This trend is accelerating worldwide as renewable energy prices drop; the U.S. Energy Information Administration predicts that renewable energy will be the leading source of primary energy consumption by 2050 [2]. Wind and solar are expected to dominate growth, representing over 70% of electric generating capacity additions by 2050 [2].

Techno-economic energy decision models are widely used to explore the least-cost pathways to provide economic, sustainable, and resilient energy. However, despite their sophisticated capabilities, many energy decision tools are limited in their ability to guide decisions. A gap exists between what energy models recommend as "optimum" in theory, and what individuals, businesses, or utilities choose to deploy in reality. This research explores why these gaps exist, and how adaptations to technical modeling capabilities or the way results are communicated can increase clean energy deployment.

Chapter 2 presents an energy decision model that recommends the optimal mix of renewable energy, conventional generation, and energy storage technologies to meet cost savings, resilience, and energy performance goals at a site. Given the complexities of building loads, utility rate tariffs, renewable energy resources, and technology operating decisions, this mixed-integer program is difficult to solve in the time limits required for deployment, so we propose solution-expediting techniques. The resulting paper, entitled "Optimizing Design and Dispatch of a Renewable Energy System," is intended for submission to *Applied Energy*. The contributions of this dissertation writer include: 1) working with partners to understand their energy questions, and designing our modeling approach to answer these questions; 2) conducting a literature review of common approaches to similar energy optimization problems, and an analysis of remaining gaps; 3) contributing to development of the optimization model; and 4) developing case studies that demonstrate the model's capabilities.

Chapter 3 expands upon the energy decision model presented in Chapter 2 by developing diverse solutions to aid partners in making decisions under uncertainty. Assessing uncertainty can be a significant challenge in optimization models, especially uncertainties in the model structure, such as the role that non-economic factors play in energy purchase decisions, the heterogeneity of decision makers, and the role that social norm and culture may play. We develop techniques to search the solution space for alternative near-optimal, maximally different solutions. Multiple good quality solutions provide the decision maker an opportunity to select the best solution for the real-life problem, including criteria that could not be expressed in the model. The resulting paper, entitled "Developing Diverse Solutions to Inform Energy Solutions," is intended for submission to *INFORMS Journal on Applied Analytics*. The contributions of this dissertation writer include: 1) conducting a literature review of existing approaches to developing alternate solutions; 2) adapting existing techniques from other fields to an energy optimization model; and 3) developing case studies to demonstrate how alternate solutions may be used to inform better energy decisions.

Chapter 4 considers the non-economic factors that impact energy decisions, such as a desire for increased resilience, and develop a methodology to incorporate this into the energy optimization model. Recent increases in widespread, long-duration, and costly grid outages have highlighted the importance of energy resilience, but the monetary benefits of resilience solutions are not well understood. We develop techniques to quantify the amount of resilience a system provides, as well as its corresponding value. We then integrate this value into energy optimization models to understand how inclusion of this value may change investment and operational decisions. The resulting paper, entitled "Integrating the Value of Electricity Resilience in Energy Planning and Operations Decisions," was published in the *IEEE Systems Journal*. The contributions of this dissertation writer include: 1) conducting a literature review of existing approaches to valuing resilience; 2) developing the modeling approach; and 3) developing the campus planning case study to demonstrate how integrating a time-varying value of resilience may change investment and operational decisions.

Chapter 5 considers how other more qualitative aspects of decision-making impact energy decisions, and evaluate opportunities for energy decision tools to address these. We conduct a survey of 30 federal energy managers, city planners, and university sustainability staff that have used energy decision tools, to understand the key drivers of their energy decisions, how tools informed their decisions, and the gap between the solution recommended by tools and the solution implemented. We identify potential tool improvements that, if implemented, could start to close this gap and result in increased energy deployment from decision tools. The resulting paper, entitled "The Gap Between Energy Modeling and Deployment," is intended for publication in *Energy Research and Social Science*. The contributions of this dissertation writer include: 1) conducting a literature review of the gap between modeling and realized deployment; 2) conducting interviews with partners to understand energy decision drivers and use of tools; and 3) conducting qualitative data analysis of interview results to identify trends; and 4) developing recommendations for tool improvements that may increase clean energy deployment.

To complete the thesis, the following work is planned:

- Develop additional case studies and obtain testimonials from clients that show the benefits of diverse solutions in Chapter 3
- Complete qualitative data analysis on interview data and identify trends in Chapter 5
- Submit the papers described in Chapter 2, 3, and 5 to journals

CHAPTER 2

OPTIMIZING DESIGN AND DISPATCH OF A RENEWABLE ENERGY SYSTEM

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To be submitted to *Applied Energy*

2.1 Abstract

Renewable energy technologies are becoming increasingly important due to diminishing supplies of conventional non-renewable resources. We demonstrate the capabilities of an optimization model that minimizes costs and carbon emissions, while adhering to system sizing demands for a variety of venues, e.g., suburban homes or local hospital. Given the size of realistic instances, we propose solution-expediting techniques to our mixed-integer program to solve under the time limits required.

2.2 Introduction

Distributed energy resources–including solar photovoltaics (PV), battery storage, and wind–are being adopted at an ever-increasing pace. With prices decreasing 41-73% (depending on technology) between 2008 and the time of this writing, consumers are rapidly adopting these technologies [3]. Additionally, projections show that as PV deployment grows from 2% to 22% of world electric capacity, 33% of that new capacity will be behind-the-meter [4]. While capital cost reductions have been critical to deployment growth, economic performance of distributed resources is also heavily dependent on system performance, the utility tariff against which the distributed energy resource is operating (e.g., costs, time-of-use structures, tiers), and the economic environment in which the system operates (e.g., incentives and net metering policies). To enable continued, cost-effective deployment, it is critical that developers and building owners are able to size and operate integrated distributed energy resource systems to maximize utility benefits under these considerations [5].

As the renewable energy market has matured and grown, determining system design has evolved from simple rules-of-thumb, to step-by-step work flows, to spreadsheet tools, to detailed modeling software. While each of these methods can be useful, an increasingly complex problem setting–including tariff and policy considerations–requires a structured modeling framework to capture economic and operational trade-offs. REopt Lite™, a mixed-integer programming model, has been developed to help address this need. This paper describes the corresponding complete mathematical formulation, briefly mentions some solution-expediting techniques to solve problem instances within an acceptable amount of time for deployment purposes, and demonstrates how the corresponding optimization-based solutions navigate the appropriate trade-offs between system sizes and operational strategies.

Specifically, REopt Lite evaluates the economic viability of grid-connected wind, solar, and battery storage behind a single utility meter using hourly (or sub-hourly) time fidelity over a representative year. The model minimizes discounted cashflow associated with costs and savings while adhering to constraints on fuel use, system operations, system capacities, load balancing, grid sales, rate tariffs, and a variety of other interoperability and logical restrictions. The model recommends an optimally sized mix of renewable energy, conventional generation, and energy storage technologies, while simultaneously optimizing the corresponding dispatch strategy. The model is applicable across a wide range of sites, including: residential homes, commercial and industrial sites, university campuses, military installations, and microgrids. Figure 2.1 shows the model's high-level structure with inputs in blue and outputs in green.

The benefits of mathematical optimization for energy design and dispatch problems are numerous: (i) no requirement for the user to pre-select technology types or sizes, (ii) a well-structured problem definition, and (iii) guaranteed global optimality (or some quantitative measure from it). Despite this, large-scale, comprehensive design and dispatch optimization models have not typically been made available to the wider research and analysis community in a web-based framework. There are two primary reasons for this: (i) realistic model

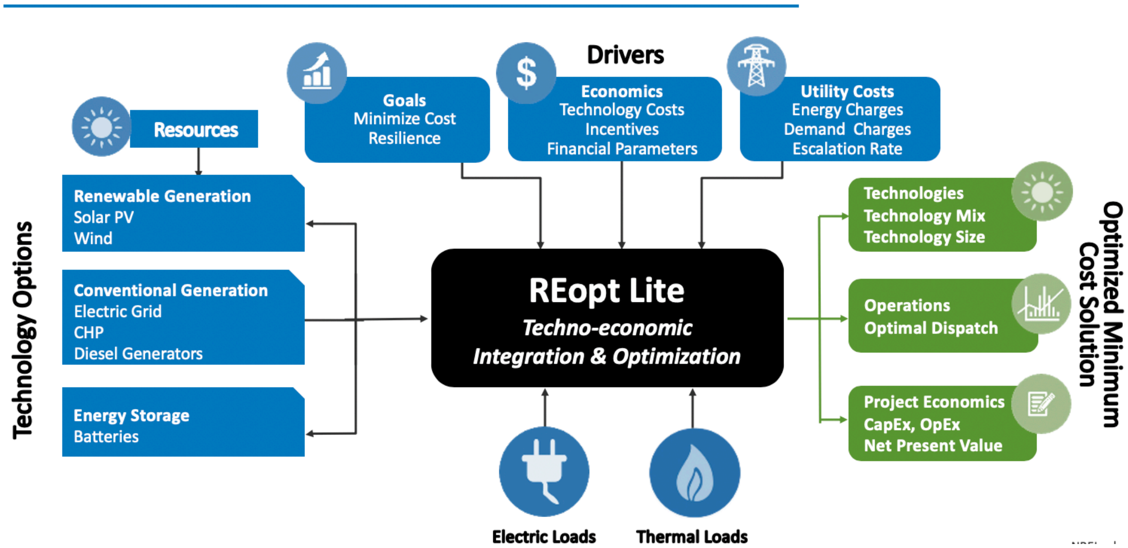


Figure 2.1: The REopt Lite system, where the blue boxes above, to the left of and underneath the center box containing the model name are inputs, and the green boxes to the right of center display the outputs

instances with complex tariff and technology combinations can be time-consuming to solve; and (ii) the model formulations are complex and require intimate knowledge of data input requirements and model operation, thereby restricting the user base to a small team of developers and expert users. REopt Lite is a comprehensive model whose instances achieve operationally feasible run times, but whose access is less limited than that of most academic models owing to its user-friendly web tool, application programming interface, and open-source code base [6]. Correspondingly, the contributions of this paper are: (i) the presentation of a detailed mathematical formulation of a complex design and dispatch model; (ii) the construction of such a model that allows for its generality and extensibility; and (iii) an analysis of the corresponding solutions through case studies.

The organization of the remainder of this article is as follows: Section 2.3 reviews the extant literature on renewable energy system optimization and associated modeling approaches. Section 2.4 outlines the primary model inputs and the general modeling architecture. Section 2.5 contains the mathematical formulation of the optimization model, with corresponding explanations. Section 2.6 provides the computational setup, highlights the techniques used to enable reasonable solve times for model instances, and presents results that emphasize the capabilities of the model. Section 2.7 concludes with avenues for future work.

2.3 Literature Review

Optimally making the simultaneous decisions of determining design and dispatch is NP-hard, and consists of incorporating nonlinear functional forms and integrality restrictions. Common approaches in the literature separate the problem into two. Some authors provide heuristics that yield a good, but not optimal, solution to the design problem [7–11]; these take a dispatch strategy that satisfies load balance as given [12], [13]. Problem restrictions such as addressing a shorter time horizon or reducing load variability might compromise the quality of the solution, even if the model itself becomes more tractable [14], [15]. Conversely, Abbey and Joos [16] fixes design decisions to obtain an optimal dispatch strategy.

An increasing number of models in the literature simultaneously consider the design and dispatch problem (e.g., [17], [18], [19], [20], [21], [22], [23], [24], [25], [26]). However, rather than using an exact solution approach, these models rely on simulation, evolutionary algorithms, and/or reduce the scope of the problem if they rely on exact solution approaches. In particular, although Pruitt et al. [21] makes both design and dispatch decisions for a combined heat and power system, the pricing structure and operational details of the technologies are not as sophisticated as those we consider. Upadhyay and Sharma [27], Theo et al. [28] and Wang and Hijazi [29] provide reviews on the literature associated with hybrid distributed energy resource optimization models.

While many of the optimization techniques described in the literature are implemented only in research models, a growing number are also available in techno-economic distributed energy optimization tools. These tools provide analysis of project feasibility and decision support to guide energy investments and support the increasing need for assessment of clean energy investment options. Review articles by Connolly et al. [30] and Ringkjøb et al. [31], the latter of which assesses 75 models used for analyzing energy and electricity systems from short-term operation to long-term energy system planning at the local and national energy scales between 2012-2018. The majority of these are energy-economy models that analyze energy and climate policy at regional, national, and international scales, but seven are used for site-specific project identification and analysis: RETScreen, EnergyPro, TRNSYS, HOMER, SAM, iHOGA, DER-CAM, and DESOD. The majority of these are simulation tools, while iHOGA, DER-CAM, and DESOD are based on mathematical optimization.

RETScreen is a clean energy management software system for energy efficiency, renewable energy, and cogeneration project feasibility analysis Thevenard et al. used to identify and assess the technical and financial viability of clean energy projects. Developed in Excel, it is a free downloadable tool and has 690,000 users in 222 countries worldwide. RETscreen uses analytical methods to simulate user-specified technology sizes. Each technology is analyzed separately through a five-step process involving costs, greenhouse gases, finance, sensitivity and risk. RETScreen does not model the integration of multiple technologies nor optimize technology size, though some researchers have used the Excel solver to add an optimization feature for their own research [33]. EnergyPro is a commercial modeling software package for techno-economic design, analysis, and optimization [34]. It is typically used to evaluate cogeneration and tri-generation projects, but can also consider other types of distributed energy. It can be used to design systems or optimize the operation of existing systems by dividing the year into calculation periods, and then allocating production through a series of loops according to a set of priority-based rules [35]. This technique provides an implementable solution, though not one guaranteed to be globally optimal. TRNSYS is a transient systems simulation program used to assess the performance of thermal and electrical energy systems and to conduct detailed simulations of technology performance based on user-specified technology sizes and other input parameters [36]. It does not inherently optimize technology size nor economics, but it can be combined with other programs to do so. For example, the TESS Optimization Library couples TRNSYS with Lawrence Berkeley National Lab's GenOpt program to minimize cost [37]. GenOpt allows the user to select from a library of optimization algorithm options including generalized pattern search, particle swarm optimization, hybrid global optimization, discrete Armijo Gradient, Nelder and Mead's Simplex, and Golden Section and Fibonacci algorithms. HOMER is a software employed for microgrid and distributed generation power system design and analysis [38]. It has a broad user base, with over 200,000 users in 190 countries. Analytical methods within HOMER simulate all possible combinations of user-specified technology sizes, and the software then sorts them based on a user-specified metric to demonstrate how the economics change with different technology types and sizes. This approach can be computationally intensive because it requires many simulations, and does not guarantee optimality. The System Advisor Model (SAM) is a techno-economic software model widely used to guide renewable energy decisions [39]. It provides detailed performance and financial models to evaluate a range of renewable energy technologies and storage through direct purchase, power purchase agreements, or third-party ownership. SAM uses analytical methods to simulate user-specified technology sizes and does not optimize system size. It generally does not model technology integration, with the exception of PV-battery systems.

The software described thus far require the specification of technology sizes, which are often unknown during early project feasibility assessments. Extensions of these models also determine optimal system size. For example, Improved Hybrid Optimization by Genetic Algorithms (iHOGA) is software for simulating and optimizing hybrid electric systems [40]. iHOGA uses genetic algorithms to determine the number and type of each technology, optimal control strategy (selected from load following, cycle charging, or hybrid strategies), and state of charge set point. iHOGA also allows optimization using enumeration to evaluate all possible combinations of components and multi-objective optimization. The Distributed Energy Resources-Customer Adoption Model (DER-CAM) is a mixed-integer linear program that determines optimal portfolio, sizing, placement, and dispatch for buildings or microgrids [41, 42], while considering load shifting, peak shaving, power export agreements, and ancillary service markets. Although some renditions of the model account for detailed electrical distribution, loads are not considered at a detailed, e.g., hourly or daily, level, fewer technologies are included at as fine a level of detail, and detailed economic incentives are missing. However, DER-CAM's ability to find a guaranteed optimal solution is unique among the tools reviewed thus far. Bracco et al. also present software, DESOD, to optimize an energy system, this one with combined heat and power (which is outside the scope of our current work). However, this model ensures that all thermal loads are satisfied by distributed energy, i.e., there is no connection to the utility for thermal energy; it models separate buildings and the pipeline connection between building; the load patterns are given by "typical days," rather than for every hour of the year; and, technology sizes, at least in some cases, are discrete. The authors expedite solutions by shortening the time horizon.

The existing models in this space provide users with a variety of effective approaches for evaluating energy investment decisions, but do have some limitations. A few (such as RETscreen and SAM) do not assess integrated suites of technologies, which are becoming increasingly common as distributed energy resource deployment grows. Many (with the exception of DER-CAM) cannot guarantee an optimal solution. Nearly all (except SAM) fail to provide transparency into the exact model formulation and code, though recent research has highlighted the importance of open access to data and code to facilitate higher quality analysis [44]. Finally, most of the existing models are oriented toward expert-level users, requiring hours of training. For further detail regarding optimization of renewable energy systems, see the following review papers, and the references contained therein [45–50]. REopt Lite attempts to fill the identified gaps by providing a guaranteed optimal solution, while also improving accessibility and ease of use in that it requires just three user inputs, while also offering over one hundred optional inputs for advanced users.

2.4 Model Inputs and Structure

This section describes the primary inputs to the optimization model and its general structure to provide context for the mathematical formulation laid out in Section 2.5. (The REopt Lite user manual provides complete documentation [51].)

2.4.1 Model Inputs

We categorize the model inputs as follows: site-related, financial, and technological, and include those related to the geographic location of the site under consideration, including:

- *Site location*: This encompasses all of the renewable energy resource and climate zone data; the model leverages and integrates open data sets such as the National Solar Radiation Database [52] and the Wind Integration National Dataset Toolkit [53].

- *Electricity tariff structure*: The utility tariff can either be obtanend from the Utility Rate Database [54] or by entering a custom rate structure.

- *Site-level inputs*: These include net metering limits, space available for renewable project development, and the site load profile (hourly or finer granularity).

The financial inputs cover all of the economic parameters used to escalate and discount costs, thus ensuring that initial costs are weighed appropriately against recurring costs and revenue streams.

- *Financial inputs*: Discount rate, annual electricity cost escalation rate, annual operations and maintenance escalation rate, and analysis period are all part of these inputs.

The technology inputs cover the costs, incentives, and technical performance characteristics for each technology.

- *Technology costs*: These include capital cost, fixed and variable operating costs, and fixed project costs.

- *Financial incentives*: These relate to federal, state, local, and utility incentives, covering both production-based and capacity-based incentives.

- *System characteristics*: These consist of minimum and maximum system sizes, minimum turndown limits (as applicable), fuel consumption curves for generators, module types or turbine size classes, and other technical parameters. For the PV and wind turbine models, REopt Lite uses the System Advisory Model (SAM) simulation core [39] to combine renewable resource data with technical parameters from which to estimate system performance.

- *Battery energy storage*: This is given according to a "reservoir" model, and includes inputs for inverters, rectifiers, and round-trip efficiency of the battery, as well as minimum state of charge. The energy and power capacity of the system, given minimum and maximum values for both, are optimized independently. Inputs also include replacement year, and expected energy capacity and power costs upon replacement.

2.4.2 Model Structure

We define primary aspects of the model architecture, focusing on system sizing, the way in which size is connected to production, and how that production interfaces with load balancing constraints. Additionally, we outline the handling of the tariff structure, including tiers and demand ratchets.

- *System sizing*: Each technology possesses a piecewise linear cost curve that accounts for economies of scale, and incorporates capacity-based incentives, i.e., the base cost curve can be modified to account for a $/kW incentive cost reduction. The system size is indexed on the segments of that curve, and constrained to occupy a single segment with the corresponding price. Additionally, for each technology class (e.g., PV), two technologies are initialized in the model: one is able to benefit from net energy metering by receiving full retail value for export energy, and the other is unable to receive this benefit in that exports are valued at a wholesale rate. The model selects only one technology within a technology class, and the technology that has net metering available is constrained by a system size capacity equal to the net metering limit for the site.

- *Rated production*: For each technology–excluding storage–the production on a time step-by-time step basis is constrained to be less than the system size, and the rated production is scaled by two correction factors (i) to account for hourly production of a system of a given capacity due to limited resources, for example, scaling down energy generation from a 100kW wind turbine based on wind resources for the given hour; and (ii) to address any degradation that the system is expected to experience over the analysis period, for example, the degradation of PV panel output over 20 years. Rated production is constrained to operate above a minimum turndown for applicable technologies (e.g., diesel generators) using a switch constraint.

- *Storage system considerations*: These systems are handled separately from the other technologies, and can be charged by the technologies in the model–or the grid–and can discharge to meet the site demand or export to the grid. Energy and power capacities of the battery are constrained to be greater than the stored energy and charge or discharge capacity, respectively, across all time steps.

- *Load balancing constraints*: These restrictions account for all generation (from scaled rated production, grid purchases, and battery discharging) and ensure that it is equal to the demand (from site load, battery charging, and energy exports) across all time steps.

