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Abstract

Distributed energy resources have been almost exclusively deployed and operated under a decentralized decision-making process. In this paper, we assess the evolution of a power system with centrally planned utility-scale generation, transmission, distribution, and distributed resources. We adapt a capacity expansion model to represent both centralized and decentralized decision-making paradigms under various electricity rate structures. This paper shows that a centralized planning approach could save 7% to 37% of total system costs over a 15-year time horizon using a Western United States utility as a case study. We show that centralized decision-making deploys substantially more utility-scale solar and distributed storage compared to a decentralized decision-making paradigm. We demonstrate how a utility could largely overcome the complications of decentralized distributed resource decision-making by incentivizing regulators to develop electricity rates that more closely reflect time- and location-specific, long-run marginal costs. The results from this analysis yield insights that are useful for long-term utility planning and electric utility rate design.

Keywords: distributed energy resources; decentralized decision-making; electricity rate structure; power system; resource planning; rooftop solar

Abbreviations

Abbreviation	Description
ATB	Annual Technology Baseline (NREL annual cost study)
BPS	Bulk Power System
CCGT	Combined Cycle Gas Turbine
DER	Distributed Energy Resources
DG	Distributed Generation
GAP	Grid Access and Planning (model)
IRP	Integrated Resource Plan(ning)
LBNL	Lawrence Berkeley National Laboratory
LSE	Load Serving Entity
NEM	Net Energy Metering
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
OPF	Optimal Power Flow
PNNL	Pacific Northwest National Laboratory
PV	Photovoltaic
RoR	Run-of-river
SCCT	Simple Cycle Combustion Turbine
TOU	Time-of-use

1. Introduction

Decisions about the deployment and operation of distributed energy resources (DER) have almost exclusively been made "behind the meter" and based on the cost of equipment, financing and subsidies available, and electricity rates. Utility planners have generally not been involved in determining where and how much distributed generation should be installed. It follows that the decisions to invest in distributed resources have not stemmed from any coordinated planning effort, and the decisions to operate these resources generally do not respond to any coordinated dispatch process. In this paper, we investigate the economic value of coordinating the planning, procurement, and operation of DER.

To date, distribution utilities have grappled with DER adoption by using the feeder hosting capacity to cap the deployment of distributed generation in locations where system reliability may be adversely affected. Reliability concerns related to DER may include voltage and frequency control, reactive power management, less predictable power output, and bi-directional power flows that increase operational complexity [1]. Utilities occasionally need to upgrade or repower distribution systems and circuits to accommodate DER [2]. DER also benefit distribution systems by reducing losses, deferring system capacity expansion, alleviating feeder loading, and, in some cases, improving reliability for end-use customers [3]. Unfortunately, it is difficult to quantify these benefits because DER investment and dispatch are not coordinated with utility-level investment and dispatch. It should be noted that load serving entities (LSEs) that make bulk power system (BPS) investment and/or operation decisions have started to track these behind-the-meter resources more closely for their short- and long-term planning [4]. Furthermore, there are a small but growing number of utilities that are considering installing and operating owned behind-the-meter DER, which suggests this study could have immediate real-world applications [5].

The lack of control over any DER deployment and the traditional separation of distribution and BPS planning means that LSEs have limited opportunities to manage uncertainty associated with DER. Consequently, LSEs need to forecast adoption and operation of DER in an effort to characterize the net demand they will face in the future. It follows that decentralized additions of DER into the distribution network are most likely misaligned with the least-cost expansion of the BPS. This misalignment is exacerbated in cases where DER adoption forecasts are inaccurate.

DER adoption has increased substantially over the last 15 years driven by technology cost declines, favorable rate structures including net-metering and increased block pricing, and public awareness [6]. The residential photovoltaic (PV) market has grown 44% *annually* since 2005 and about 2.5% of households in the U.S. have installed a PV system [7]. This aggregate figure masks the fact that distributed PV is much more prevalent in certain states like Hawaii, California, and Arizona where 31%, 11%, and 9% of households have PV as of 2018, respectively. PV is the most prevalent residential distributed generation technology, but there could be substantial adoption of batteries as a distributed resource in the near future due to lower costs and increases in efficiency/capacity [8]. DER adoption is expected to continue to grow rapidly [9], which will only increase the inefficiencies associated with the lack of coordination between bulk power and distribution systems.

In this paper, we evaluate an important, yet understudied topic: *the economic value of fully integrating DER into a long-term utility planning process*. To explore this topic, we follow a typical utility planning process by (1) forecasting demand; (2) accounting for existing and future resources (utility-scale and DER); and (3) running a capacity expansion model to determine the least-cost pathway to meet future demand. We use a tool that evaluates least-cost expansion and operation of generation, transmission, distribution, *and* DER systems: the Grid Access and Planning (GAP) model [10]. The GAP model was originally programmed as a social planner with a centralized decision-making paradigm. We adapt GAP by splitting the customer (i.e. behind-the-meter) and utility decisions to simulate the decentralized decision-making approach that characterizes the industry. The centralized version of the tool provides the counterfactual to assess the differences with a decentralized decision-making framework associated with DER deployment and operation. Therefore, in this paper, the decentralized scenarios are the "business as usual" or *status quo* cases, whereas the centralized scenario is the simulated counterfactual against which the decentralized scenarios are compared.

Before proceeding, it should be noted that at present it might not be politically or technically feasible to centralize the decisions of deployment and operation of distributed resources. However, this analysis makes an important contribution to the literature by quantifying the economic impact of decentralized investment and operation as they already occur in practice—a topic that has not been evaluated before. More specifically, we measure the differences in technology types, sizes, locations, and operational schemes between centralized and decentralized investment and operation of the power system over its full scope, from distribution to transmission and generation

Based on this assessment, for example, electricity rates could be designed to achieve specific deployment or operation objectives that are a proxy for potentially more efficient decisions made by a centralized operator. Results from this paper have important policymaking implications as they highlight how long-term planning processes could be improved by integrating bulk power and distribution system planning [11]. This study answers the following specific research questions:

- What are the cost differences between decentralized versus centralized investment in and operation of DER?
- What are the technological and operational differences between a system managed with a decentralized decision-making structure versus a centralized one?
- What impacts do rates have on DER adoption and how does decentralized DER adoption compare to the centralized decision-making outcome under different rate structures?
- What changes could be implemented in the utility planning processes to address the challenges of decentralized decision-making?

This manuscript is organized as follows. Section 2 contains a short review of relevant literature. The GAP model, its adaptation to a decentralized framework, and its calibration are explained in Section 3. Section 4 includes a case study and Section 5 describes key results. Section 6 concludes with several findings that are relevant to utility IRP processes. All figures and tables are our own unless noted.

2. Relevant Literature

Increased adoption of DER in the past decade is driving research into its impacts on distribution, transmission, and generation, and how these impacts are mediated by alternative decision-making paradigms. This paper addresses the second topic by comparing the effect that centralized and decentralized decision-making paradigms have on power system expansion with DER. This section then provides an overview of the literature on the impacts of DER adoption on power systems, with a focus on the physical and economic effects of DER adoption on the planning, design, and operation of power systems.

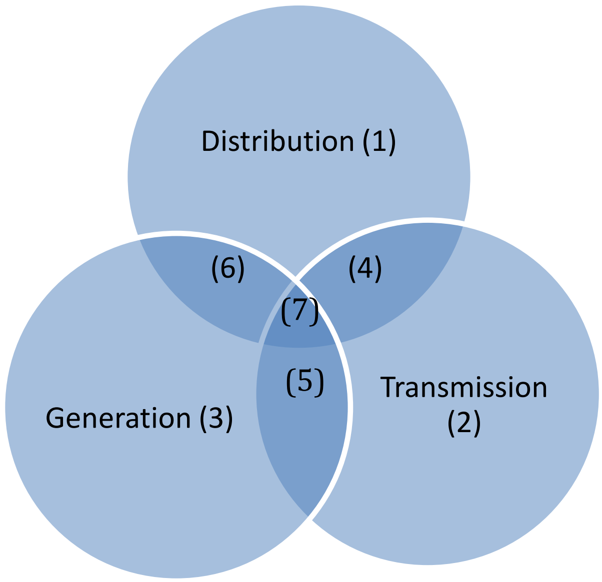
Research on the impacts of DER in power systems has largely been organized around the traditional divisions between the distribution, transmission, and generation components of the power system. Fewer studies have assessed the cross-component impacts, i.e. in the generation-transmission components or across distribution-generation components. We describe this components-related research in Figure 2.1 below and identify the different areas of research within each component and across components. Areas 1, 2, and 3, represent research focused on DER impacts in either distribution (including behind the meter), transmission, or generation components of the power system. Areas 4, 5, and 6, represent papers that address the impacts of DER on the distribution and transmission, transmission and generation, or generation and distribution interfaces. For example, work that studies how DER adoption could displace utility scale generation would be located in area 6. Area 7 represents papers that concurrently address impacts of DER on the three components of the power system.