- *Tariff modeling*: The tariff model accounts for three main components (i) energy charges, (ii) demand charges, and (iii) fixed or minimum charges. Central to this modeling are grid purchases, which depend on the time step and energy tier. To capture time-of-use energy charges, grid purchases are costed on hourly basis. Additionally, tiered energy costs are incorporated through multiple tier pricing in each hour, with binaries ensuring that monthly tier amounts are filled in the correct order. Two types of demand charges are modeled (i) a monthly demand that is greater than any grid purchase (summed over tiers) for the hours in that month, and (ii) a time-of-use demand that can have multiple on- or off-peak periods. The time-of-use demand is forced to be greater than or equal to grid purchases for the hours in that period for the month. Demand "lookback" levels (e.g., ratchets) can also be applied to a percent of peak demand for a set of months. Finally, the monthly and time-of-use demand variables account for tiered demand charges.

The following section provides the corresponding mathematical formulation and descriptions of the constraints.

2.5 Optimization Model ($\mathcal{R}$)

We define here, in alphabetic order within a group, indices and sets, parameters, and variables, in that order, and then state the objective function and the constraints. We choose as our naming convention calligraphic capital letters to represent sets, lower-case letters to represent parameters, and upper-case letters to represent variables; in the latter case, Z-variables are binary, and represent design and operational decisions, respectively. X-variables represent continuous decisions, e.g., quantities of energy. All subscripts denote indices. Names with the same "stem" are related, and superscripts and "decorations" (e.g., hats, tildes) differentiate the names with respect to, e.g., various indices included in the name or maximum and minimum values for the same parameter.

2.5.1 Sets and Parameters

Sets

$\mathcal{B}$	Storage systems
$\mathcal{C}$	Technology classes
$\mathcal{E}$	Electrical power ratchet pricing tiers
$\mathcal{F}$	Fuel types
$\mathcal{H}$	Time steps
$\mathcal{K}$	Subdivisions of power rating
$\mathcal{M}$	Months of the year
$\mathcal{N}$	Monthly peak electrical power demand pricing tiers
$\mathcal{R}$	Peak electrical power demand ratchets (i.e., non-monthly billing periods)
$\mathcal{S}$	Power rating segments
$\mathcal{T}$	Technologies
$\mathcal{U}$	Total electrical energy pricing tiers
$\mathcal{V}$	Net metering regimes

Subsets and Indexed Sets

$H^{\mathrm{g}} \subseteq \mathcal{H}$	Time steps in which grid purchasing is available
$\mathcal{H}_m \subseteq \mathcal{H}$	Time steps within a given month m
$\mathcal{H}_r \subseteq \mathcal{H}$	Time steps within electrical power ratchet r
$\mathcal{K}_t \subseteq K$	Subdivisions applied to technology t
$\mathcal{K}^{\mathrm{c}} \subseteq K$	Capital cost subdivisions
$\mathcal{K}^{\mathrm{f}} \subseteq K$	Fuel burn subdivisions
$\mathcal{M}^{\mathrm{lb}}$	Look-back months considered for peak pricing
$S_{tk} \subseteq S$	Power rating segments from subdivision k applied to technology t
$\mathcal{T}_b \subseteq \mathcal{T}$	Technologies that can charge storage system b
$\mathcal{T}_c \subseteq \mathcal{T}$	Technologies in class c
$T \subseteq \mathcal{T}$	Technologies that burn fuel type f
$\mathcal{T}_u \subseteq \mathcal{T}$	Technologies that may access electrical energy sales pricing tier u
$\mathcal{T}_v \subseteq \mathcal{T}$	Technologies that may access net-metering regime v
$T^{\mathrm{f}} \subseteq T$	Fuel-burning, electricity-producing technologies
$\mathcal{T}^{\mathrm{td}} \subseteq \mathcal{T}$	Technologies that cannot turn down, i.e., PV and wind
$U^{\mathrm{c}} \subseteq U^{\mathrm{s}}$	Electrical energy curtailment pricing tiers
$U^{\mathrm{p}} \subseteq U$	Electrical energy purchase pricing tiers
$U^{\mathrm{s}} \subseteq U$	Electrical energy sales pricing tiers
$U^{\mathrm{sb}} \subseteq U^{\mathrm{s}}$	Electrical energy sales pricing tiers accessible by storage
$U^{\mathrm{s}}_t \subseteq U^{\mathrm{s}}$	Electrical energy sales pricing tiers accessible by technology t
$U^{\mathrm{nm}} \subseteq U^s$	Electrical energy sales pricing tiers used in net metering

Scaling Parameters

Δ	Time step scaling	[h]

Parameters for Costs and their Functional Forms

c^{afc}	Utility annual fixed charge	[$]
c^{amc}	Utility annual minimum charge	[$]
c^{cb}_{ts}	y-intercept of capital cost curve for technology t in segment s	[$]
c^{cm}_{ts}	Slope of capital cost curve for technology t in segment s	[$/kW]
c^{e}_{uh}	Export rate for energy in energy demand tier u in time step h	[$/kWh]
c^{g}_{uh}	Grid energy cost in energy demand tier u during time step h	[$/kWh]
c^{kW}_{b}	Capital cost of power capacity for storage system b	[$/kW]
c^{kWh}_{b}	Capital cost of energy capacity for storage system b	[$/kWh]
c^{omb}_{b}	Operation and maintenance cost of storage system b per unit of energy rating	[$/kWh]
c^{omp}_{t}	Operation and maintenance cost of technology t per unit of production	[$/kWh]
$c^{\mathrm{om}\sigma}_{t}$	Operation and maintenance cost of technology t per unit of power rating, including standby charges	[$/kW]
c^{r}_{re}	Cost per unit peak demand in tier e during ratchet r	[$/kW]
c^{rm}_{mn}	Cost per unit peak demand in tier n during month m	[$/kW]
c^{u}	Unit cost of fuel type f	[$/MMBTU]

Demand Parameters

δ^{d}_{h}	Electrical load in time step h	[kW]
$\bar{\delta}^{\mathrm{gs}}_{u}$	Maximum allowable sales in electrical energy demand tier u	[kWh]
δ^{h}_{h}	Heating load in time step h	[kW]
δ^{lp}	Look-back proportion	[fraction]
$\bar{\delta}^{\mathrm{mt}}_{n}$	Maximum monthly electrical power demand in peak pricing tier n	[kW]
$\bar{\delta}^{\mathrm{t}}_{e}$	Maximum power demand in ratchet e	[kW]
$\bar{\delta}^{\mathrm{tu}}_{u}$	Maximum monthly electrical energy demand in tier u	[kWh]

Incentive Parameters

$\bar{\imath}_{t}$	Upper incentive limit for technology t	[$]
i^{n}_{v}	Net metering and interconnect limits in net metering regime v	[kW]
i^{r}_{t}	Incentive rate for technology t	[$/kWh]
$\bar{\imath}^{\sigma}_{t}$	Maximum power rating for obtaining production incentive for technology t	[kW]

Technology-specific Time-series Factor Parameters

f^{ed}_{th}	Electric power de-rate factor of technology t at time step h	[unitless]

Technology-specific Factor Parameters

f^{d}_{t}	Derate factor for turbine technology t	[unitless]
f^{l}_{t}	Levelization factor of technology t	[fraction]
f^{li}_{t}	Levelization factor of production incentive for technology t	[fraction]
f^{pf}_{t}	Present worth factor for fuel for technology t	[unitless]
f^{pi}_{t}	Present worth factor for incentives for technology t	[unitless]
${}^{\mathrm{td}}_{t}$	Minimum turn down for technology t	[unitless]

Generic Factor Parameters

f^{e}	Energy present worth factor	[unitless]
f^{om}	Operations and maintenance present worth factor	[unitless]
f^{tot}	Tax rate factor for off-taker	[fraction]
f^{tow}	Tax rate factor for owner	[fraction]

Power rating and Fuel Limit Parameters

b^{fa}	Amount of available fuel for type f	[MMBTU]
$\underline{\ }^{\sigma}_{c}$	Minimum power rating for technology class c	[kW]
$\bar{b}^{\sigma}_{t}$	Maximum power rating for technology t	[kW]
${}^{\sigma\mathrm{s}}_{tks}$	Minimum power rating for technology t, subdivision k, segment s	[kW]
$\bar{b}^{\sigma\mathrm{s}}_{tks}$	Maximum power rating for technology t, subdivision k, segment s	[kW]

Efficiency Parameters

η^{+}_{bt}	Efficiency of charging storage system b using technology t	[fraction]
η^{-}_{b}	Efficiency of discharging storage system b	[fraction]
η^{ac}	Absorption chiller efficiency	[fraction]
η^{b}	Boiler efficiency	[fraction]
η^{ec}	Electric chiller efficiency	[fraction]
$\eta^{\mathrm{g+}}$	Efficiency of charging electrical storage using grid power	[fraction]

Storage Parameters

$\bar{w}^{\mathrm{bkW}}_{b}$	Maximum power output of storage system b	[kW]
${}^{\mathrm{bkW}}_{b}$	Minimum power output of storage system b	[kW]
$\bar{w}^{\mathrm{bkWh}}_{b}$	Maximum energy capacity of storage system b	[kWh]
${}^{\mathrm{bkWh}}_{b}$	Minimum energy capacity of storage system b	[kWh]
w^{d}_{b}	Decay rate of storage system b	[1/h]
${}^{\mathrm{mcp}}_{b}$	Minimum percent state of charge of storage system b	[fraction]
w^{0}_{b}	Initial percent state of charge of storage system b	[fraction]

Fuel Burn Parameters

m_t^{fb}	y-intercept of the fuel rate curve for technology t	[MMBTU/h]
m_t^{fm}	Slope of the fuel rate curve for technology t	[MMBTU/kWh]

2.5.2 Variables

Boundary Conditions

$X_{b,0}^{\text{se}}$	Initial state of charge for storage system b	[kWh]

Continuous Variables

X_b^{bkW}	Power rating for storage system b	[kW]
X_b^{bkWh}	Energy rating for storage system b	[kWh]
X_{re}^{de}	Peak electrical power demand allocated to tier e during ratchet r	[kW]
X_{bh}^{dfs}	Power discharged from storage system b during time step h	[kW]
X_{mn}^{dn}	Peak electrical power demand allocated to tier n during month m	[kW]
$_{th}$	Fuel burned by technology t in time step h	[MMBTU/h]
X_{uh}^{g}	Power purchased from the grid for electrical load in demand tier u	
	during time step h	[kW]
X_h^{gts}	Electrical power delivered to storage by the grid in time step h	[kW]
X^{mc}	Annual utility minimum charge adder	[$]
X_t^{pi}	Production incentive collected for technology t	[$]
X^{plb}	Peak electric demand look back	[kW]
X_{tuh}^{ptg}	Exports from production to the grid by technology t in demand tier u	
	during time step h	[kW]
X_{bth}^{pts}	Power from technology t used to charge storage system b during time step h	[kW]
X_{th}^{rp}	Rated production of technology t during time step h	[kW]
X_t^{σ}	Power rating of technology t	[kW]
$X_{tks}^{\sigma\text{s}}$	Power rating of technology t allocated to subdivision k, segment s	[kW]
X_{bh}^{se}	State of charge of storage system b at the end of time step h	[kWh]
X_{uh}^{stg}	Exports from storage to the grid in demand tier u during time step h	[kW]

Binary Variables

Z_{mn}^{dmt}	1 If tier n has allocated demand during month m; 0 otherwise	[unitless]
Z_{re}^{dt}	1 If tier e has allocated demand during ratchet r; 0 otherwise	[unitless]
Z_v^{nmil}	1 If generation is in net metering interconnect limit regime v; 0 otherwise	[unitless]

Z_t^{pi}	1 If production incentive is available for technology t; 0 otherwise	[unitless]
$Z_{tks}^{\sigma\mathrm{s}}$	1 If technology t in subdivision k, segment s is chosen; 0 otherwise	[unitless]
Z_{th}^{to}	1 If technology t is operating in time step h; 0 otherwise	[unitless]
Z_{mu}^{ut}	1 If demand tier u is active in month m; 0 otherwise	[unitless]

2.5.3 Objective Function

$$
\begin{aligned}
\text{Minimize } & \underbrace{\sum_{t\in T, k\in K^{\mathrm{c}}, s\in S_{tk}} \left(c_{ts}^{\mathrm{cm}} \cdot X_{tks}^{\sigma\mathrm{s}} + c_{ts}^{\mathrm{cb}} \cdot Z_{tks}^{\sigma\mathrm{s}} \right)}_{\text{Total Technology Capital Costs}} + \\
& \underbrace{\sum_{b\in B} \left(c_b^{\mathrm{kW}} \cdot X_b^{\mathrm{bkW}} + (c_b^{\mathrm{kWh}} + c_b^{\mathrm{omb}}) \cdot X_b^{\mathrm{bkWh}} \right)}_{\text{Total Storage Costs}} + \\
& (1 - f^{\mathrm{tow}}) \cdot f^{\mathrm{om}} \cdot \left(\underbrace{\sum_{t\in T} c_t^{\mathrm{om}\sigma} \cdot X_t^{\sigma}}_{\text{Fixed O\&M Costs}} + \underbrace{\sum_{t\in T^{\mathrm{f}}, h\in H} c_t^{\mathrm{omp}} \cdot X_{th}^{\mathrm{rp}}}_{\text{Variable O\&M Costs}} \right) + \\
& (1 - f^{\mathrm{tot}}) \cdot \left(\underbrace{\Delta \cdot \sum_{\in F} c^{\mathrm{u}} \cdot \sum_{t\in T, h\in H} f_t^{\mathrm{pf}} \cdot_{th}}_{\text{Total Production Costs}} \right) + \\
& (1 - f^{\mathrm{tot}}) \cdot f^{\mathrm{e}} \cdot \Bigg(\underbrace{\Delta \cdot \sum_{u\in U^{\mathrm{p}}, h\in H^{\mathrm{g}}} c_{uh}^{\mathrm{g}} \cdot X_{uh}^{\mathrm{g}}}_{\text{Total Demand Charges}} + \\
& \underbrace{\sum_{r\in R, e\in E} c_{re}^{\mathrm{r}} \cdot X_{re}^{\mathrm{de}}}_{\text{Peak Ratchet Charges}} + \underbrace{\sum_{m\in M, n\in N} c_{mn}^{\mathrm{rm}} \cdot X_{mn}^{\mathrm{dn}}}_{\text{Peak Monthly Demand Charges}} - \\
& \underbrace{\Delta \cdot \left(\sum_{h\in H^{\mathrm{g}}} \left(\sum_{u\in U^{\mathrm{sb}}} c_{uh}^{\mathrm{e}} \cdot X_{uh}^{\mathrm{stg}} + \sum_{t\in T, u\in U_t^{\mathrm{s}}} c_{uh}^{\mathrm{e}} \cdot X_{tuh}^{\mathrm{ptg}} \right) \right)}_{\text{Total Energy Exports}} + \\
& \underbrace{c^{\mathrm{afc}} + X^{\mathrm{mc}}}_{\text{Total Fixed Charges}} \Bigg) - \\
& (1 - f^{\mathrm{tow}}) \cdot \underbrace{\sum_{t\in T} X_t^{\mathrm{pi}}}_{\text{Production Incentives}}
\end{aligned}
$$

The objective function minimizes the sum of capital costs, fixed operations and maintenance costs, total energy costs and subtracts incentives. The capital cost is comprised of equipment costs and storage costs. The total energy costs is a combination of total production costs, total demand charges, peak ratchet and monthly demand charges, total energy exports, and total fixed charges.

2.5.4 Constraints

This section contains both mathematical expressions and text descriptions for all constraints in the model. In general, the text descriptions are written to convey the spirit of the constraint and may not address every index in *for all* or *summation* statements when they are not central to how the constraint operates.

Fuel constraints

$$\Delta \cdot \sum_{t \in T, h \in H} {}_{th} \leq b^{\mathrm{fa}} \quad \forall f \in F \tag{2.1a}$$

$$ {}_{th} = m_t^{\mathrm{fm}} \cdot f_{th}^{\mathrm{p}} \cdot X_{th}^{\mathrm{rp}} + m_t^{\mathrm{fb}} \cdot Z_{th}^{\mathrm{to}} \quad \forall t \in T^{\mathrm{f}}, h \in H \tag{2.1b}$$

Constraint (2.1a) restricts fuel consumption (which is a function of (i) its total energy produced, and (ii) its number of operating hours) to a prespecified limit for each fuel type, and allows different technologies to burn the same type of fuel. Constraint (2.1b) relates the production of a fuel-burning technology to its fuel consumption using an offset linear function.

Switch Constraints

$$X_{th}^{\mathrm{rp}} \leq \bar{b}_t^{\sigma} \cdot Z_{th}^{\mathrm{to}} \quad \forall t \in T, h \in H \tag{2.2a}$$

$$ {}_t^{\mathrm{td}} \cdot X_t^{\sigma} - X_{th}^{\mathrm{rp}} \leq \bar{b}_t^{\sigma} \cdot (1 - Z_{th}^{\mathrm{to}}) \quad \forall t \in T, h \in H \tag{2.2b}$$

Constraint set (2.2) restricts the rate of production to an operating window between a system's minimum turn down and its maximum size. Constraint (2.2a) limits a system's output to its maximum power rating if it is on, and 0 otherwise. Constraint (2.2b) forces a lower bound for the minimum power at which a technology can operate if it is on; the constraint is void otherwise.

Storage System Constraints

Boundary Conditions and Size Limits

$$X^{\text{se}}_{b,0} = w^{0}_{b} \cdot X^{\text{bkWh}}_{b} \quad \forall b \in \mathcal{B} \tag{2.3a}$$
$$w^{\text{bkWh}}_{b} \leq X^{\text{bkWh}}_{b} \leq \bar{w}^{\text{bkWh}}_{b} \quad \forall b \in \mathcal{B} \tag{2.3b}$$
$$w^{\text{bkW}}_{b} \leq X^{\text{bkW}}_{b} \leq \bar{w}^{\text{bkW}}_{b} \quad \forall b \in \mathcal{B} \tag{2.3c}$$

Constraint (2.3a) sets the initial state of charge for each storage system as a fraction of its energy rating, and constraints (2.3b) - (2.3c) restrict the size of the storage system between the lower and upper bounds for capacity and output, respectively. In this sense, we assume that the power and energy rating of each storage system may be optimized separately.

Storage Operations

$$X^{\text{pts}}_{bth} + \sum_{u \in U^{\text{s}}_{t}} X^{\text{ptg}}_{tuh} \leq f^{\text{p}}_{th} \cdot f^{\text{l}}_{t} \cdot X^{\text{rp}}_{th} \quad \forall b \in B,\ t \in T,\ h \in H^{\text{g}} \tag{2.3d}$$
$$X^{\text{pts}}_{bth} \leq f^{\text{p}}_{th} \cdot f^{\text{l}}_{t} \cdot X^{\text{rp}}_{th} \quad \forall b \in B,\ t \in T,\ h \in H \setminus H^{\text{g}} \tag{2.3e}$$
$$X^{\text{se}}_{bh} = X^{\text{se}}_{b,h-1} + \Delta \cdot \left(\sum_{t \in T} (\eta^{+}_{bt} \cdot X^{\text{pts}}_{bth}) + \eta^{\text{g}+} \cdot X^{\text{gts}}_{h} - X^{\text{dfs}}_{bh} / \eta^{-}_{b} \right) \quad \forall b \in B,\ h \in H^{\text{g}} \tag{2.3f}$$
$$X^{\text{se}}_{bh} = X^{\text{se}}_{b,h-1} + \Delta \cdot \left(\sum_{t \in T} (\eta^{+}_{bt} \cdot X^{\text{pts}}_{bth}) - X^{\text{dfs}}_{bh} / \eta^{-}_{b} \right) \quad \forall b \in B,\ h \in H \setminus H^{\text{g}} \tag{2.3g}$$
$$X^{\text{se}}_{bh} \geq^{\text{mcp}}_{b} \cdot X^{\text{bkWh}}_{b} \quad \forall b \in \mathcal{B}, h \in \mathcal{H} \tag{2.3h}$$

Constraints (2.3d) and Constraint (2.3e) restrict the electrical power dispatched for each technology and time period to the corresponding total production, in the former case to storage and to the grid for hours in which grid purchase is available, and in the latter case to storage only when grid purchase is unavailable. Constraints (2.3f) and (2.3g) provide inventory balance for the state of charge of storage system b at the end of time period h, respectively: (i) for hours in which grid purchase is available, and (ii) for hours in which grid-purchased electricity is not available, in which case the grid-to-storage decision variable values, X_h^{gts}, are zero, i.e., not included in the constraint. Constraint (2.3h) forces the state of charge to be greater than or equal to the minimum battery power rating.

Operational Nuance

$$X_b^{\mathrm{bkW}} \geq \sum_{t \in T_b} X_{bth}^{\mathrm{pts}} + X_h^{\mathrm{gts}} + X_{bh}^{\mathrm{dfs}} \quad \forall b \in \mathcal{B}, h \in \mathcal{H}^{\mathrm{g}} \tag{2.3i}$$

$$X_b^{\mathrm{bkW}} \geq \sum_{t \in T_b} X_{bth}^{\mathrm{pts}} + X_{bh}^{\mathrm{dfs}} \quad \forall b \in \mathcal{B}, h \in \mathcal{H} \setminus H^{\mathrm{g}} \tag{2.3j}$$

$$X_b^{\mathrm{bkWh}} \geq X_{bh}^{\mathrm{se}} \quad \forall b \in \mathcal{B}, h \in \mathcal{H} \tag{2.3k}$$

Constraints (2.3i) and (2.3j) impose limits on the power used to charge electrical storage; in both cases, the upper bound is the system's power rating. Similarly, constraints (2.3k) limit each storage system's discharge power to its power rating.

<u>Production Incentive Cap</u>

$$X_t^{\mathrm{pi}} \leq \min \left\{ M \cdot Z_t^{\mathrm{pi}} , \sum_{h \in H} \Delta \cdot i_t^{\mathrm{r}} \cdot f_t^{\mathrm{pi}} \cdot f_{th}^{\mathrm{p}} \cdot f_t^{\mathrm{li}} \cdot X_{th}^{\mathrm{rp}} \right\} \quad \forall t \in T \tag{2.4a}$$

$$X_t^{\sigma} \leq \bar{\imath}_t^{\sigma} + \bar{b}_t^{\sigma} \cdot (1 - Z_t^{\mathrm{pi}}) \quad \forall t \in T \tag{2.4b}$$

Constraint (2.4a) calculates total production incentives, if available, for each technology. Constraint (2.4b) sets an upper bound on the size of system that qualifies for production incentives, if production incentives are available.

Power rating

$$X_t^{\sigma} \leq \bar{b}_t^{\sigma} \cdot \sum_{s \in S_{tk}} Z_{tks}^{\sigma \mathrm{s}} \quad \forall c \in C, t \in T_c, k \in K_t \tag{2.5a}$$

$$\sum_{t \in T_c, s \in S_{tk}} Z_{tks}^{\sigma \mathrm{s}} \leq 1 \quad \forall c \in C, k \in K \tag{2.5b}$$

$$\sum_{t \in T_c} X_t^{\sigma} \geq {}_c^{\sigma} \quad \forall c \in C \tag{2.5c}$$

$$X_{th}^{\mathrm{rp}} = X_t^{\sigma} \quad \forall t \in T^{\mathrm{td}}, h \in H \tag{2.5d}$$

$$X_{th}^{\mathrm{rp}} \leq f_{th}^{\mathrm{ed}} \cdot X_t^{\sigma} \quad \forall t \in T \setminus T^{\mathrm{td}}, h \in H \tag{2.5e}$$

$${}_{tks}^{\sigma \mathrm{s}} \cdot Z_{tks}^{\sigma \mathrm{s}} \leq X_{tks}^{\sigma \mathrm{s}} \leq \bar{b}_{tks}^{\sigma \mathrm{s}} \cdot Z_{tks}^{\sigma \mathrm{s}} \quad \forall t \in T, k \in K_t, s \in S_{tk} \tag{2.5f}$$

$$\sum_{s \in S_{tk}} X_{tks}^{\sigma \mathrm{s}} = X_t^{\sigma} \quad \forall t \in T, k \in K_t \tag{2.5g}$$

Constraint (2.5a) allows nonzero power ratings only for the selected technology and corresponding subdivision in each class. Constraint (2.5b) allows at most one technology to be chosen for each subdivision in each class. Constraint (2.5c) limits the power rating to the minimum allowed power rating for a technology class. Constraint (2.5d) prevents renewable technologies from turning down; rather, they must provide output at their nameplate capacity. Constraint (2.5e) limits rated production from all non-renewable technologies to be less than or equal to the product of the power rating and the derate factor for each time period. Constraint (2.5f) imposes both lower and upper limits on power rating of a technology, allocated to a subdivision in a segment, and Constraint (2.5g) sums the segments to equal a size for a given technology and subdivision.

Load Balancing and Grid Sales

$$\begin{aligned} \sum_{t \in \mathcal{T}} (f_{th}^{\mathrm{p}} \cdot f_t^{\mathrm{l}} \cdot X_{th}^{\mathrm{rp}}) + \sum_{b \in B} X_{bh}^{\mathrm{dfs}} + \sum_{u \in U^{\mathrm{p}}} X_{uh}^{\mathrm{g}} = \sum_{t \in \mathcal{T}} (\sum_{b \in B} X_{bth}^{\mathrm{pts}} + \sum_{u \in U_t^{\mathrm{s}}} X_{tuh}^{\mathrm{ptg}}) \\ + \sum_{u \in U^{\mathrm{sb}}} X_{uh}^{\mathrm{stg}} + X_h^{\mathrm{gts}} + \delta_h^{\mathrm{d}} \quad \forall h \in H^g \end{aligned} \tag{2.6a}$$

$$\sum_{t\in\mathcal{T}}(f^{\mathrm{p}}_{th}\cdot f^{\mathrm{l}}_{t}\cdot X^{\mathrm{rp}}_{th})+\sum_{b\in B}X^{\mathrm{dfs}}_{bh}=\sum_{b\in B,t\in\mathcal{T}}\left(X^{\mathrm{pts}}_{bth}+\sum_{u\in U^{\mathrm{c}}}X^{\mathrm{ptg}}_{tuh}\right)+\delta^{\mathrm{d}}_{h}\quad\forall h\in H\setminus H^{\mathrm{g}}\tag{2.6b}$$

$$\sum_{u\in U^{\mathrm{p}}}X^{\mathrm{g}}_{uh}\geq X^{\mathrm{gts}}_{h}\quad\forall h\in H^{\mathrm{g}}\tag{2.6c}$$

$$\sum_{b\in B}X^{\mathrm{dfs}}_{bh}\geq\sum_{u\in U^{\mathrm{sb}}}X^{\mathrm{stg}}_{uh}\quad\forall h\in H^{\mathrm{g}}\tag{2.6d}$$

$$\Delta\cdot\sum_{h\in H^{\mathrm{g}}}\left(X^{\mathrm{stg}}_{uh}+\sum_{t\in T_u}X^{\mathrm{ptg}}_{tuh}\right)\leq\bar{\delta}^{\mathrm{gs}}_{u}\quad\forall u\in U^{\mathrm{sb}}\tag{2.6e}$$

$$\Delta\cdot\sum_{h\in H^{\mathrm{g}},t\in T_u}X^{\mathrm{ptg}}_{tuh}\leq\bar{\delta}^{\mathrm{gs}}_{u}\quad\forall u\in U^{\mathrm{s}}\setminus U^{\mathrm{sb}}\tag{2.6f}$$

Constraint (2.6a) balances load by requiring that the sum of power (i) produced, (ii) discharged from storage, and (iii) purchased from the grid is equal to the sum of (i) the power charged to storage, (ii) the power sold to the grid from in-house production or storage, (iii) the power charged to storage directly from the grid, and (iv) the electrical load on site. Constraint (2.6b) provides an analogous load-balancing requirement for hours in which the site is disconnected from the grid due to an outage. Constraint (2.6c) restricts charging of storage from grid production to the grid power purchased for each hour. Similarly, constraint (2.6d) restricts the sales from the electrical storage system to its rate of discharge in each time period. Constraints (2.6e) and (2.6f) restrict the annual energy delivered to the grid by pricing tier based on pre-specified limits, such as those imposed by net-metering restrictions; the former allows both storage and production to contribute, whereas the latter restricts the contribution to production only for certain technologies.

Rate Tariff Constraints

Net Meter Module

$$\sum_{v\in V}Z^{\mathrm{nmil}}_{v}=1\tag{2.7a}$$

$$\sum_{t\in T_v}f^{\mathrm{d}}_{t}\cdot X^{\sigma}_{t}\leq i^{\mathrm{n}}_{v}\cdot Z^{\mathrm{nmil}}_{v}\quad\forall v\in V\tag{2.7b}$$

$$\Delta \cdot \sum_{h \in H^{\mathrm{g}}} \left(\sum_{u \in U^{\mathrm{nm}}, t \in T_u} X^{\mathrm{ptg}}_{tuh} + \sum_{u \in U^{\mathrm{nm}} \cap U^{\mathrm{sb}}} X^{\mathrm{stg}}_{uh} \right) \leq \Delta \cdot \sum_{u \in U^{\mathrm{p}}, h \in H^{\mathrm{g}}} X^{\mathrm{g}}_{uh} \tag{2.7c}$$

Constraint (2.7a) limits the net metering interconnect limit to a single regime at a time. Constraint (2.7b) restricts the sum of the power rating of all technologies to be less than or equal to the net metering interconnect limit regime. Constraint (2.7c) ensures that energy sales at net-metering rates do not exceed the power purchased from the grid.

Monthly Total Demand Charges

$$\Delta \cdot \sum_{h \in H_m} X^{\mathrm{g}}_{uh} \leq \bar{\delta}^{\mathrm{tu}}_{u} \cdot Z^{\mathrm{ut}}_{mu} \quad \forall m \in M, u \in U^{\mathrm{p}} \tag{2.8a}$$

$$Z^{\mathrm{ut}}_{mu} \leq Z^{\mathrm{ut}}_{m,u-1} \quad \forall u \in U^{\mathrm{p}} : u \geq 2, m \in M \tag{2.8b}$$

$$\bar{\delta}^{\mathrm{tu}}_{u-1} \cdot Z^{\mathrm{ut}}_{mu} \leq \Delta \cdot \sum_{h \in H_m} X^{\mathrm{g}}_{u-1,h} \quad \forall u \in U^{\mathrm{p}} : u \geq 2, m \in M \tag{2.8c}$$

Constraint (2.8a) limits the quantity of electrical energy purchased from the grid in a given month from a specified pricing tier to the maximum available. Constraint (2.8b) forces pricing tiers to be charged in a specific order, and constraint (2.8c) forces one pricing tier's purchases to be at capacity if any charges are applied to the next tier.

Peak Power Demand Charges: Months

$$X^{\mathrm{dn}}_{mn} \leq \bar{\delta}^{\mathrm{mt}}_{n} \cdot Z^{\mathrm{dmt}}_{mn} \quad \forall n \in N, m \in M \tag{2.9a}$$

$$Z^{\mathrm{dmt}}_{mn} \leq Z^{\mathrm{dmt}}_{m,n-1} \quad \forall n \in N : n \geq 2, m \in M \tag{2.9b}$$

$$\bar{\delta}^{\mathrm{mt}}_{n-1} \cdot Z^{\mathrm{dmt}}_{mn} \leq X^{\mathrm{dn}}_{m,n-1} \quad \forall n \in N : n \geq 2, m \in M \tag{2.9c}$$

$$\sum_{n \in N} X^{\mathrm{dn}}_{mn} \geq \sum_{u \in U^{\mathrm{p}}} X^{\mathrm{g}}_{uh} \quad \forall m \in M, h \in H_m \tag{2.9d}$$

Constraint (2.9a) limits the energy demand to the maximum demand required. Constraint (2.9b) forces monthly demand tiers to become active in a prespecified order. Constraint (2.9c) forces demand to be met in one tier before the next demand tier. Constraint (2.9d) defines the peak demand to be greater than or equal to all of the demands across the time horizon, where an equality is induced by the sense of the objective function.

Peak Power Demand Charges: Ratchets

$$X^{\mathrm{de}}_{re} \leq \bar{\delta}^{\mathrm{t}}_{e} \cdot Z^{\mathrm{dt}}_{re} \quad \forall e \in E, r \in R \tag{2.10a}$$
$$Z^{\mathrm{dt}}_{re} \leq Z^{\mathrm{dt}}_{r,e-1} \quad \forall e \in E : e \geq 2, r \in R \tag{2.10b}$$
$$\bar{\delta}^{\mathrm{t}}_{e-1} \cdot Z^{\mathrm{dt}}_{re} \leq X^{\mathrm{de}}_{r,e-1} \quad \forall e \in E : e \geq 2, r \in R \tag{2.10c}$$
$$\sum_{e \in E} X^{\mathrm{de}}_{re} \geq \sum_{u \in U^{\mathrm{p}}} X^{\mathrm{g}}_{uh} \quad \forall r \in R, h \in H_r \tag{2.10d}$$
$$X^{\mathrm{plb}} \geq \sum_{n \in N} X^{\mathrm{dn}}_{mn} \quad \forall m \in M^{\mathrm{lb}} \tag{2.10e}$$
$$\sum_{e \in E} X^{\mathrm{de}}_{re} \geq \delta^{\mathrm{lp}} \cdot X^{\mathrm{plb}} \quad \forall r \in R \tag{2.10f}$$

Constraints (2.10a)-(2.10d) correspond to constraints (2.9a)-(2.9d), but for non-monthly billing periods to which we refer as *ratchets*. The charge applied for each ratchet is a linear function of the greater of the peak electrical demand during the ratchet and a fraction of the peak demand that occurs over a collection of months during the year; we refer to this collection as *look-back months*. Constraint (2.10e) enforces a lower limit on the look-back demand for each look-back month. Constraint (2.10f) ensures that the peak demand for each ratchet is no lower than a fraction of the look-back demand.

Minimum Utility Charge

$$\begin{aligned} X^{\mathrm{mc}} \geq & c^{\mathrm{amc}} - \Bigg(\underbrace{\Delta \cdot \sum_{u \in U^{\mathrm{p}}, h \in H^{\mathrm{g}}} c^{\mathrm{g}}_{uh} \cdot X^{\mathrm{g}}_{uh}}_{\text{Total Demand Charges}} + \underbrace{\sum_{r \in R, e \in E} c^{\mathrm{r}}_{re} \cdot X^{\mathrm{de}}_{re}}_{\text{Peak Ratchet Charges}} + \\ & \underbrace{\sum_{m \in M, n \in N} c^{\mathrm{rm}}_{mn} \cdot X^{\mathrm{dn}}_{mn}}_{\text{Peak Monthly Charges}} - \\ & \underbrace{\Delta \cdot \left(\sum_{h \in H^{\mathrm{g}}} \left(\sum_{u \in U^{\mathrm{sb}}} c^{\mathrm{e}}_{uh} \cdot X^{\mathrm{stg}}_{uh} + \sum_{t \in T, u \in U^{\mathrm{s}}_{t}} c^{\mathrm{e}}_{uh} \cdot X^{\mathrm{ptg}}_{tuh} \right) \right) \Bigg)}_{\text{Total Energy Exports}} \end{aligned} \tag{2.11}$$

Constraint (2.11) enforces a minimum payment to the utility provider, which is a fixed constant less charges incurred from total demand, peak ratchets and peak monthly payments, plus sales from exports to the grid.

<u>Non-negativity</u>

$$X^{\text{plb}}, X^{\text{mc}} \geq 0 \tag{2.12a}$$
$$X^{\sigma}_{t} \geq 0 \quad \forall t \in T \tag{2.12b}$$
$$X^{\text{rp}}_{th} \geq 0 \quad \forall t \in T, h \in H \tag{2.12c}$$
$$X^{\text{ptg}}_{tuh} \geq 0 \quad \forall t \in T_u, h \in H, u \in U \tag{2.12d}$$
$$X^{\text{stg}}_{uh}, X^{\text{g}}_{uh} \geq 0 \quad \forall h \in H, u \in U \tag{2.12e}$$
$$X^{\text{pi}}_{t} \geq 0 \quad \forall t \in T \tag{2.12f}$$
$$X^{\text{de}}_{re} \geq 0 \quad \forall r \in R, e \in E \tag{2.12g}$$
$$X^{\text{dn}}_{mn} \geq 0 \quad \forall m \in M, n \in N \tag{2.12h}$$
$$X^{\text{gts}}_{h} \geq 0 \quad h \in H \tag{2.12i}$$
$$X^{\text{bkW}}_{b}, X^{\text{bkWh}}_{b} \geq 0 \quad b \in B \tag{2.12j}$$
$$X^{\sigma\text{s}}_{tks} \geq 0 \quad \forall t \in T,\ k \in K,\ s \in S_{tk} \tag{2.12k}$$
$$X^{\text{pts}}_{bth} \geq 0 \quad \forall b \in B,\ t \in T,\ h \in H \tag{2.12l}$$
$$X^{\text{se}}_{bh}, X^{\text{dfs}}_{bh} \geq 0 \quad \forall b \in B,\ h \in H \tag{2.12m}$$
$$X^{\text{f}}_{th}, X^{\text{fb}}_{th} \geq 0 \quad \forall t \in T,\ h \in H \tag{2.12n}$$

<u>Integrality</u>

$$Z^{\text{nmil}}_{v} \in \{0,1\} \quad \forall v \in V \tag{2.13a}$$
$$Z^{\sigma\text{s}}_{tks} \in \{0,1\} \quad \forall t \in T,\ k \in K,\ s \in S_{tk} \tag{2.13b}$$
$$Z^{\text{pi}}_{t} \in \{0,1\} \quad \forall t \in T \tag{2.13c}$$
$$Z^{\text{to}}_{th} \in \{0,1\} \quad \forall t \in T, h \in H \tag{2.13d}$$
$$Z^{\text{dt}}_{re} \in \{0,1\} \quad \forall r \in R, e \in E \tag{2.13e}$$
$$Z^{\text{dmt}}_{mn} \in \{0,1\} \quad \forall m \in M, n \in N \tag{2.13f}$$
$$Z^{\text{ut}}_{mu} \in \{0,1\} \quad \forall m \in M, u \in U \tag{2.13g}$$

Finally, constraints (2.12) ensure all of the variables in our formulation assume non-negative values. In addition to non-negativity restrictions, constraints (2.13) establish the integrality of the appropriate variables.

2.6 Results

To demonstrate its capabilities, we exercise the model ($\mathcal{R}$) at four locations across the United States while considering PV, wind, and battery storage as possible technology types included in the system design. Each location experiences a different climate, possesses different building types [55], and is subject to different utility rate structures, the latter of which add complexity to the model due to seasonal pricing, energy tiers, and time-varying demand.

2.6.1 Inputs

Table 2.3, Table 2.4, and Table 2.5 provide information on the location, building type, and utility rate tier types, respectively. Cases 1 and 3 possess a rate structure that contains multiple time-of-use periods, which are used to control the time at which consumers use electricity, e.g., rates are higher from 5PM to 8PM to induce lower demand during this time window. Cases 2 and 3 have energy and demand tiers, respectively, signifying that energy is priced according to the season and consists of the product of time and demand for the former tier types, and that rates are proportional to demand for the latter characteristic. Demand rates are fixed per kW of usage. Case 4 considers a simple utility rate structure which serves as a baseline while modeling a campus for a company consisting of five large office buildings. Utility rate structures not only add complex trade-offs, they also increase the size of the model, thereby increasing the difficulty of finding a solution.

Table 2.3: Characteristics for each location detailing the building type, utility company name and rate structure

Case	Location	Building Type	Utility Company Name	Rate Structure
1	San Diego, CA	Hospital	San Diego Gas and Electric	AL-TOU Primary (Above 500kW)
2	Des Moines, IA	Hospital	MidAmerican Energy	Rate GD - General Demand Service
3	Greenville, SC	Large office	Duke Energy Carolinas	Optional Power Service, Time-of-Use, General Service (OPT)
4	Cheyenne, WY	Campus	Cheyenne Light Fuel & Power	Secondary General Service

Table 2.4: Characteristics highlighting the number of energy tiers, time-of-use periods, and charges

Location	Energy Tiers	Time-of-Use Periods	Charges [$/kWh]		
			Min	Avg	Max
San Diego, CA	1	6	0.09	0.11	0.14
Des Moines, IA	3	1	0.05	0.06	0.07
Greenville, SC	1	2	0.04	0.06	0.08
Cheyenne, WY	1	1	0.06	0.06	0.06

Table 2.5: Characteristics highlighting the number of demand tiers, time-of-use periods, and charges

Location	Demand Tiers	Time-of-Use Periods	Charges [$/kW]		
			Min	Avg	Max
San Diego, CA	1	3	20.87	35.49	47.85
Des Moines, IA	1	1	10.89	10.89	10.89
Greenville, SC	3	3	1.35	11.21	18.45
Cheyenne, WY	1	1	19.89	19.89	19.89

Different locations exhibit renewable energy variability, associated with wind and solar production factors (see Table 2.6). Solar production factors show similar seasonal patterns for each location, as opposed to wind production factors which exhibit pronounced variability; both provide an efficiency return on renewable electricity that can be used for either storage or demand. Each case has demands that vary both seasonally and by building type. Typically, utility rates are differentiated by seasons: summer (June to September) and winter (October to May). Cases 1 and 2 require relatively more electricity than cases 3 and 4 during non-peak periods due to the nature of the building types. Hospitals typically operate continuously, while large office buildings have a significantly reduced load in the evenings and on the weekends . Tables Table 2.7 and Table 2.8 provide technical and economic parameters associated with all of the cases, and used in formulation ($\mathcal{R}$).

Table 2.6: Renewable Energy average production factors

Location	PV	Wind
San Diego, CA	0.17	0.07
Des Moines, IA	0.15	0.34
Greenville, NC	0.15	0.21
Cheyenne, WY	0.16	0.41

Table 2.7: Renewable energy parameters used in ($\mathcal{R}$)

PV parameters	**Value**	**Reference**
Array type	Rooftop, Fixed	[56]
Array azimuth	180°	[56]
Array tilt	10°	[56]
DC-to-AC size ratio	1.2	[56]
System losses	14%	[56]
Capital cost	$1,600/kW	[57]
O&M cost	$16/kW	[57]
Federal incentive percentage	26%	[58]
Depreciation schedule	5-year MACRS*	[58]

Wind parameters	**Value**	**Reference**
Size class	Midsize (101-999 kW)	[59]
Capital cost	$4,440/kW	[59]
O&M cost	$40/kW	[59]
Federal incentive percentage	18%	[58]
Depreciation schedule	5-year MACRS*	[58]

Battery parameters	**Value**	**Reference**
Rectifier efficiency	96%	[60]
Round-trip efficiency	97.5%	[60]
Inverter efficiency	96%	[60]
Minimum state of charge	20%	[60]
Initial state of charge	50%	[-]
Battery life	10 years	[60]
Energy capacity cost	$420/kWh	[61]
Energy replacement cost	$200/kWh	[61]
Power capacity cost	$840/kW	[61]
Power replacement cost	$410/kW	[61]
O&M cost	$0/kW	[-]
Federal incentive percentage	26%	[58]
Depreciation schedule	7-year MACRS*	[58]

*MACRS: Modified Accelerated Cost Recovery System

Table 2.8: System wide parameters used in ($\mathcal{R}$)

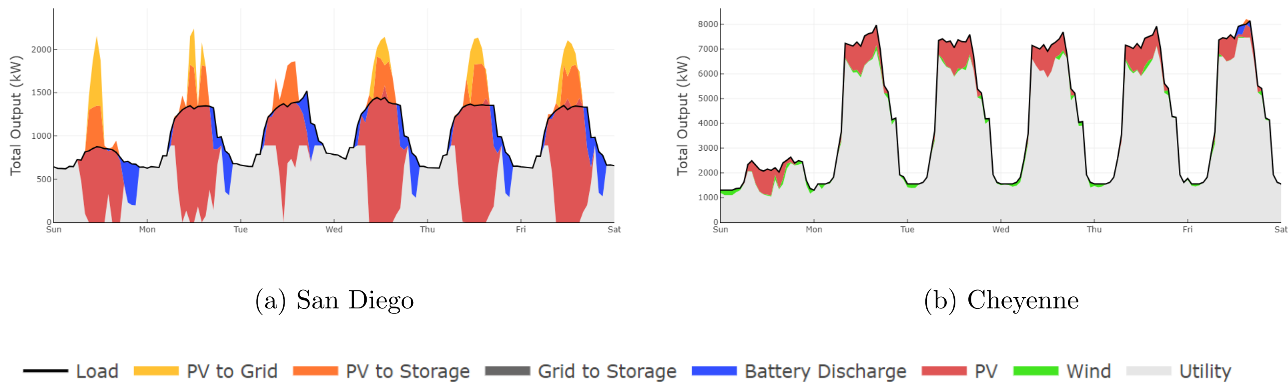
General economic parameters	Value	Reference
Electricity cost escalation rate	2.3%	[62]
Host discount rate	8.3%	[57]
Host effective tax rate	26%	[57]
O&M cost escalation rate	2.5%	[57]
Analysis period	25 years	[57]

2.6.2 Solution

Instances of ($\mathcal{R}$) were solved on a Dell Power Edge R410 server with two Intel Xeon E5520s at 2.27 GHz, 28GB of RAM, and a 1TB HDD using CPLEX 12.10.0.0. Model ($\mathcal{R}$) produces a technology mix (see Table Table 2.9) and corresponding optimal dispatch (see Figure Figure 2.2). Cases 1 and 4 procure the largest capacity of technology types to offset the dependence of utilities. In San Diego, the dispatch shows more reliance on PV and storage to offset the high time-of-use energy and demand charges during peak-demand hours. This corresponds to peak shaving, where the power provided by the grid is offset by renewable energy and storage during the peak demand hours. Cheyenne, however, has a much simpler rate structure and cheaper rates, and exhibits peak shaving through the use of PV, wind and storage. The relatively higher production factors for both PV and wind, and the relatively low operations and maintenance costs outweigh the high initial fixed charge and the intermittency of the technologies, which aid in peak shaving. Cheyenne and Greenville exhibit similar electric load profiles; however, the overall load is higher in Cheyenne, amplifying the technology system sizes in Cheyenne relative to those in Greenville, while not necessarily adopting a new technology. The technology mix output that model ($\mathcal{R}$) suggests is an initial assessment for the consumer. Further examination such as a site visit of the location is needed to ensure the solution can be carried out.

Table 2.9: Case technology mix

Location	PV [kW]	Wind [kW]	Battery Storage Power [kW]	Battery Storage Capacity [kWh]
San Diego, CA	3008.7	0.0	475.1	2457.3
Des Moines, IA	56.0	0.0	0.0	0.0
Greenville, SC	39.6	0.0	31.7	41.7
Cheyenne, WY	1666.9	203.8	551.2	1013.1



(a) San Diego

(b) Cheyenne

Figure 2.2: San Diego and Cheyenne's dispatch output during its peak demand

While model ($\mathcal{R}$) suggest the use of PV and/or storage for cases 2 and 3, the economic benefits are marginal relative to those of the "Business-As-Usual" case, in which each location is solely dependent on utilities (see Table Table 2.10). As a consumer, evaluating the "Business-As-Usual" and model ($\mathcal{R}$)'s economic costs, the NPV provides perspective and allows the consideration of opportunity costs between time to install the renewable energy technologies and overall cost savings.

Table 2.10: Comparison of financial costs for the year

Location	Business-As-Usual [$]	Model ($\mathcal{R}$) [$]	NPV [$]
San Diego, CA	15,825,528	13,122,538	2,702,990
Des Moines, IA	7,638,959	7,636,460	2,499
Greenville, SC	6,273,711	6,264,840	8,871
Cheyenne, WY	34,634,914	34,171,398	463,516

2.7 Future Work

We intend to implement combined heat and power technologies that could potentially improve resiliency and reduce utility cost of the overall model for a given facility. In addition, we intend to improve the solution times of REopt Lite using a decomposition procedure.

Unique among most models in this field, REopt Lite is presented in a web-based platform, also accessible via an application programming interface and open source software. This allows REopt Lite to be easily integrated in other models or customized for new use cases. It also enables analysis-at-scale whereby evaluations of thousands of sites or sensitivities can easily be scripted. Finally, REopt Lite is free and publicly available to ensure maximum availability and accelerate clean energy deployment impact.

CHAPTER 3

DEVELOPING DIVERSE SOLUTIONS TO INFORM ENERGY DECISIONS

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To be submitted to *INFORMS Journal on Applied Analytics*

3.1 Abstract

Energy optimization models are widely used to guide energy decisions for building owners, communities, and nations. However, many of the issues these models analyze are uncertain, and research around how to handle structural uncertainty like the role that non-economic factors play in energy purchase decisions is limited. Modeling to generate alternatives (MGA) is one technique that can help address this by generating alternate, near-optimal solutions. Providing multiple good quality feasible solutions can help the decision maker select a solution that works best for the real-life problem, which may be different than the mathematical model. Most of the research on MGA techniques in energy has focused on national scale energy system optimization models. This work extends the literature by adapting MGA techniques to energy optimization for a building or cluster of buildings behind a single utility meter. We find that a combination of integer-cut and continuous variable constraints can generate solutions diverse in both technology type and technology size. The work presented here may enable building owners and campus energy managers to make more effective and efficient decisions to increase the speed and scale of clean energy deployment.

3.2 Background

The global energy system is rapidly changing. In the United States, electricity generation from renewable energy sources has doubled in the past ten years, and currently accounts for about 18% of total generation [1]. This trend is accelerating worldwide as renewable energy prices drop; the United States Energy Information Administration (2019) predicts that renewable energy will be the leading source of primary energy consumption by 2050. Wind and solar technologies are expected to dominate growth, representing over 70% of electric generating capacity additions by 2050 [2].

Techno-economic energy decision models are used to inform the deployment of these technologies, answering questions around how new capacity is sized, where it is located, how it is operated to meet demand and reliability requirements, and how it is integrated with the existing system [30, 63]. Many existing models cover a variety of technologies and address energy efficiency, renewable energy, and sustainable transportation. They are applied at national [64], regional [65], community [66–68], microgrid [69, 70] and building scales to guide the planning and design of technically feasible and economically viable systems.

Energy optimization models are widely used to explore the least cost pathways to provide economic, sustainable, and resilient energy [45, 71, 72]. However, despite their sophisticated capabilities, many models are limited in their ability to guide decisions. These tools typically focus on the quantitative aspects of decision-making that lend themselves to modeling, such as dollars saved or kilowatt-hours generated. They often do not, however, account for more qualitative (but no less important) aspects such as uncertainty, non-monetary costs, or bevavioral factors [50]. Pfenninger et al. suggest that assessing uncertainties is one of the major challenges and shortcomings of optimization models. Uncertainties can be classified as parametric or structural [74]. Parametric uncertainty arises from lack of knowledge about empirical values associated with model parameters, such as variability in renewable energy resource, load, or future energy prices. Structural uncertainty relates to uncertainties in the model structure such as the role that non-economic factors play in energy purchase decisions, the heterogeneity of decision makers, and the role that politics, social norms, and culture may play in decisions.

Yue et al. review the primary techniques that address uncertainty, and find that most studies use simple scenario analysis or sensitivity analysis. However, when only a few scenarios are run, this can actually obscure other equally plausible alternatives [76]. More systematic and rigorous approaches include four main techniques: Monte Carlo analysis, stochastic programming, robust optimization, and modeling to generate alternatives. The first three methods provide efficient approaches to deal with parametric uncertainty, while the last is used to address structural uncertainty. While methods for addressing parametric uncertainty are well researched, structural uncertainty has received less attention in the literature, though analysts have highlighted its importance [77]. Modeling to generate alternatives is one approach to addressing structural uncertainty. In this technique, the solution space is searched for alternative near-optimal, maximally different solutions. Multiple, good quality solutions provide the decision maker an opportunity to select the best solution for the real-life problem, including criteria that could not be expressed in the model.

The literature generally divides modeling to generate alternatives models into two approaches. The first technique relies on iteratively solving the optimization model, each time with a constraint that excludes the solution found previously. The second technique relies on the branch and bound tree, and develops alternate solutions based on a deeper exploration of the tree. An example of the first technique is the Hop-Skip-Jump method proposed by Brill et al.. Initially applied to land use planning and later airline routing [79], it solves the original problem to obtain an initial optimal solution, and then obtains a diverse, alternative solution by minimizing the weighted sum of the decision variables that appear in previous solutions, while constraining the amount the solution to be within some range of the original optimal objective function. This technique can reveal edge solutions, in which slight changes to input assumptions can produce very different solutions.

Examples of the second technique are approaches that modify the standard branch-and-bound algorithm to directly explore the search tree. Danna et al. develop a two-phase systematic algorithm to maximize solution diversity. In the first phase, a standard branch-and-bound tree is constructed and explored to find the optimal solution. Its nodes are kept (rather than discarded) for the second phase. During the second phase, the tree is reused and all integer solutions within a defined percentage of the optimum value are kept. This method provides an acceptable level of diversity of solutions, but diversity is focused on integer variables. In subsequent work, Danna and Woodruff develop diversity measures that consider continuous variables. They use the average variance of each variable as a measure of diversity, and show that the scale of the continuous variables is problematic. They conclude that for problems with a mix of binary, general integer, and continuous variables, maximizing the binary diversity metric does not result in maximizing diversity of the continuous variable metrics because it can be dominated by a binary variable with a value of one. They find there is room for improvement in how continuous and general integer variables are handled. They suggest future research that forms cohesive clusters and selects one representative from each as the set of diverse solutions. They also suggest modifying the algorithm generating solutions to increase the diversity of solutions produced in the first place, potentially by exploring different parts of the branch-and-bound tree successively.

Several researchers have applied the Hop-Skip-Jump approach in national or global energy planning models. DeCarolis applies Brill's Hop-Skip-Jump technique to explore alternative energy futures in the U.S. electric sector. He finds that small increases in optimal system cost can lead to significantly different solutions, and that, compared to the base case, the modeling to generate alternatives scenarios provide a more diverse set of technologies. Trutnevyte et al. also employ modeling to generate alternatives to explore different pathways for the UK electricity sector transition to clean energy, finding many near-optimal solutions with different power generation mixes. Price and Keppo explore the near cost optimal solution space of the global energy-environment-economy model to assess the diversity of different global energy system transition pathways, and the stability of results in the least cost pathway. They use a modified version of the Hop-Skip-Jump technique that maximizes the difference in primary energy consumption from each technology between solutions, while constraining the totally system cost to be within some slack range of the optimal system cost. This method produces more diverse solutions in their application.

Voll et al. employ integer cut constraints developed by Fazlollahi et al. for energy optimization models that determine the size, location, and operation of energy generating equipment in campus energy systems. They start by calculating the optimal solution, and then add an integer-cut constraint that excludes the newly generated solution from consideration, repeating the addition of cuts until either a maximum number of solutions is generated, or a maximum relative optimality gap is reached. The objective function values of the alternate solutions are typically within about 1% of the optimum objective function value. The generated solutions are then analyzed to separate technology choices into three buckets. Features that are in all the near-optimal solutions are considered "must-have," while features that are in none are considered "must avoid." The features that are in some but not all of the near-optimal solutions are considered the "real choices." This method works best when modeling discrete pieces of equipment with specific sizes, rather than continuously sized variables.

Jing et al. further build on this work by developing a portfolio-constraint-based approach for multi-objective optimization based on the MGA method and the eps-constraint method. They apply their method to urban energy system design, considering a case study in which CHP, absorption chiller, PV, battery, and thermal storage power 12 buildings. Rather than providing decision makers with one optimal design, they quantify the economic and environmental benefits that different technologies bring to the system design, called the "impact space." By varying the threshold value of portfolio constraints that act to exclude technologies or restrict the capital cost investment of a technology to a certain percent of the total project investment, certain solutions are produced. These are presented as a pareto optimal frontier with different degrees of availability for each technology. This approach is more easily integrated into multi-objective formulations than is Hop-Skip-Jump because it leaves the objective function unmodified and does not require integer cuts.

The second modeling to generate alternatives approach of deeper exploration of the branch and bound tree has been used in limited applications to develop alternative solutions for energy systems. Yokoyama et al. build on the work of Danna et al. by using the branch-and-bound method to collect alternative solutions for a cogeneration system. They use a hierarchical relationship between design and operation variables to prioritize alternate values for design variables and reduce computation time.

Much of the work on modeling to generate alternatives in energy systems modeling has concentrated on national or global energy models, with only a few examples of applications in smaller urban and campus settings. The work presented here extends the existing literature by applying modeling to generate alternatives techniques to energy optimization for a building or cluster of buildings behind a single utility meter. This may enable building owners and campus energy managers to make more effective and efficient decisions about energy deployment.

3.3 Methodology

In this section, we briefly introduce the energy optimization model and case study scenario. We then test three MGA approaches to generate alternate solutions. We first start with the branch-and-bound search techniques that have been implemented in commercial solvers, and then evaluate integer-cut techniques based on the HSJ method. Finally, we evaluate constraints on continuous variables. The effectiveness of each approach is compared.

3.3.1 Model and Case Study

We use the REopt Lite model for our test case. REopt Lite is a techno-economic decision support model used to optimize energy systems for buildings, campuses, communities, and microgrids. The primary application of the model is for optimizing the integration and operation of behind-the-meter energy assets. Formulated as a deterministic mixed-integer linear program, REopt determines the optimal selection, sizing, and dispatch strategy of technologies chosen from a candidate pool such that electrical and thermal loads are met at every time step at the minimum life cycle cost [88]. The model formulation is given in Chapter 2. The model is coded in AMPL and run on a Dell PowerEdge R410 machine with 16 processors (2.72 GHz each) and 12 GB of RAM using CPLEX version 12.9.0.0. On average, instances solve to optimality in less than a minute.

The case study site is a mid-rise apartment building in Arkansas with an average load of 33 kW. We evaluate whether distributed energy technologies (photovoltaics, wind power, and battery storage) can reduce life cycle cost of energy to the site while sustaining the load during a six hour outage. The modeling assumptions and datasets used are described in Table 3.1.

Table 3.1: Datasets used in the analysis

Input	**Assumption**	**Reference**
Location	Searcy, AR	N/A
Building Type	Mid-rise apartment	[55]
Annual energy consumption	285,224 kWh	[55]
Grid outage period	January 1, 5pm-11pm	N/A
Utility rate	$0.20/kWh	[89]
Analysis period	25 years	[90]
Discount rate	8.10%	[90]
Utility cost escalation rate	2.60%	[91]
Inflation rate	2.50%	[90]
Net metering limit	300 kW	[58]
PV capital cost (after incentives)	$1087/kW	[58, 90]
PV O&M cost	0	[90]
Battery capital cost (after incentives)	$479/kWh + $958/kW	[58, 92]
Battery O&M cost	0	[92]
Wind capital cost (after incentives)	$2,712/kW	[58, 93]
Wind O&M cost	$35/kW/year	[93]
Solar resource	National Solar Radiation Database	[94]
Wind resource	Wind Integration National Dataset Toolkit 2012 data	[95]

3.3.2 Approach 1: Alternate Solutions from the Branch and Bound Tree

Methodology Many commercial solvers provide a solution pool capability wherein they generate multiple solutions. A traditional branch-and-bound algorithm would delete nodes from the search tree as soon as they are pruned due to infeasibility or due to having an inferior node bound. The solution pool instead retains feasible but suboptimal nodes with demonstrated integer solutions and may also populate the pool with possible additional "n-best" solutions. CPLEX allows the user to modulate the solution pool by defining the number of solutions in the pool, methods for adding and replacing additional solutions, the maximum gap between alternate solutions and the optimal, and diversity of solutions [96]. Xpress and Gurobi also provide options to search for n-best solutions, but they do not have options for encouraging diversity [97, 98]. Because CPLEX provides options for developing more diverse solutions, we use CPLEX for the research presented in this paper.

It is important to note that the solution pool in all three solvers distinguishes solutions by the value of discrete variables only. There is an infinite number of possible values for a continuous variable, and it is not practical to enumerate all of them. Therefore, the solution pool gives only one solution for each set of discrete variables, even though there may exist several solutions that have the same values for all discrete variables but different values for continuous variables. In effect, we are only getting the first, second, third, etc. best choices for the discrete variables, and not the continuous. For our problem in which some of the key decision variables are continuous, this could be limiting.

We start by testing a single case and adjusting the characteristics of the solution pool to see how this impacts the alternate solutions developed. We develop scenarios that adjust three features of the solution pool: populate, pool intensity, and pool replace. Populate is set to either 0 (where the populate algorithm is not run to add more solutions to the pool) or 1 (where the populate algorithm is run after finding the optimal MIP solution). Pool intensity is set to 1, 2, 3, or 4, and as the number increases, the algorithm tries harder to add solutions to the pool. Pool replace is set to either 1 (keep best solutions) or 2 (keep most diverse solutions). Pool capacity is always set to 3, and populate limit is always set to 5.

Results Given the setting described above, the solution pool provides three diverse alternate solutions (1.1, 1.2, and 1.3), summarized in Table 3.2. The most diverse solutions come from setting populate to 1, pool intensity to 2 or greater, and pool replace to 2. The first alternate solution removes the battery from the technology mix, while reducing PV size and increasing wind size. The LCC increases by 9% above the optimal case. The second solution contains the same technology mix as the optimal solution, but with somewhat different technology sizes, resulting in a lifecycle cost increase of 6%. The last alternate solution has a much larger PV and battery, but this results in an LCC that is 160% higher than the optimal, so it is unlikely to be considered. The other alternate solutions provided by the solution pool are very close to the optimal or the three alternate solutions shown in Table 3.2, so they are not included here. Adjustments to other solution pool settings may produce additional alternate solutions, but given limitations of time and scope, they were not explored here.

Table 3.2: Alternate Solutions Recommended with Solution Pool

	LCC ($)	**PV (kW)**	**Wind (kW)**	**Battery (kW)**	**Battery (kWh)**	**LCC Difference (%)**
Optimal Solution	504,882	62.44	41.53	11.54	46.02	0
Alternate Solution 1.1	549,188	40.18	84.27	0	0	9
Alternate Solution 1.2	533,094	46.83	56.47	7.5	45.62	6
Alternate Solution 1.3	1,311,015	541.00	27.00	87.72	1000	160

An ideal set of alternate solutions might include ones where PV, wind, and battery are each zero in at least one solution. In this case, most of the diversity is around the battery size, which could be because it has three binary variables associated with it (charging, discharging, and battery level). PV and wind have only one binary associated with them (whether they are operating in a given time step) which may lead to less diversity in the PV and wind sizes since CPLEX distinguishes solutions by the value of discrete variables only.

These results show that the solution pool function can be used to generate alternate, diverse solutions, but may have some limitations for problems where the most important variables are continuous rather than binary. While further testing could be done on other problems, given the importance of continuous variables in our model, we next consider an alternate method called integer-cut constraints. These have been employed successfully to develop alternate solutions for similar energy optimization models making decisions about size, location, and operation of energy generating technologies.

3.3.3 Approach 2: Integer-Cut Constraints

Methodology In order to develop a set of alternate solutions that are diverse not just in size of technologies, but in which technologies are included, we use an integer-cut approach. We generate an optimal solution, and then add a constraint (or cut) that precludes the optimal solution and run the model again. This forces the model to find an alternate solution that is different from the optimal solution in at least one technology. We repeat this process iteratively to generate additional solutions until there is no longer a feasible solution. This is formulated as:

Minimize Life Cycle Cost (see objective function in Chapter 2)

subject to

$$Z_{th}^{\text{to}} \leq y_t^{\text{to}} \quad \forall t \in \mathcal{T}, h \in \mathcal{H} \tag{3.1a}$$

$$\sum_{t \in \mathcal{T}'} y_t^{\text{to}} \leq |\mathcal{T}'| - n \tag{3.1b}$$

and constraints ((3a))-((17)) (see Chapter 2)

where $\mathcal{T}$= set of all technologies, $\mathcal{T}'$= set of all technologies operating in base case, y_t^{to}= 1 if technology t ever operates and 0 otherwise, Z_{th}^{to}= 1 if technology t operates in timestep h and

0 otherwise, and $n =$ the number of technologies that must be different. We create a binary variable y_t^{to} to track whether a technology t ever operates in any timestep. Constraint (3.1a) ensures this binary is 1 if the technology operates in any hour. Constraint (3.1b) then sums over all the technologies that operate in the optimal solution and requires that the alternate solution is different from the optimal solution by at least n technologies. In this example, we use $n = 1$. Note that in our formulation, PV and wind are part of the set $\mathcal{T}'$, but battery is not, so this method encourages diversity of PV and wind in results, but not battery.

Results Compared to Approach 1, Approach 2 provides solutions that are more diverse in technologies included, as expected (see Table 3.3). Given that the optimal solution includes PV and wind, this technique provides three alternate solutions (one with PV only, one with wind only, and one with neither technology) before we reach infeasibility because there are no technologies left to exclude from the solution. In the first alternate solution, wind is excluded, and LCC increases by 4%. In the second alternate solution, PV is excluded, and the LCC increases by 6%. In the third solution, both PV and wind are excluded and the LCC increases by 17%.

Table 3.3: Alternate Solutions Recommended with Integer-Cut Constraints

	LCC ($)	**PV (kW)**	**Wind (kW)**	**Battery (kW)**	**Battery (kWh)**	**LCC Difference (%)**
Optimal Solution	504,687	62.55	41.17	11.64	47.04	0
Alternate Solution 2.1	526,543	105.70	0	23.13	161.50	4
Alternate Solution 2.2	534,380	0	52.71	8.52	21.14	6
Alternate Solution 1.3	610,999	0	0	23.13	164.07	17

Of the two methods, which each generate three alternate solutions, Approach 2 provides the alternate solution with the objective value closest to the optimal objective function value, while Approach 1 provides the second closest. The "no-wind" solution from Approach 2 may be particularly helpful to the decision maker, because small wind turbines can require more detailed on-site measurements and maintenance, involving added effort the site owner may not want to take on.

These results show that integer cuts can be used to generate alternate, diverse solutions that are different not just in technology size, but also in which technologies are included in the solution set. However, this is not a replacement for APPROACH 1. The two approaches developed different alternate solutions, all of which may be useful to the decision maker, so a combination of the two approaches is recommended.

3.3.4 Approach 3: Continuous Variable Constraints

Methodology In APPROACH 3, rather than adding constraints to cut out technologies, instead we add constraints that restrict the size of technologies to be at least some percent different from the previous solution. This may provide solutions with either different technology sizes or different technology combinations. This is formulated as:

Minimize Life Cycle Cost (see objective function in Chapter 2)

subject to

$$X \geq (1+n)X^* - M\alpha \tag{3.2a}$$
$$X \leq (1-n)X^* + M(1-\alpha) \tag{3.2b}$$

and constraints ((3a))-((17)) (see Chapter 2)

where X= size of technology, X^*= size of technology in the previous case, n= decimal percent difference, α= binary logic constraint (1 if technology X^* is greater than X and 0 otherwise). Constraints (3.2a) and (3.2b) restrict the size of the technologies to be some percentage greater than or less than its size in the previous solution. In this example, we use n= 0.5, so technologies must be at least 50% bigger or smaller than the previous solution.

Results The results (see Table 3.4) are similar to what we achieved in APPROACH 1, in that the alternate solutions are diverse in system sizes, but not in which technologies are included in the objective function. This method, however, provides solutions that are closer to the optimal objective function value than either APPROACH 1 or 2 (within 0.3-1.5% of the optimal). For the decision maker, these solutions provide alternatives that have little to no impact on economics. Furthermore, it can be accomplished without the CPLEX solution pool diversity function which is not widely available in other solvers. While we could continue to generate additional alternate solutions using this approach, given limitations of time and scope for this project, we restrict this example to three alternate solutions.

Table 3.4: Alternate Solutions Recommended with Continuous Constraints

	LCC ($)	**PV (kW)**	**Wind (kW)**	**Battery (kW)**	**Battery (kWh)**	**LCC Difference (%)**
Optimal Solution	504,687	62.55	41.17	11.64	47.04	0
Alternate Solution 3.1	512,316	93.83	20.6	17.20	104.03	1.5
Alternate Solution 3.2	506,681	46.92	46.10	10.31	33.58	0.3
Alternate Solution 3.3	509,922	80.70	23.05	16.53	97.44	1.0

3.4 Discussion

The results show that all three methods can provide alternate solutions for the decision maker. Integer-cuts are useful in generating diverse technology mixes, while continuous variable constraints are useful in generating diverse technology sizes for the same technology mix. These approaches were more effective in generating diverse and near-optimal solutions than the commercial solver solution pool function, which relies primarily on alternate solutions from the branch and bound tree. All three methods provided useful alternate solutions, but none on their own provided a complete set. Using multiple diversity approaches in tandem can provide alternate solutions that are diverse in both technology and technology size, while still close to the optimal objective value.

Figure 3.1 shows the optimal solution, and the seven alternate solutions within 10% of the objective function value. These results prove our hypothesis correct and provide the decision maker with a useful set of near-optimal choices that may be considered alongside more qualitative factors not represented in the model when making an energy investment decision.

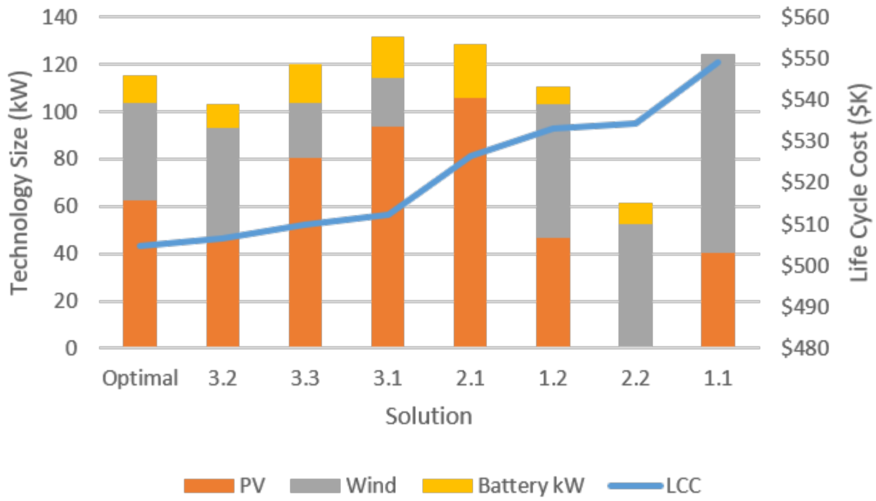

Figure 3.1: Comparison of optimal solution to the set of near-optimal choices

3.5 Future Work

As a next step in this research, we will investigate alternative implementations of the Hop-Skip-Jump method to further refine modeling to generate alternatives techniques for building-scale energy optimization modeling. DeCarolis formulates a new objective function that minimizes the weighted sum of decision variables that appear in the previous solutions. The new objective function value is constrained to within some slack range of the optimal objective function value. Price and Keppo maximize the difference in primary energy consumption from each technology (e.g., PV, wind) between the current solution and all previous solutions, with total system cost constrained to be within some slack range of the optimal system cost. Follow on work will also evaluate additional scenarios with more technology options including combined heat and power, and explore methods for including the battery in integer-cut constraints.

Providing multiple diverse solutions is one tactic to address the inherent structural uncertainty in models, stemming from the role that non-economic factors, politics, social norms, and culture may play in decisions. Another approach is to attempt to quantify these factors and integrate them in models. Research has shown that behavioral patterns are as significant as the techno-economic drivers of transitions [99], but because behavior is difficult to capture explicitly in techno-economic energy systems models, most do not account for it. Wilson and Dowlatabadi find that energy conservation models routinely fail to capture aversion to risk, uncertainty, and irreversibility; heterogeneity of preferences within a population; transaction costs of searching for and processing information; sensitivity to changes in the attributes of energy services; and the relative unimportance of energy costs as a proportion of total expenditure. Similar themes have been found in residential solar programs where non-monetary costs such as information search costs, uncertainty about future performance, operations and maintenance requirements, and perceptions of quality, sacrifice, and opportunity cost are important components of PV value typically not captured in models [101, 102]. National scale energy-economy models often have similar limitations, failing to capture factors in real-world micro-economic decisions that are not purely price-driven, such as social norms and customs, individual values, aesthetics, branding, and perceived reliability [103].

While most techno-economic models do not incorporate social or behavioral concepts, Mau et al. serve as an exception in that they describe a hybrid energy-economy model that contains both an explicit representation of the technologies in the economic system and a realistic representation of behavior. The model captures consumer behavior through three parameters: the private discount rate, the market heterogeneity parameter, and the intangible cost factor for each technology. They show that including preference dynamics for different alternative vehicle technologies enhances the behavioral realism of the model, and potentially better informs policy makers seeking to induce technological change. Li builds on the work of Mau et al. by integrating behavioral considerations into a system dynamic model of the UK energy system. Non-optimal actor behavior is explored through varying five parameters: demand elasticity, market heterogeneity, intangible costs and benefits, hurdle rates, and replacement rate. Based on these behavior models, Li finds that behavioral considerations can be at least as important as technological factors and can make or break an energy transition. This shows the fragility of strategies based on the assumption that price signals will be tightly geared to actual actor responses in the energy system. These early examples of blending economic and social science approaches demonstrate both the feasibility and the importance of considering social-behavioral factors in techno-economic models.

3.6 Conclusions

While economic optimization models are useful, once cost-optimal pathways for achieving energy system change are well explored, the question then turns to one of implementation. Here, rational optimization models are limited in their ability to assess the viability of achieving practical targets in the presence of social and political barriers [105]. Exploring changes to behavior, institutions, and culture will be important to expanding the solution space. The full integration of quantitative modeling and qualitative factors may be unlikely; however, realism and representation of behavior can be improved.

While initial work in the research community has focused on integrating behavioral considerations into national energy systems models to better inform policy decisions, little work has been done to integrate behavior into smaller scale building and community energy decision models. Because much of our future clean energy deployment is expected to be distributed at the building and community level, it is important to accurately guide building owners and community leaders to clean energy projects with the highest chances of successful deployment. Therefore, future work will focus on applying research in integrating behavioral considerations from the national modeling space to local decision models.

CHAPTER 4

INTEGRATING THE VALUE OF ELECTRICITY RESILIENCE IN ENERGY PLANNING AND OPERATIONS DECISIONS

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Published in the *IEEE Systems Journal*

4.1 Abstract

Recent increases in the number of natural disasters resulting in widespread, long-duration, and costly outages have brought energy system resilience to the forefront. As system owners and operators seek to improve system resilience, they often find it challenging to assess the costs and benefits of resilience investments. Costs are fairly well understood and measured, but benefits are less so. There are many resilience metrics that attempt to measure resilience benefit, but existing methods for calculating metrics and incorporating value of resilience in energy decisions are not easily executed. To address this, we developed a method for modeling the value of resilience that is flexible and scalable across multiple types of models. This paper describes a framework for incorporating duration-dependent customer damage functions (CDFs) into grid- and campus-scale planning and operations models. In two case studies, we consider how the duration-dependent value of resilience influences investment and operation decisions. We find that in both cases, knowledge of the value of lost load (VoLL) provides opportunities to reduce the lifecycle cost of energy through adjusted investment or operational decisions. The primary contribution of this research is to integrate the duration-dependent value of resilience in energy decisions. This work will be useful to grid operators interested in reducing the value of customer losses during grid outages, as well as campus or site owners evaluating resilience investments.

Index Terms—Energy resilience, energy planning and operations model, resilience metric, value of resilience

4.2 Background

Recent increases in the number of natural disasters resulting in widespread, long-duration, and costly outages have brought energy system resilience to the forefront. Energy system resilience focuses on preparing for, absorbing, adapting to, and recovering from disruptions [106–109]. Compared to reliability, which typically deals with routine, shorter-term events and smaller-scale impacts, energy resilience addresses low-probability, high-consequence events with large-scale and long-duration consequences [110]. While reliability metrics are mature and widely adopted [111], resilience metrics are not.

Utilities and communities seeking to identify and invest in resilience solutions must be able to quantify the costs and benefits of these investments. While the cost of a given resilience measure is fairly well understood (e.g., the costs of labor and materials to underground specific power lines), the resulting benefits are more difficult to assess, particularly due to a lack of supporting data [112]. Several approaches have been developed to quantify resilience, including the Resilience Analysis Process [113] and a matrix format for quantifying energy resilience [114]; however, while many metrics have been proposed [111, 114, 115], most remain immature [115], and, no generally agreed-upon resilience metrics are used widely today [110, 113, 115–118]. Furthermore, it is likely that no one metric can be used to quantify resilience, because metrics depend strongly on circumstances, goals, and perspectives.

At the highest level, resilience metrics can be categorized as "attribute-based" or "performance-based," where the former refers to more qualitative metrics that describe what makes a system resilient (e.g., robust, adaptive, flexible) [111] and the latter refers to the quantitative metrics that are needed to inform resilience investment decisions [113, 118]. These include metrics such as hours of outage or load not served, percentage of customers experiencing an outage, number of critical services without power, and time to recovery.

While quantifying the amount of resilience a system provides is important, it is not enough. To weigh the cost of a resilience investment against the benefit, we must also quantify the corresponding value that is retained or added. In general, there are two approaches to valuing resilience: 1) bottom-up approaches, which assess the value of resilience based on customer preferences or behavior; and 2) economy-wide approaches, which measure how power interruptions affect economic performance. Bottom-up approaches can be further divided into stated or revealed preference methods. Stated preference methods use surveys to ask customers about their willingness to avoid a power interruption. Revealed preference methods use real-world data to estimate a value, such as the amount that customers have paid to avoid the consequences of a power interruption (e.g., the cost of purchasing and maintaining a backup generator). Economy-wide approaches analyze the effects of power interruptions on regional economics, using indicators such as economic output and employment [119].

The value of lost load (VoLL) is an example of a bottom-up approach based on stated preference, where contingent valuation is used to estimate the value of avoided power interruptions. VoLL is a monetary metric which describes the costs associated with electric grid outages, and it represents an approximate price that consumers are willing to pay for uninterrupted electricity. VoLL is often defined as a static dollar ($)/kilowatt-hour (kWh) value that does not vary with outage duration or magnitude of lost load [120–125], such that one could multiply VoLL times the integral of the lost load to estimate the total cost of a disruption of electricity supply. VoLL typically ranges from $1-300$/kWh, and it varies with the attributes and context of an outage (e.g., customer type, timing, duration, season, region, and location) [117, 124].

VoLL has traditionally been applied to reliability events, but may also be adapted to inform resilience cost-benefit analyses [110, 117, 118, 126, 127]. Some work has been done to incorporate VoLL into resilience decisions by including the VoLL in the cost of energy for microgrid investment decisions [128] or by developing microgrid system designs that minimize both the cost of energy and the cost of not meeting the load [129]. Other researchers have demonstrated the effects of valuing resilience on optimal system costs and sizes for PV and storage systems that provide backup power during grid outages [119, 130–133]; however, in all of these cases, researchers have assumed a static or constant VoLL. Analysis of VoLL for outages lasting longer than 12 hours is limited, and existing methods (e.g., customer surveys) do not capture the indirect spillover effects to the greater economy that are associated with longer-duration outages. While the specific relationship with time is not well understood, research suggests that costs compound with the duration of a large-scale outage [127, 128], resulting in a potentially lower \$/kWh cost to customers, but higher total economic costs due to the longer duration outage [111, 117].

Since resilience is tested during long-duration outages, it is important to consider how the VoLL may change over the temporal arc of an outage that extends for days or weeks. Customer damage functions (CDFs) extend the concept of VoLL by showing how the value changes with duration, season, time of day, or notice of the outage. CDFs show how the magnitude of customer losses (per kilowatt [kW] interrupted) change over an outage period [134]. Some initial efforts have been made to include CDFs in planning and investment models. Moslehi includes a CDF in a model to optimize a microgrid design for an office building [135]. Hanna integrates CDFs in a microgrid planning and investment model to find the optimal trade-off between cost and reliability [136]. The use of CDFs is not yet widespread, however, beyond these initial examples.

This work builds on the existing literature by considering a CDF in two scales of energy decision models, microgrid and macrogrid. In the following section, we outline a framework for estimating a CDF. We then demonstrate its application in two case studies. First, we apply it to a grid-scale operations model, and, second, to a behind-the-meter planning and operations model. Our goal is to understand whether the change in VoLL over the duration of the outage (represented by the CDF) changes investment and operational decisions. In other words, the research question we are seeking to answer in this article is, do we need to use the more complex duration-dependent CDF, or is the static VoLL sufficient?

4.3 Framework for Modeling CDFs for Power Outages

Current methods of modeling CDFs for power outages typically rely on average costs ($/event) for lost load with no time consideration, static values ($/kWh) that do not change over the outage, or extrapolation of costs from a few specific points estimated with survey data. These methods are ineffective at capturing the impact of outage duration on customer damage. We address some of the gaps by adopting a framework developed by [137], which accounts for the effects of outage duration when estimating the customer cost of a power outage.

First, we separate outage costs into categories, depending on whether the costs vary with outage duration. Fixed costs are the same, regardless of outage duration, while variable costs change over time. Variable costs can be further separated by whether the cost is dependent on the loss of perishable inventory (stock) where applicable. Hence, outage costs are equal to the sum of the following three categories:

- Fixed costs: Costs that are independent of outage duration, such as loss of computer data, damage to machinery, and lost production during system reboot
- Flow costs: Costs that are a function of outage duration, such as lost worker and machinery productivity or loss of utility services (e.g., streetlights or water treatment)
- Stock Costs: Costs due to the damage or spoilage of a perishable stock, such as food spoilage, steel cooling, or stolen or broken assets from looting and vandalism.

Then, we combine the terms into a single function that can be used to holistically capture how damages occur over time (as shown in Figure 4.1). The functional forms for each cost category and examples of how these are estimated for different building types are described in [137]. The ultimate shape, slope, and value will depend on customer inputs related to their individual loads and costs. Additionally, different resilience solutions may impact avoid different categories of costs. For example, the quick response time of a UPS system can avoid fixed costs, while a backup diesel generator may avoid flow and stock costs.

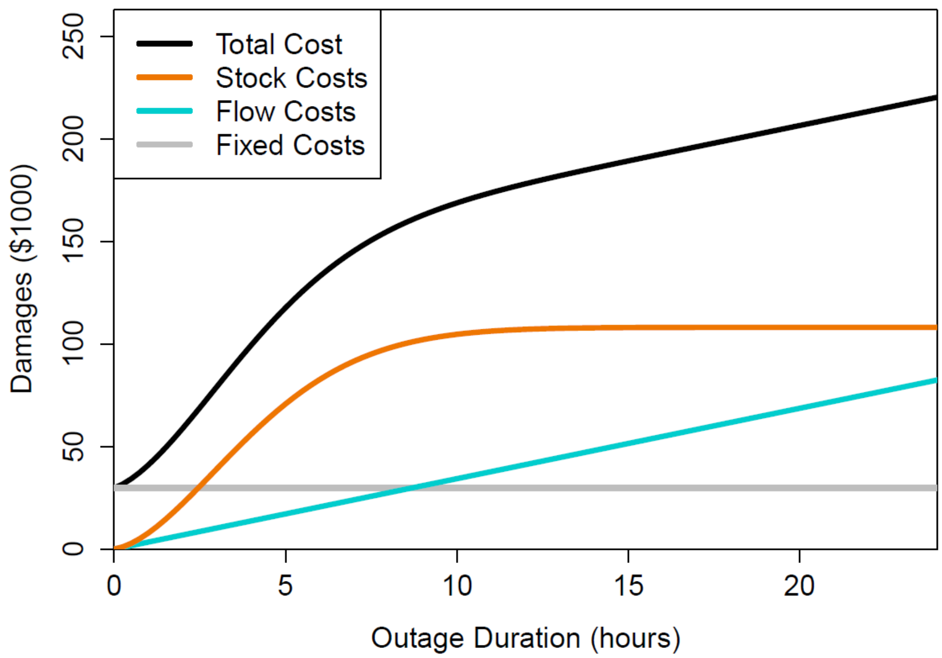

Figure 4.1: CDF for an example manufacturing facility with average load of 500 kW [?]

This process can be performed for a single customer or a group of customers, depending on the desired scale or granularity of the analysis. A single damage function could be used to describe a grid node, neighborhood, or city, using individual customer damage categories and number of customers in each category. Conversely, it would be possible to create unique damage functions for each individual building and optimize each of the buildings for resilience independently. In the next sections, we demonstrate how these damage functions can be used to inform energy investment and operational decisions by applying them in two models: a grid-scale operations model and a campus-scale planning and operations model.

4.4 Grid-Scale Production Cost Model Case Study

4.4.1 Methodology

In the first case study, we consider how the CDF could be used to guide grid operator decisions during a resilience event. If a grid operator has knowledge of the time-varying CDFs for different types of customers, can the operator strategically allocate limited resources (transmission or generation) to minimize the total cost of the outage to its customers? We focus on transmission and generation resources; while distribution is also important, it is not represented in our model. The model presented here is primarily used for planning, though a similar methodology could be used to develop a tool for real-time prioritization of feeder restoration.

To understand the ability to adjust system dispatch schedules based on expected customer damages, we implemented the CDFs concept in an adapted production cost modeling framework called the Scalable Integrated Infrastructure Planning (SIIP) tool. Production cost models simulate power system operations at daily, hourly, or sub-hourly scales using detailed load, transmission, and generator fleet data. In principal, production cost models optimize system scheduling decisions, determining the least-cost generation commitment and dispatch schedule to meet system demand, subject to the physical and regulatory requirements of system operations.

It is important to distinguish between the two different types of costs that have been discussed so far in this paper, since they represent fundamentally different financial consequences. CDFs represent losses experienced by customers, whereas the SIIP tool optimizes around system costs associated with the unit commitment and dispatch of grid-scale assets. Therefore, an apparent misalignment occurs when minimizing system costs based on customer damagers, since grid operators are most-directly motivated to minimize their own system costs. A grid operator is not directly responsible for a community's resilience, nor will it receive direct financial compensation for a community's improved resilience. However, electricity supply is a key component of community resilience and, in turn, this case study can be thought of as an evaluation of optimal grid operations from a societal perspective.

Most production cost models can represent generator and line outages, but they treat the VoLL as a constant value that does not vary over the duration of the outage (shown as the static cost curve in Figure 4.2), and lost load is the decision variable. In this case study, we model a CDF where the VoLL varies over the duration of the outage (shown as the duration-dependent cost curve in Figure 4.2) to understand the impact on operator decisions and costs. This formulation represents the costs of the outage as a function of both outage duration and outage magnitude, both of which are decision variables, and leads to a non-linear objective function. To linearize the model, while still varying the CDF over the outage duration, we approximate the magnitude of the lost load with a fixed value over the entire duration of the outage. We can then replace outage duration (the x-axis in Figure 4.2) with the cumulative amount of lost load at up to that hour of the outage. This allows us to express the cost of the outage as a function of magnitude of the outage (see Figure 4.3), which can be incorporated in the linear optimization as a piecewise cost function.

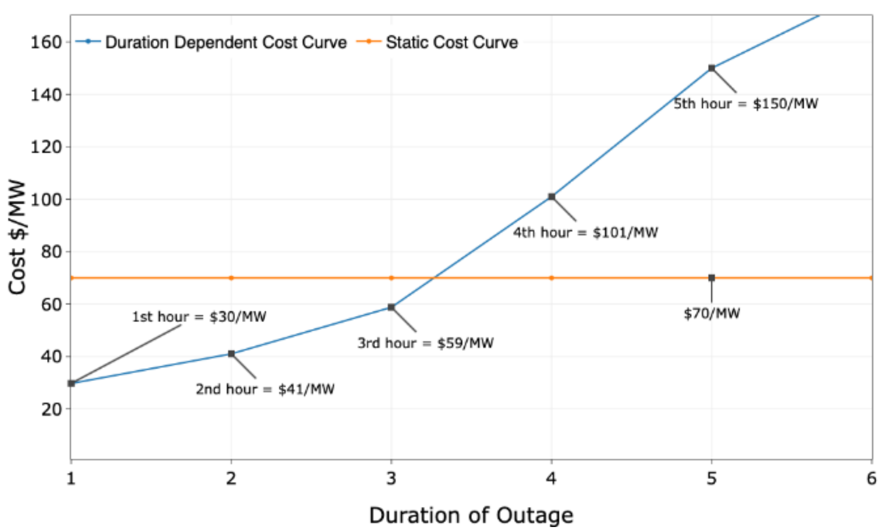

Figure 4.2: Outage cost as a function of duration

We make two additional simplifications. First, we break the load into two distinct types: base and cyclic. We assume the base component is constant throughout the day, while the cyclic component varies by time of day, with a significant peak. The base component aligns with our previous fixed value approximation of the magnitude of lost load but introduces significant error for the cyclic component. A reasonable approximation of the CDF for the

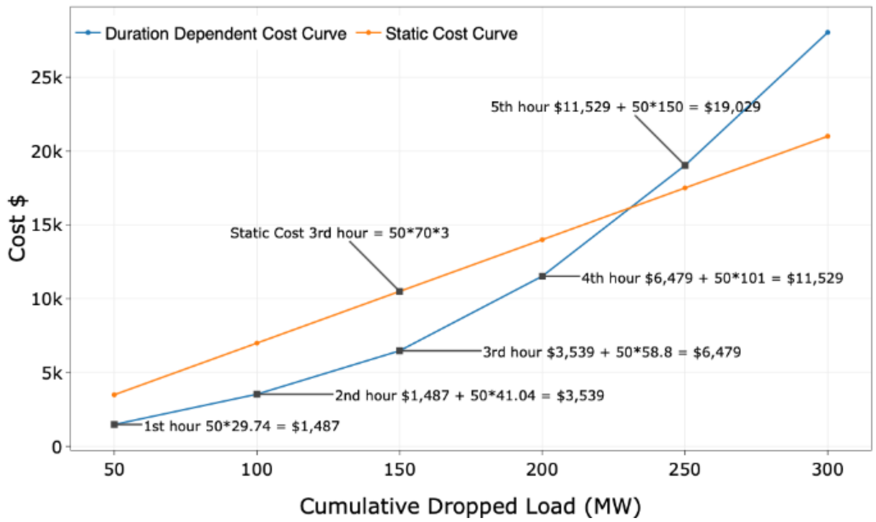

Figure 4.3: Outage cost as a function of lost load

cyclic component can be made by transforming the duration dependent curve (Figure 4.2) into a cumulative dropped load curve where the incremental lost load in time t is equivalent to the average cyclic load for all periods t at each bus. This approximation enables a piecewise linear representation of lost load and only introduces inaccuracies when the average of the cyclic load values for periods t does not match the total average cyclic load. For example, if the amount of cyclic load dropped in the 1st hour of the outage is 50 MW and the avg. cyclic load is 30MW for a particular bus. The approximated cost of dropping the cyclic load would be \$1720 (30MW * \$30/MW + 20MW * \$41/MW) vs. the correct cost \$1500 (of 50MW *\$30/MW). Finally, we assume the model can choose to either serve the entire load at a bus or drop the entire bus load at any given timestep. Serving only part of the load represented by a CDF is not allowed.

The mathematical formulation is similar to a classic unit commitment formulation, but instead of deciding the commitment of power plants, our decision variable is whether to serve power to a bus or not. The objective function is to minimize the total system cost—including the fixed and duration-dependent outage cost along with generation costs. The model can represent CDFs of individual loads, or aggregate multiple loads at each bus into a single CDF. The example test system results scale the generic CDF in Table 4.1 by bus load levels to generate a diverse set of outage costs.

This information is used by the model to select the bus and type of load to serve at each timestep to minimize the CDF during a state when there is not enough energy to serve all loads. The CDF is considered in concert with all other system operational cost parameters to represent a situation where operators can make informed decisions on both the scheduling of generation and unserved load to optimize system operation.

Table 4.1: Base CDF for RTS-GMLC Test Case.

Duration (hr.)	**Cost ($)**	**Duration (hr.)**	**Cost ($)**
1	29.74	**9**	162.72
2	41.04	**10**	168.76
3	58.84	**11**	173.75
4	79.25	**12**	178.07
5	99.46	**13**	181.98
6	117.68	**14**	185.66
7	133.04	**15**	189.22
8	145.41	**16**	192.71

At each timestep, the resilient dispatch model is presented with information about the costs associated with not serving load at each bus over the next several timesteps, allowing the model to optimize the service of load, considering the cost of not serving load now versus sometime in the next several time steps. The look-ahead window duration is user-defined. For the application presented here, the look-ahead window has a duration of four hours. If a load is not served, the CDF remains unchanged, and the next timestep encounters a CDF commiserate with not serving load for two time periods. This assembly allows for a mixed-integer linear-programming representation of CDFs to optimize the service of critical loads at critical times in a degraded operational state.

Several assumptions guided our modeling approach and scenario representation. First, the model is intended to help a system operator redispatch the system once a resilience event has occurred or has been forecasted. Second, we assumed that operators would only enter this mode of operation if the system is compromised to an extent where the demand in the system cannot be met with the generation and transmission assets on the grid for the expected duration of the disruption. Finally, we assumed that the disruption was large enough to create a generation and/or transmission capacity shortage, but not so large as to create a fundamental system stability issue or to completely isolate a large portion of the network.

Under these modeling assumptions, we simulated an outage where all-natural gas generators were offline for 12 hours. This could be caused by an event like an earthquake or a fault that passes through the energy infrastructure. For simplicity in this scenario, we assumed that the generator unit-commitment schedule (the on/off status of generators) was predetermined and not subject to re-optimization during the event. This assumption is made for modeling simplicity and computational tractability, although in principal, the approach could be extended to re-optimize unit commitment decisions to further optimize operations during resilience events. The assumption that unit-commitment is fixed during an event may be valid during events where the forecast window is short, and the event duration is not very long. We modeled the Reliability Test System of the Grid Modernization Laboratory (RTS-GMLC) (Figure 4.4) consisting of three regions with 70 buses and 150 generators. The total power lost was 1,600 MW, or 15% of total capacity. We simulate two scenarios, first using constant VoLL across all buses, and second using a duration-dependent CDF, which also varies by bus.

4.4.2 Results

We found the total lost load in MWh was approximately the same in both the static VoLL and duration-dependent CDF cases; however, small operational differences were observed as the two cases are exposed to different costs and drop different buses. The total cost of the outage was 22% lower when the grid operator had knowledge of how the CDF varied by time and bus. The number of locations affected increased with the duration-dependent CDF, but

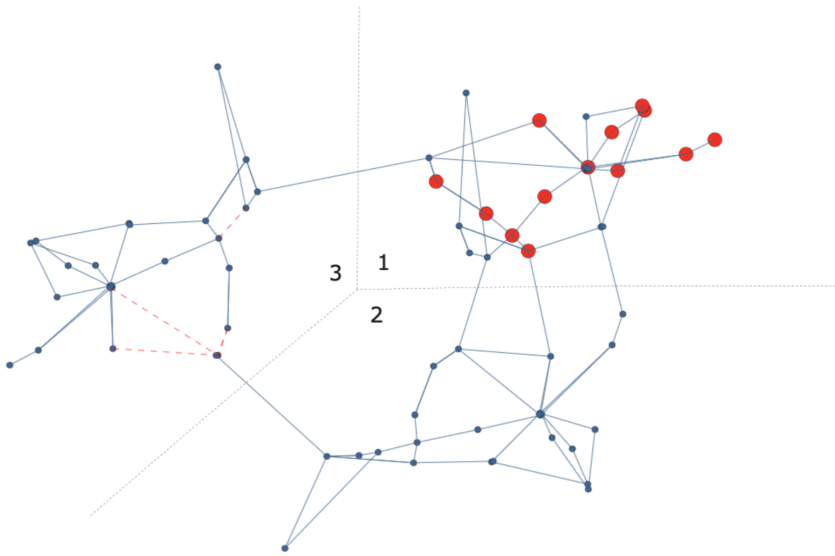

Figure 4.4: The RTS GMLC test system consists of 3 regions with 70 buses and 150 generators

the maximum number of hours of outage experienced by any bus on the network was only six hours, compared to 15 hours when assuming a static VoLL. This is because after a few hours, the cost of not serving a bus becomes very high, encouraging the operator to restore power and move the outage to a different bus with a lower CDF. The average number of outage hours experienced in the network is also lower. The static VoLL model results in fewer but longer outages because the model does not move the outage around. The CDF model behaves like a rolling brownout, affecting more consumers but for fewer hours. The results for each scenario are described in Table 4.2.

Table 4.2: Outage Impacts for Static VOLL Versus Duration-Dependent CDF.

	Static VoLL	**Duration-Dependent CDF**
Total Cost of Outage ($)	903,040	705,763
Total Load Lost (MWh)	22,149	21,788
Number of Locations Affected	30	51
Max Hours of Outage at Bus (hours)	15	6
Average Hours of Outage (hours)	5.07	4.20
Cumulative Hours of Outage (hours)	152	214

Figure 4.5 and Figure 4.6 show an example of the difference in operations between the static VoLL and the duration-dependent CDF scenarios in Region 1. As generation assets in all three regions are affected by the simulated outage, the duration-dependent CDF model chooses to start the outage in Region 1 for the first few hours, and then moves the outage to Region 2. When the net load in the system starts to rise in the evening, the outages are moved to Region 1 for a few periods, then split among all the regions on the buses that were not affected earlier. This behavior of moving the outage around is consistent in most of our simulations with the duration-dependent CDF model.

A different dispatch is observed when using a static VoLL. Outages are primarily clustered around the buses with low demand. The outages do sometimes move because bus demand is changing, and the model minimizes system cost by serving as much load as it can with the available generation assets, while being forced to make a binary decision on whether to serve a bus. This leads to some end-users suffering longer outages than in the duration-dependent CDF scenario (15 hours versus six hours). In real-world systems, these longer outages could lead to failure of critical resources like communications networks, water and food supplies, or emergency services. While the number of locations affected is lower in the static VoLL scenario, the cost of outage is higher.

While results will vary by event and CDF, this case study shows that knowledge of the duration-dependent CDFs (rather than just a static VoLL) at each node could result in different dispatch decisions and a lower total outage cost. However, it is important to note that the difficulty in balancing active and reactive power to maintain voltage and frequency while restoring the weakened system may impose practical limitations on the order of load restoration that is not accounted for in this model.

4.5 Campus Planning and Operation Case Study

4.5.1 Methodology

In the second case study, we consider how the duration-dependent CDF can be used to guide resilience investment and operation decisions for a campus, base, or building owner.

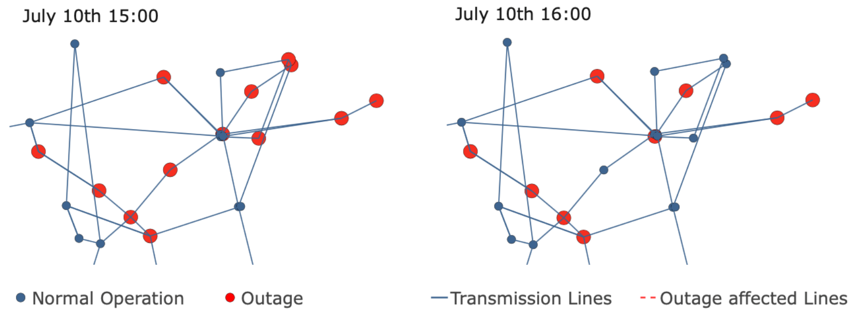

Figure 4.5: Region 1 system dispatch with duration-dependent CDFs at each bus

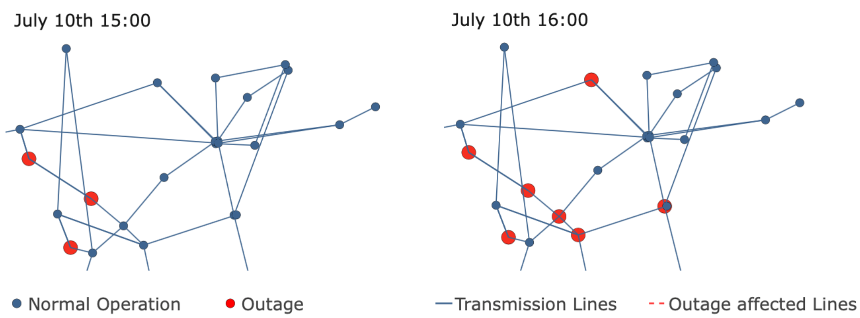

Figure 4.6: Region 1 system dispatch with static VoLL at each bus

If the site owner understands the duration-dependent magnitude of losses they will incur during an outage (rather than just a static VoLL), will they make different investment and operational decisions to minimize their lifecycle cost of energy?

Under prior work in [131], we incorporated a static $/kWh VoLL and sized microgrid components for maximum economic benefit, as measured by the net present value of investing in the energy system. Benefits from electricity bill reduction by optimally dispatching PV and storage assets during grid-connected operation, as well as the benefit of surviving grid outages, were considered. However, that analysis focused on designing systems to survive expected outages in a typical year as represented by the customer average interruption duration index (CAIDI). This study presents a new methodology that considers the full distribution of outage durations, allowing us to analyze less frequently occurring, longer-duration outages that target resilience in addition to reliability.

To quantify the impact of having a duration-dependent CDF on owner investment and operation decisions, we modeled a PV and battery system installed to provide power to a large office building in Miami, Florida. Key site characteristics and modeling assumptions are summarized in Table 4.3 and Table 4.4.

Table 4.3: Site Characteristics and Utility Rate Information.

Case Study Assumptions	
Location	Miami, Florida
Building type	Large office[1]
Total Annual Energy Consumption (kWh)	8.0 M
Average load (kW)	913
Serving utility	Florida Power & Light Company
Rate tariff	GSLDT-1[2]
Max demand charge ($/kW)	13.63
Max energy charge ($/kWh)	0.0631
Time-of-use component	Energy and demand

To integrate a duration-dependent CDF into site investment decisions, we must consider the full distribution of outages over the project lifecycle to accurately capture the duration-dependent effects. We separate outages into common events (e.g., those caused by typical reliability issues, such as lightning strikes, equipment failure, and human error) and extreme events (e.g., those caused by larger-scale, rarer events, such as natural disasters and cascading failures on the scale of resilience considerations). Common events occur more frequently and are generally of shorter duration compared to extreme events.

We assume that both outage types are exponentially distributed, allowing us to characterize the entire distribution using mean outage duration. While the assumption of exponentially distributed outages may under-estimate the likelihood of very long outages, this error will not significantly impact the valuation of a PV and battery system which can only support critical load for a relatively short duration.

Data on mean outage durations for common and extreme outage events are not publicly available. However, utilities do provide data on mean outage durations during major and

Table 4.4: Technical and Economic REopt Modeling Assumptions[3]

Economic Assumptions	
Ownership model	Direct purchase
Analysis period	20 years
Corporate tax rate	26%
Nominal discount rate	8.1%
Inflation rate	2.5%
Electricity escalation rate	2.6%
Available incentives	30% ITC, 5-year MACRS
PV Assumptions	
PV capital costs	$2,000/kW
PV O&M	$16/kW/year
Annual degradation rate	0.5%
Inverter efficiency	96%
BOS efficiency	86%
Battery Assumptions	
Battery capital costs	$500/kWh + $1,000/kW
Battery replacement cost	$230/kWh + $460/kW
Replacement schedule	Single replacement in Year 10
AC-AC round-trip efficiency	90%
Minimum state-of-charge	20%

non-major event days. By assuming common outage events have a mean duration close to outages during non-major event days, and extreme outage events have an average duration close to outages during major event days, we can parameterize an outage distribution using publicly available outage data (Table 4.5). Figure 4.7 shows the resulting probability distribution of the length of outages in the southeastern United States. As outage duration increases, the fraction of outages due to extreme events increases as well.

Table 4.5: Average SAIFI and CAIDI Statistics for the Southeastern United States (EIA 2014-2018)

Outage Distribution Assumptions		
Non-major event days	SAIFI	1.33 outages/year
	CAIDI	1.6 hours/outage
Major event days	SAIFI	0.35 outages/year
	CAIDI	11 hours/outage

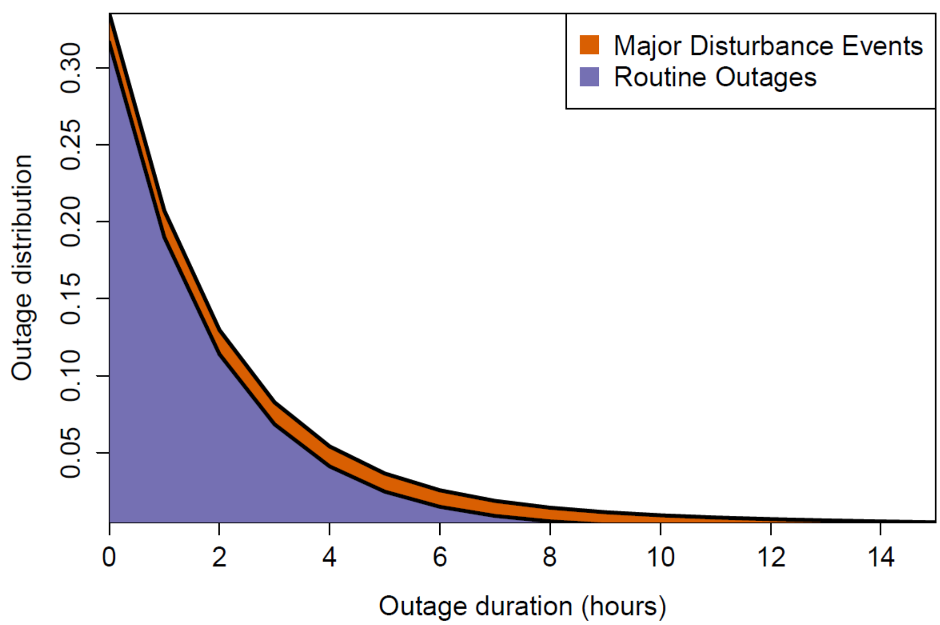

Figure 4.7: Probability distribution of different outage types

Additionally, we assume outages occur with equal frequency across the year and that outage duration is independent of outage start time. We also assume no advanced warning comes before an outage event.

Next, we developed a duration-dependent CDF using the framework described in Section II. We used data on outage costs for large commercial and industrial customers from [127] to estimate the fixed and flow costs experienced by the large office building (with stock costs assumed to be zero)[4]. To compare the duration-dependent CDF with an equivalent constant VoLL, we set the constant VoLL as shown in Equation 4.1, so expected outage costs without a backup system for both the CDF and constant VoLL scenarios are equal:

$$ConstantVoLL = FlowCost + (FixedCosts)/CAIDI \tag{4.1}$$

Figure 4.8 shows the two methods of valuing lost load compared in this analysis, and cost breakdowns for each method of valuing lost load are summarized in Table 4.6.

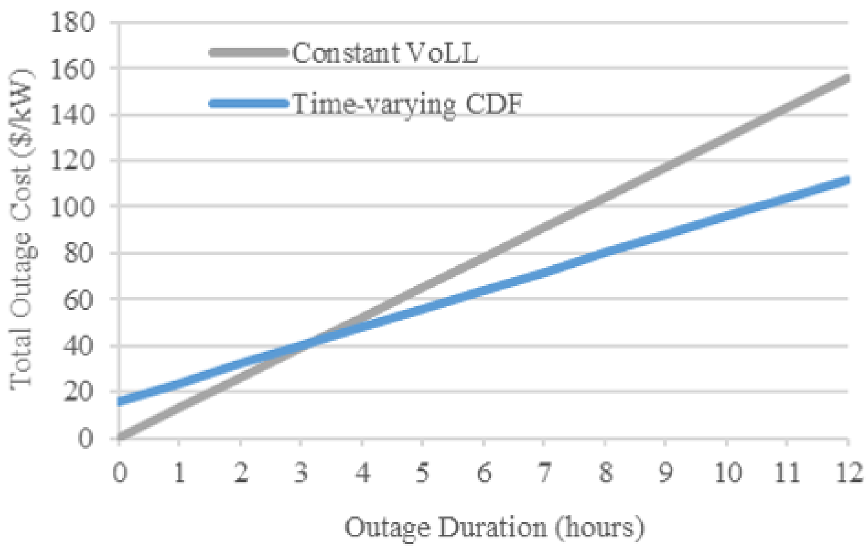

Figure 4.8: Total outage cost as a function of outage duration

The value of resilience of a backup system is the difference in outage costs with and without the system. We assume outage costs begin once the system fails to meet critical load and assume the system cannot be restarted once it fails. A system can prevent fixed

[4]We assume that the systems modeled cannot address momentary interruptions (e.g. those lasting on the order of a few seconds); therefore, costs associated with these momentary interruptions are not included in the outage cost estimates and momentary interruptions are not included in the modeled outage distributions.

Table 4.6: Cost Components in the Modeled Outage Cost Functions

	Constant VoLL	**CDF**
Fixed cost	$0/kW	$16/kW
Flow cost	$13/kW	$8/kW
Stock cost	$0/kW	$0/kW

outage costs if the outage duration is less than the duration for which the system can supply energy (denoted as (t)). The system also reduces flow outage costs by the amount of critical load supplied during the outage. Equation 4.2 displays the system value for an outage starting at time t, with a critical load profile of L, and a distribution of outage durations f(δ).

$$V(t) = \int_0^{\tau(t)} f(\delta)(C_{fixed} + C_{flow} \int_0^{min(\tau,\delta)} L(t+z)dz)d\delta \tag{4.2}$$

Total resilience value can be calculated by taking the average of Equation 4.2 across each hour of the year and multiplying by the present value of the expected number of outages over the system lifetime.

Finally, to co-optimize technology sizing for both grid-connected benefits and resilience value, we developed an algorithm using a techno-economic optimization model called REopt [88]. Formulated as a mixed-integer linear program, REopt solves a deterministic optimization problem to determine the optimal selection, sizing, and dispatch strategy of technologies chosen from a candidate pool, such that electrical and thermal loads are met at every timestep at the minimum lifecycle cost. In this case, we size the system to maximize grid-connected benefits and resilience value but assume the system is dispatched solely to maximize grid-connected benefits. This assumption captures the fact that a system operator typically does not know beforehand when outages will occur or how long an outage will last. Because REopt is a mixed-integer linear program, and the value of resilience equation 4.2, is nonlinear, an iterative process was used to converge on the optimal PV and battery sizes.

REopt solves for the optimal system size S^* to minimize the total cost of electricity over the project lifecycle. Denoting $R(S)$ as the revenue generated by the system and C as the unit costs of the system components (where S and C are vectors that include PV, battery, and inverter costs), then REopt can be described as solving the following equation:

$$S^*(C) = \arg\min_s C * S - R(S) \tag{4.3}$$

Let $v(S) \equiv V(S)/S$ denote the per-unit value of resilience, where V is given by Equation 4.2. Then once the value of resilience value is included, the true optimal system size becomes

$$\begin{aligned} S^{**}(C) &= \arg\min_s C * S - R(S) - v(S)S \\ &= \arg\min_s (C - v(S)) * S - R(S) \\ &= S^*(C - v(S^{**})) \end{aligned} \tag{4.4}$$

If the per-unit value of resilience of the optimal system is known, then the co-optimized system is equal to the REopt solution where the per-unit resilience value is subtracted from the per-unit system costs. While we obviously do not know the resilience value of the optimal system because the optimal system is what we are trying to solve for, this framework allows for an iterative process to determine the optimal system size. At each iteration, we solve REopt using the component costs minus the resilience benefits, and then update the resilience benefit estimates using the solved system sizes as inputs to the value of resilience calculation as given by 4.2 [5]. This approach is summarized below in Algorithm 1:

S_{start} can be set to zero if the system size is nonzero without considering resilience benefits. Otherwise, a nonzero initial battery size may be required to account for the case where a battery is not cost-effective when the value of resilience is not modeled, but the battery is cost-effective when the value of resilience is incorporated. We further assume that the inverter is sized to meet peak critical load and only focus on the resilience benefits of the PV and battery storage capacity.

[5] In this case study, the battery inverter sized is able to meet peak critical load; therefore, additional inverter capacity does not add to the value of resilience. We also assume the battery serves critical load net of PV generation, and the battery receives the full portion of fixed cost reductions.

Algorithm 1 Iterative Approach to Determine the Co-optimal System Size

$S_0 = S\_start$
repeat
$S_1 = \text{arg}min_s[C - v(S_0)]S - R(S)$
$\rightarrow$ Solve using REopt$\text{S}_0 = S_1$
until $|v(S_1) - v(S_0)| <$ tolerance
$\rightarrow$ Determined from Eq. 1
return S_1

4.5.2 Results

We solved for optimal technology sizes, co-optimizing for both grid-connected benefits and resilience value for a range of critical load factors, to compare the effects of incorporating a time-varying CDF over having a constant VoLL. Figure 4.9 displays the average outage survival duration for various critical load factors. Due to the relatively high cost of battery storage, the systems only provide backup power for relatively short outages. However, because a large fraction of outages is of short duration, the co-optimized systems more than double average survival duration in all cases without a value of resilience. Furthermore, having a time-varying CDF increases the total system value compared to a constant VoLL, particularly for mid-range critical load factors (e.g., 30%-60%). This is because the systems sized for these load levels are best able to prevent the fixed costs from short-duration outages but are unable to provide power for long-duration outages, so how costs vary over the duration of the outage greatly impacts sizing decisions. Because systems are able to prevent most outages and survive the full outage duration at critical load factors below 30%, and systems are not able to prevent or survive most outages at critical load factors above 60%, differences between how lost load is valued at those critical load factors are not as impactful in the overall optimization.

Table 4.7 displays the numerical results for a system with a 50% critical load factor. The "No resilience value" scenario assumes the system cannot provide backup power, so full outage costs are incurred over the analysis period. Moving from a constant VoLL to

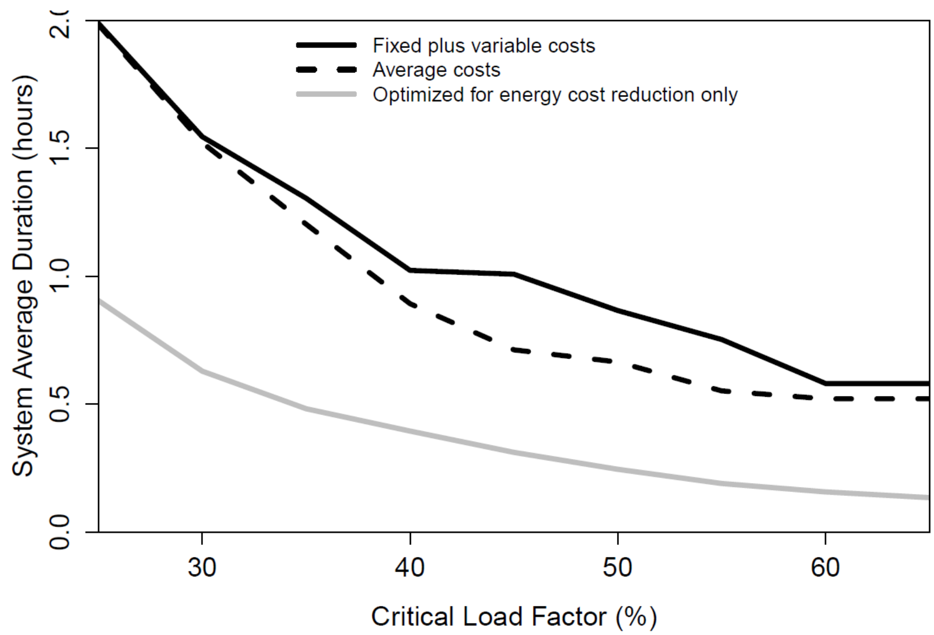

Figure 4.9: Average outage survival duration for various critical load factors

a time-varying CDF increases optimal PV size by 13% and optimal battery size by 16%. Even though the system can only provide backup power for a relatively short duration, it still reduces a significant percentage of outage costs, up to 32%, with the time-varying CDF approach reducing total outage costs by an additional 10% over the constant VoLL scenario. This analysis suggests that a PV and battery backup system can provide resilience value, even if it can only support load for a short duration. Furthermore, not considering the time-dependent nature of costs incurred over an outage can cause a site owner to underinvest in backup systems and not fully capture the value of resilience such systems provide.

Table 4.7: Optimal System Sizing and Cost Results

	No resilience value	**Constant VoLL**	**CDF**
PV size (kW)	265	283	321
Battery size (kWh)	300	599	692
Average outage survival (hours)	0.24	0.66	0.87
Total outage cost ($)	315,319	238,788	214,853
Outage cost reduction (%)	0	24	32
Value of resilience ($)	0	76,531	100,466

Because short-duration outages occur at the highest frequency, system sizing decisions at sites with high fixed costs or flow and stock costs that skew toward the first few hours of an outage can be significantly impacted by knowledge of how the VoLL varies over time. Assuming a constant VoLL in these scenarios can result in undersized systems and suboptimal lifecycle economics. Furthermore, as the probability of extreme events increases in the future, knowledge of outage distributions and duration-dependent costs will become increasingly more important. The higher frequency of longer-duration outages places more value on additional hours survived, so the marginal benefit of new systems will not decline as steeply as a function of the system size. While the magnitude of the impact on investment decisions between assuming a constant VoLL or a duration-dependent CDF will vary by location, site characteristics, outage distributions, and other cost assumptions, this case study shows how knowledge of a CDF can change investment decisions to reduce outage costs.

4.6 Conclusions and Future Work

As system owners and operators seek to improve system resilience, they must be able to weigh the cost of a resilience investment against the benefit it provides. While a static VoLL is traditionally used for valuing reliability investments targeted at shorter term outages, resilience is tested during long-duration outages, so it is important to consider how the VoLL changes over the temporal arc of an outage. This work showed that integrating the duration-dependent CDF, rather than the traditional static VoLL, into energy decision models can change both investment and operational decisions.

In the grid-scale operations case study, we saw that knowledge of the duration-dependent CDF (rather than just a static VoLL) at each node resulted in different dispatch decisions and a 22% lower total outage cost for the system evaluated. Similarly, in the campus-scale planning case study, the results showed that only considering a static VoLL led site owners to underinvest, sizing smaller, suboptimal PV and battery systems. When the duration-dependent CDF was known, the site was able to decrease total outage costs by 10%. Knowledge of duration-dependent CDFs is especially important for sites with high fixed costs, or flow and stock costs that skew toward the first few hours of an outage. Assuming a constant VoLL in these scenarios can result in undersized systems and suboptimal lifecycle economics. Furthermore, as the probability of extreme events increases in the future, knowledge of outage distributions and duration-dependent costs will become increasingly more important. The higher frequency of longer-duration outages places more value on additional hours survived, so the marginal benefit of new systems does not decline as steeply as a function of the system size.

While this work represents an important step forward, the models and case studies presented here address only a narrow part of resilience. Disruptive events include four stages (i.e., prepare, absorb, recover, and adapt), and resilience solutions need to address all of these. Our modeling capabilities are currently focused on the absorb phase, but these could be expanded to address broader resilience solutions. For example, the model used for the grid-scale case study could be expanded to inform decision-making for recovery by adding a real-time component with the ability to bring generators and transmission lines back online subject to repair cost, as well as optimizing the order in which units come back. This model could also be coupled with a commitment model to update unit commitment schedules and loads to reflect recovery from the event. Ultimately, the grid-scale modeling can be expanded to capacity-expansion modeling to not just operate systems for greater resilience, but design systems for greater resilience.

In addition to the narrow scope of the models, another limitation is that they are deterministic, mixed-integer linear programs, while the characteristics of resilience events are highly uncertain and nonlinear. Using a stochastic modeling framework such as Monte Carlo analysis to represent uncertainties around outage characteristics (type, time, and duration of event), load, and CDF values, and a nonlinear model to more accurately capture resilience values that change over time, may lead to more informative results.

A final important area for future research is resilience valuation data. The case studies presented here were based on hypothetical CDFs. In reality, data on VoLL and how it varies over time is quite limited. Therefore, even if we improve the modeling methods, it may still be difficult to get the detailed customer valuation data required for this type of assessment to produce meaningful results. Further research in this area is needed to develop CDFs for a range of buildings and engage with utilities to develop CDFs for larger-scale analyses (whole neighborhoods or cities) that reflect not just utility costs but the larger societal costs of resilience events, and how these may change in the future with regional growth. Additionally, more information is needed to understand the value of supporting only a fraction of the critical load. In our model, we assumed we must support all of the critical load at a bus to avoid the outage cost, but, in reality, there is likely some value to supporting only part of the load.

Beyond the limitations of the specific methods presented here, broader questions should be addressed in future work. Understanding how VoLL evolves over the temporal arc of a resilience event is a useful step forward in valuing resilience investments—but this is only one component of resilience value. To assign an appropriate value to resilience during a large-area, long-duration resilience event, we must also understand the nature, extent, and evolution of system-wide consequences and interactions due to sectoral interdependencies (e.g., water and natural gas), then translate the consequences of such an event to impacts on societal welfare through health, safety, and the economy. This is beyond the scope of the work presented here, but important for future efforts aimed at valuing resilience investments.

4.7 Acknowledgements

This work was authored by Alliance for Sustainable Energy, LLC, the manager and operator of the National Renewable Energy Laboratory for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

CHAPTER 5

THE GAP BETWEEN ENERGY DECISION MODELS AND DEPLOYMENT

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To be submitted to *Energy Research and Social Science*

5.1 Abstract

There are many energy decision models that evaluate the technical and economic feasibility of energy efficiency, renewable energy, and sustainable transportation. Recommendations from these models can be used to guide the optimum economic deployment of clean energy technologies. However, a gap exists between what energy models recommend as "optimum" in theory, and what individuals, businesses, or utilities choose to deploy in reality. This paper explores why these gaps exist, and how adaptations to technical modeling capabilities or the way results are communicated can increase clean energy deployment. Keywords—energy decision model, renewable energy, deployment, adoption

5.2 INTRODUCTION

The global energy system is rapidly changing. In the US, electricity generation from renewable energy sources has doubled in the past ten years, and currently accounts for about 18% of total generation [1]. This trend is accelerating worldwide as renewable energy prices drop; the U.S. Energy Information Administration predicts that renewable energy will be the leading source of primary energy consumption by 2050 [2]. Wind and solar are expected to dominate growth, representing over 70% of electric generating capacity additions by 2050 [2].

How will this new capacity be sized? Where will it be located? How will it be operated to meet demand, and ensure reliability of the grid? How will it be integrated with the existing system? The answers to these questions are informed by techno-economic energy decision models. Hundreds of these models exist, covering a range of technologies from energy efficiency, to renewable energy, to sustainable transportation. They guide energy and policy decisions at geographic scales from individual buildings to national grids, and at time scales ranging from second-to second operational decisions to 25-year life cycle investment decisions [138].

Energy decision models are important for identifying technologies that will provide reliable, sustainable, and economic energy to end users. These are often complex decisions based on technology performance, costs, loads, resource availability, rate tariff structures, market value streams, and incentives. Often, these may change hour-to-hour or even minute-to-minute over the course of a year. Energy decision models can effectively process this complex information and provide an assessment of technical feasibility as well as economic metrics to help the user determine whether a technology is a good economic investment.

Despite their sophisticated capabilities, many energy decision tools are limited in their ability to guide decisions. These tools typically focus on the quantitative aspects of decision-making that lend themselves to modeling, like dollars saved or kilowatt-hours generated. They often do not, however, account for more qualitative (but no less important) aspects like uncertainty, non-monetary costs, or influence of social networks [50]. Figure 5.1 categorizes energy models by their spatial and temporal resolution and the degree of uncertainty they incorporate. Techno-economic energy decision models primarily lie in the engineering and economic space, and rarely incorporate social science factors.

Because much of what impedes clean energy deployment is political will, public acceptance, and behavior, neglecting these factors can result in significant deviation between modeling outcomes and actual results. For example, researchers in the United Kingdom (UK) conducted a retrospective analysis of the scenario modeling used to map possible UK energy futures over 25 years. They found that actual real-world developments were entirely outside the range of scenarios the models predicted, indicating that the scenarios failed to even bound, much less accurately predict, the resulting future. This was attributed to

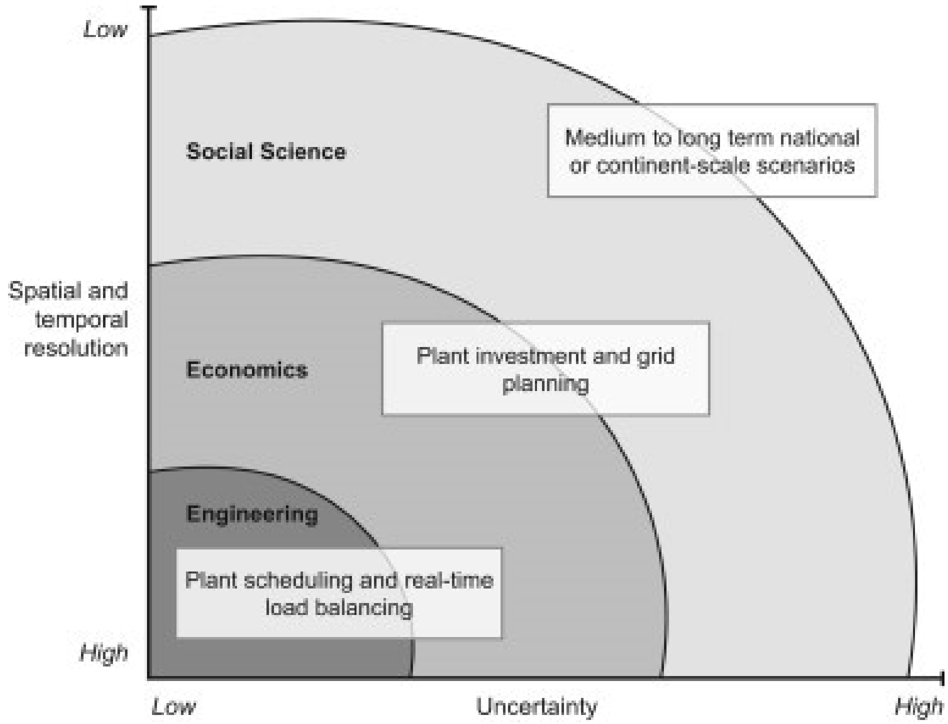

Figure 5.1: Energy decision model scales.[73]

the fact that the forces that turned out to be most important in driving energy systems change were not always captured in the models, particularly softer aspects like institutional or governance changes [139].

Research has repeatedly shown that actual deployment levels are typically lower than what is technically and economically feasible in models [140, 141]. This is recognized in energy conservation literature as the "energy efficiency gap" [142]. This has been attributed to various factors, including slow technology adoption and models that do not represent the full costs of adoption or high discount rates of consumers. These factors lead bottoms-up models to be overly optimistic in predicting opportunities for cost-effective implementation.

In fact, research has shown that behavioral drivers are as significant as the techno-economic drivers of transitions [99]. Therefore, while techno-economic energy decision models are well-suited to predicting clean energy deployment in a perfectly rational world where all actors are driven by utility maximization, that world does not exist. Because behavior is difficult to capture explicitly in techno-economic energy systems models, most do not account for it.

Given the limitations of existing models, in this paper we consider two questions: 1) What is the gap between what techno-economic energy models recommend as "optimum" in theory, and what individuals, businesses, or utilities choose to deploy in reality?; and 2) Can adaptations to modeling capabilities or the way results are communicated close this gap to increase clean energy deployment? In the next section, we review the literature on energy decision making and technology adoption to understand the gap between models and deployment. We then consider adaptations to energy models that may address these gaps, and propose future work to evaluate the effectiveness of these measures in increasing technology deployment.

5.3 DRIVERS OF ENERGY DEPLOYMENT

Energy decisions are made at a range of levels, from individual homeowners to utilities and broader national energy investments. In this section, we summarize research on 1) residential and 2) national energy systems to understand the drivers of energy decisions at each scale.

5.3.1 Residential Energy Decisions

Much of the research on drivers of homeowner energy decisions, spanning over fifty years, has focused on residential energy efficiency. Coltrane et al. evaluate energy efficiency in buildings and observe that despite high potential for energy savings (30-50% reductions) and monetary savings, adoption rates for conservation technologies has been low [143]. Only 6% of single-family homes in the US have implemented optimal levels of energy conservation, and city buildings were only expected to implement 38% of economic conservation measures [143]. These low adoption rates led DOE to suggest there is a weak linkage between receipt of information and the motivation to act on that information [140, 144].

This weak linkage has been attributed to the social and psychological aspects of energy use [145]. Research on the delivery and receipt of energy information has helped provide an understanding of why conservation adoption rates have been lower than anticipated [102]. Programs have traditionally relied on two theories of conservation behavior: the attitude model and the rational-economic model [146]. The attitude model assumes conservation behavior will follow automatically from favorable attitudes towards conservation, and the latter assumes people will implement economically advantageous measures. While these seem reasonable, social science research shows that there is rarely a strong, direct, or consistent relationship between attitudes and action [147]. Researchers have found there is no direct relationship between energy-related attitudes and conservation behavior, and energy use is more closely associated with desire for comfort than attitudes towards energy use conservation.

Because energy efficiency and renewable energy technologies are relatively new to many people, social scientists have suggested that the adoption of these can best be modeled according to the diffusion of innovations theory [148]. Social diffusion theories recognize that the process of new technology adoption often occurs through existing social networks, and that most people adopt innovations after their effectiveness has been demonstrated through the experience of friends and neighbors. Peer influence is known to play an important role in the diffusion of innovations and in consumer decision-making [148].

Therefore, much of the energy efficiency gap can be attributed to models not accounting for individual decision making and human behavior. Wilson and Dowlatabadi find that models routinely fail to capture aversion to risk, uncertainty, and irreversibility; heterogeneity of preferences within a population; transaction costs of searching for and processing information; sensitivity to changes in the attributes of energy services, and the relative unimportance of energy costs as a proportion of total expenditure [100]. It is widely accepted that interventions to reduce the energy efficiency gap need to address these and other behavioral factors.

Similar themes have been found in residential solar programs. Rai and McAndrews find that perceived uncertainty and non-monetary costs are key to understanding why social and communication networks are important for technology diffusion [101]. The value of PV is a characteristic of the individual adopter, and includes not just the cost of the technology, but also non-monetary costs such as information search costs, uncertainty about future performance, operations and maintenance requirements, and perceptions of quality, sacrifice, and opportunity cost [102]. According to the diffusion of innovations framework [148], to reduce non-monetary costs people rely on personal evaluation of the technology by those who have already adopted in their social networks.

Rai and Robinson surveyed 365 homeowners in Texas in 2011 who had installed PV systems to explore their motivation for adopting PV, and what information they used to reduce their non-monetary costs [149]. Respondents reported that interest in energy, environmental concern, and financial savings were equally important. Over 50% of respondents reported at least moderate influence of existing PV owners on their decision to install, and those with direct contact with other PV owners in the neighborhood had the shortest decision times.

Other studies have shown similar peer effects. Bollinger and Gillingham, for example, show a causal peer effect in California, where a one percent increase in the number of PV systems installed in a zip code leads to just under a one percent increase in the adoption rate [150]. They show an even stronger effect at the street level. Palm finds that peer effects mainly occur through existing social relationships (rather than between neighbors that did not already know each other) and that they act to reduce barriers such as low trialability and low observability of the actual results of adoption [151].

5.3.2 National Energy Decisions

Outside of the residential energy market, other research has focused on renewable energy implementation at utility, national or global scales. While availability of resource and energy prices are two key inputs driving recommendations from energy models, studies evaluating the drivers of renewable energy have found that these factors do not have a defining impact on implementation rates. Instead, it is institutional factors that create favorable conditions for new technologies [152]. A study of 24 European Union countries from 1990-2006 found that fossil-based fuel prices are not significant in explaining RE use. Rather, they find that stability in policy design is a key driver, a view supported by other studies of the Netherlands [153] and Sweden [154]. Toke et al. study wind power deployment in six countries and find that permitting systems that favor wind power, robust and consistent financial support through feed-in tariffs or other incentives, and local land ownership (rather than remote, corporate ownership) were hallmarks of success [155].

Analysis of past energy transitions has shown that change is often driven by politics and the power gradients between key stakeholders that support different technologies or infrastructure. Compared to more idealistic models, real-world transitions happen more slowly and imperfectly amid shifting political, economic, and social priorities [156]. Therefore, more effort is needed to represent delays, inertia, or imperfections in energy transition modeling [99]. Furthermore, models typically assume that investment behavior will be based on rational choice and utility maximization, and therefore when costs fall below a certain inflection points, rapid adoption of clean energy technologies is observed in models. However, real-world micro-economic decisions are not purely price-driven, and factors such as social norms and customs, individual values, aesthetics, branding, and perceived reliability all play a strong role in determining choices [103]. Li argues that improved representation of behavior and more explicit representation of actors is important when using energy models for policymaking, and failure to account for these effects can lead to poor policy design for energy transitions [99].

The key drivers of energy deployment are summarized in Table 5.1. Given the large body of research analyzing why energy decision models may fail to accurately represent real world energy deployment, we next explore potential methods for incorporating behavioral considerations into energy models.

Table 5.1: Key Drivers of Energy Deployment, and Their Inclusion in Energy Models

Type	**Driver**	**Inclusion in Models**
Technical	Energy generation or savings	x
Economic	Energy price	x
	Discount rates	x
	Incentives	x
Regulatory	Unenforced, conflicting, or unstable policy	
	Land ownership	
	Ease of permitting	
Behavioral	Aversion to risk and uncertainty	
	Non-monetary costs of information	
	Heterogeneity of preference	
	Peer effects	
	Social acceptance	
	Perceived status, recognition, and pride	
	Perceived fairness in decision-making	
	Trust between community and developer	
	Individual values	
	Aesthetics, branding, perceived reliability, comfort, quality, design	

5.4 MODELING MODIFICATIONS

While most techno-economic models do not incorporate social or behavioral concepts, a few have started to tackle this challenge. A review of these early approaches is presented here to provide guidance on how other models can be adapted.

5.4.1 Bottom Up and Top Down Hybrids

Thus far, we have focused on techno-economic models, which are categorized as "bottoms-up". These determine the financially cheapest way to achieve a given target based on the best available technologies. Another class of models are "top-down" models, which describe the energy system in terms of aggregate relationships derived empirically from historical data. These are also used to predict the potential economic effects of energy-focused policies, but because of their different structure and definition of cost, they tend to predict very different outcomes. Top-down models tend to predict high costs while bottom-up models usually predict low costs. Bottoms-up models are overly optimistic because they are based on theoretical assumptions of human behavior and ignore key behavioral factors (such as risk of adopting new technologies and cost of gathering information). Top-down models include market behavior that accounts for the factors missing from bottom-up analysis, because they are based on the observed interaction of producers and consumers in the market. However, they are limited in their ability to capture the process of technological change because they are based on historical data and their aggregate level of analysis does not explicitly represent the technologies in the energy system [157].

One way to overcome the limitations of each is to develop a hybrid that combines the detailed economic modeling of specific technologies in bottoms-up models with the reliance on real market data to explain behavior in top-down models. Mau et al. describe a hybrid energy-economy model that contains both an explicit representation of the technologies in the economic system and a realistic representation of behavior [104]. The CIMS model captures consumer behavior through three parameters: the private discount rate, the market heterogeneity parameter, and the intangible cost factor for each technology. These parameters are typically estimated through literature review, judgment, and meta-analysis, but can also be provided by discrete choice models which convert market data into relationships between the characteristics of a technology and the probability of that technology being chosen.

Mau et al. quantify consumer preferences for two alternative vehicle technologies under different market share assumptions using surveys. They show that a range of attributes are important beyond price in shaping preferences, such as range, refueling convenience, and degree of market penetration ("neighbor effect"). They then include these preference dynamics in an intangible cost function in an energy-economy simulation model and allow the preferences to change with different market conditions across time. They show that when including the behavioral parameters, the model forecasts the market share of alternative vehicles will improve over time, whereas without them, the market share is flat. Including these preferences enhances the behavioral realism of the model, and potentially better informs policy makers seeking to induce technological change [104]. A similar approach is applied by Rivers and Jaccard to model choice of steam generation in industrial plants [157].

Li builds on Mau's work by integrating behavioral considerations into a system dynamic model of the UK energy system called Behavior Lifestyles and Uncertainty Energy model (BLUE) [99]. Non-optimal actor behavior is explored through varying five parameters: demand elasticity, market heterogeneity, intangible costs/benefits, hurdle rates, and retrofitting/replacement rate. Demand elasticities allow actors to exhibit different levels of sensitivity to changes in price; some may continue to use the same amount of energy in the face of price increases, while others may react to curtail their consumption. Market heterogeneity affects the extent to which costs alone drive decision making for new investments. Actors are allocated to either cost optimizing behavior, strong price sensitivity, partial price sensitivity, or price insensitive behavior. Intangible costs/benefits estimate the non-monetary costs/benefits from different investment choices. Hurdle rate settings affect actor sensitivity to up-front investment. While discount rates between 3-6% are common in energy modeling for policy assessment, individual actors may have higher discount rates because they are exposed to investment risk because there assets are not as diversified [158]. Retrofitting/ replacement rates estimate the actors' different investment cycles for new capital assets over time.

Based on these behavior models, Li finds that behavioral considerations can be at least as important as technological factors and can make or break an energy transition. This shows the fragility of strategies based on the assumption that price signals will be tightly geared to actual actor responses in the energy system [99]. Li therefore proposes a new class of models called socio-technical energy transition models (Figure 5.2) that consider not just the technical and economic aspects of technologies, but the social aspects as well.

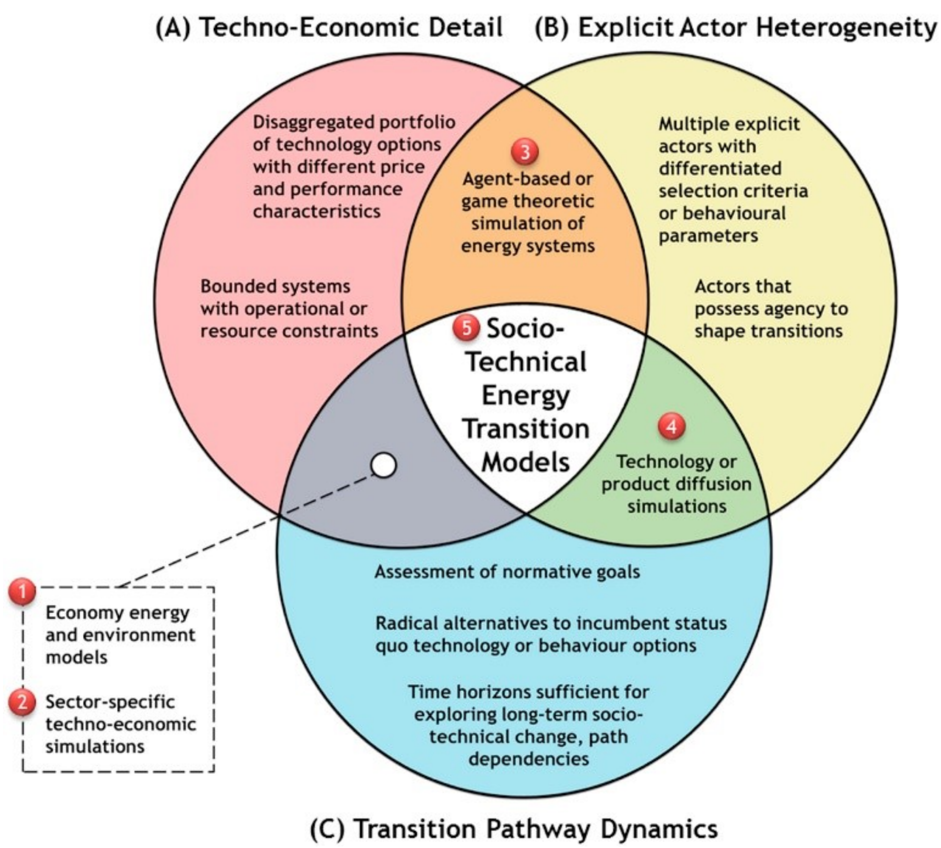

Figure 5.2: Socio-Technical Energy Transition Models. [99]

5.4.2 Integrating Economic, Behavioral, and Social Models

Beyond the closer integration of bottom-up and top-down models, Wilson and Dowlatabadi [100] provide an overview of a broader range of approaches in decision models from across the social sciences. While conventional economic models assume people are rational actors with fixed and consistent preferences motivated by utility-maximization, a range of other approaches exist. Behavioral economics models use widely varying decision heuristics and context-dependent preferences. Technology diffusion models use attitude-based evaluation of technologies and the consequences of adoption. Social psychology models approach decision models from the perspective of interacting psychological and contextual variables. Sociology models consider sociotechnical construction of demand and focus much more on the social scale than the individual scale. Wilson suggests that these approaches could be better integrated for improved modeling results. For example, economic models could incorporate time inconsistency with a changing discount rate to better represent how individuals value costs and benefits over time.

5.4.3 Discrete Choice and Agent Based Models

Similar to Mau, Li, and Wilson and Dowlatabadi, Mundaca et al. suggest that an interface between bottoms-up energy economy models and studies on consumer behavior is needed to provide more realism for technology choice decision frameworks [159]. They suggest that expanded use of discrete choice and agent-based models will help develop hybrid models that can better represent heterogeneity and behavior. Agent based modeling could be a complementary technique to address the complexities of behavior and technology choice. This approach addresses the forms in which social structures come into view from complex interaction among individuals and how those structures affect and limit individual behavior, including feedback processes for identified social structures. Based on these early examples of blending economic and social science approaches, potential parameters that can be integrated into techno-economic models to better represent behavior are summarized in Table 5.2.

Table 5.2: Behavioral Parameters that can be Integrated in Techno-Economic Decision Models

Parameter	**Description**
Discount Rate	Reflects the higher investment risk and lower diversification of individuals
Market heterogeneity	Accounts for varying degrees of savings required to invest
Intangible costs/benefits	Accounts for non-monetary costs of investment
Demand elasticity	Different levels of sensitivity to changes in price
Retrofitting/ replacement rate	Different investment cycles for new capital assets over time
Discount rate with time inconsistency	Represents how individuals value costs and benefits over time
Integration with agent based and discrete choice models	Represent how social structures affect and limit individual behavior

5.5 DELIVERY OF INFORMATION

Beyond modeling adjustments, Wilson and Dowlatabadi suggest lessons can be learned from behavioral economics on how modeling results are presented. Framing effects show that individual preferences are not fixed, and the way alternatives are presented can influence decisions. For example, framing a decision as a choice between losses versus gains can change decisions, because individuals are generally averse to losses. Furthermore, individuals tend to anchor on certain types of information, so preferences can be biased toward the initial anchor point. Also, the status quo or default option of a decision tends to be favored. The implications for a decision model are that a) utility is dependent on a reference point; and b) utility is carried by gains and losses relative to this reference point, not final outcomes. The way information is structured in different decision contexts can also influence choices [100].

Even when information is available, there is often a gap between available information and understood knowledge. Stern and Aronson note, "for information to be effective in a decision process, making it available is not enough" [160]. Research has found that the delivery of the information is key. At the residential scale, personalized information tailored to individuals, face-to-face interactions, information delivered through credible sources such as local organizations, highly visible local demonstrations, and social diffusion through friends and neighbors all increases chances of adoption. For larger utility scale projects, more interactive, deliberative communication between decision-makers, technical experts, and the public increases chance of acceptance. As demand side management, smart metering, microgrids, and community generation increase, this interactive communication will be even more important as individuals will be part of a two-way flow of knowledge rather than the traditional top-down communication to passive recipients [161].

5.6 CONCLUSIONS AND FUTURE WORK

This review has shown that while there are significant gaps between the techno-economic model's "optimum" and reality, there are well understood reasons for this gap. To better inform deployment and policy, a key challenge is to develop quantitative methods to incorporate behavioral scientific analysis in techno-economic models. Energy models can address behavioral and political considerations by introducing resource or technology deployment constraints to mimic real world barriers; introducing delays to represent inertia in decision-making; mimic non-cost barriers to technology diffusion by using hurdle rates and heterogeneous decision making; incorporate behavioral demand responses to higher energy prices using price elasticities of demand; or implementing myopic foresight (rather than perfect foresight). New approaches may require integrating techno-economic detail, actor heterogeneity, and transition pathway dynamics, or bridging between analytical disciplines like quantitative modelling and socio-technical transitions studies. Furthermore, adjusting the delivery of modeling insights by applying models in a more iterative, participatory fashion with key decision makers may prove more effective [99].

While models based around economic optimization are highly useful, once cost-optimal pathways for achieving energy system change are well explored, the question then turns to one of implementation. Here, rational optimization models are limited in their ability to assess the viability of achieving targets in the real world, where social and political barriers are common [73]. Looking beyond technology solutions to explore changes to behavior, institutions, and culture will be important to expanding the solution space. The full integration of quantitative modeling and qualitative transition approaches may be unlikely given the foundational differences between the disciplines, and some elements of socio-technical transitions may always lie outside the capability of any formal analysis. However, there is still significant room for models to improve their realism and representation of behavior. An interdisciplinary approach that recognizes the value of articulating different forms of knowledge and includes a role for both formal modelling and qualitative interpretation will bring modeling results closer to reality and improve their ability to guide individual decisions and broader policy implementation.

While initial work in the research community has focused on integrating behavioral considerations into national energy systems models to better inform policy decisions, little work has been done to integrate behavior into smaller scale building and community energy decision models. Because much of our future clean energy deployment is expected to be distributed at the building and community level, it is important to accurately guide building owners and community leaders to clean energy projects with the highest chances of successful deployment. Therefore, future work will focus on applying lessons learned in integrating behavioral considerations from the national modeling space to local decision models.

CHAPTER 6
FUTURE WORK

To complete the thesis, I plan to:

- Submit a paper on the work described in Chapter 2 to *Applied Energy* by October 2020;
- Develop additional case studies that show the benefits of diverse solutions in Chapter 3, and submit a paper on this work to the *INFORMS Journal on Applied Analytics* by December 2020;
- Complete a qualitative data analysis on the interview data collected from partners in Chapter 5, and submit a paper on this work to *Energy Research and Social Science* by February 2021.

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