Studies have generally focused on DER impacts on area 1 (distribution system) rather than area 2, the transmission system [12]. For example, [13] study the optimal decision making of a distribution utility to minimize power purchases given certain levels of PV adoption. There is no capacity expansion or forward looking component in this work. Technical analyzes have explored the impacts of PV adoption in rural feeders [14], on voltage control in urban networks [15], and of very high levels of adoption [16]. These results do not explore impacts beyond power quality issues at the distribution system level only. Area 5, the generation-transmission interface, has also been subject of substantial work especially on the very short term time horizon. For example, [17] analyzes the dynamic impacts of distributed and utility-scale PV penetration on the transmission system. A similar analysis is developed by [12], concluding that distributed systems are more favorable to system stability than utility-scale systems. However, these paper and literature is generally limited to transient analysis of the transmission system, without extending to distribution and without considering production cost and capacity expansion modeling. [18] and [13] are the only studies found that address DER impacts in area 4, the transmission and distribution sector interface (area 4). In [18], an integrated distribution-transmission model—developed by the National Renewable Energy Laboratory (NREL)—identifies the benefits of being able to forecast the impacts of distributed generation at the transmission level. The forecasts lead to improved reliability measurements and reduced generation costs. [13] does not estimate impacts of DER on the transmission system, but does consider transmission constraints on a model of a distribution company balancing DER dispatch and procurement. There are no known studies that compare the concurrent impacts of DER deployment in operation and investment on all three levels of the power system (area 7 in Figure 2.1) in a single modeling framework. This paper addresses this knowledge gap.

The diversity of papers exploring a high DER penetration future reflects the wide array of impacts of integrating these systems into the grid. We find two recurring analytical themes in the literature, which we use to organize the remainder of this section:

1. The *physical (reliability) and economic (costs and benefits) impacts* of distributed generation on the distribution, transmission, and/or generation components of the power system.
2. The *decision-making* and planning perspectives that mediate these impacts in the context of the electricity system components considered.

Figure 2.1 Component-based organization of research into impacts of DER on power systems



2.1 Physical and Economic Impacts

Papers examining the integration and optimization of distributed generation most often address their impact on distribution systems and primarily focus on rooftop solar generation. All of these papers fall in area 1 (Figure 2.1). The distribution system faces numerous physical challenges from rooftop solar penetration [7]. Voltage regulation is a significant area of research within models that explore various planning objectives, including those that (1) minimize curtailment with various control mechanisms [19]; (2) minimize the cost of utility power purchases [13] and DER generation cost [20]; (3) optimize the siting and sizing of distributed generation [21] and of distributed storage [22]; and (4) minimize distribution losses [23]. Other papers are more methodology-focused and review different power distribution planning models that address DER [24]. However, these studies are largely illustrative and not applied to actual planning problems with different objectives and planning constraints. At the transmission level (area 2 of Figure 2.1), research has examined voltage regulation and reactive power impacts [18], as well as transient and steady state stability [17]. It is important to note that few, if any, papers empirically reflect the planning challenges that utilities face: electricity production cost minimization, reliability requirements, and adherence to renewable procurement requirements.

Cost minimization is the most common criterion for economic assessments of DER adoption in the papers reviewed. However, the costs included in the objective functions vary among these papers. For example, some research focuses on minimizing the cost of utility power procurement. A paper minimizes the cost of procurement and self-owned DER while taking into consideration distribution and transmission system constraints (area 4 of Figure 2.1) [13]. Another paper addresses minimizing DER procurement and ancillary services costs, but limit the scope to the distribution system (area 1 of Figure 2.1) [20]. Papers also address costs in area 1 of Figure 2.1, including minimizing distribution losses and investment costs with storage [25] , minimizing substation delivery and investment costs through the optimal siting of DER [26] and determining least-cost distribution investments through active network management [27]. The aforementioned literature is largely limited in scope to the distribution system and DERs within it, without considering the impacts to the entire electric power system. A study closer to ours take a broad physical scope (area 5 of Figure 2.1) by minimizing the cost of transmission, generation, and storage [28]. The paper, however, is not empirical and does not consider the distribution system.

The economic assessments of the physical impacts of DER on the distribution system are based on objective functions that represent utility- or customer-centric interests. This suggests that the operational and investment decisions that inform these impacts are mediated by the decision-making framework, which we discuss in the following sub-section.

2.2 Decision-making Framework

We find that analyses of distributed generation investment and dispatch fit within either a centralized [13,20] or decentralized [29,30] decision-making framework. Current rooftop solar deployment is characterized by a decentralized approach to investment and management. Utility customers either own or lease the majority of rooftop solar PV installations and design and manage their systems for self-optimization subject to rate structures and levels [31]. *There are no known studies that compare the system-wide costs from centralized and decentralized decision-making frameworks under different levels of DER penetration.*

Existing research on these decision-making frameworks has generally neglected a topological representation of the grid and focused on the customer-utility relationship from an economic perspective (e.g., through rate incentives). Papers on this topic represent the interactions between customers and utilities using game-theoretic models, including Stackelberg games, which determine customers' utility-maximizing demand response and load shifting decisions under various utility pricing schemes and incentives [32–34]. A related branch of work studies the impact of different rate structures and net-metering policies on customer DER deployment. [31] finds that distributed PV deployment is highly sensitive to retail rate structure and [35] further refines how net-metering impacts retail customer's bill savings. On the storage side, [36] and [37] explore its scheduling and adoption under different rate structures, respectively. The preceding research generally shows that retail rate structures and net-metering play a critical role in future DER deployment. These findings motivate a more thorough examination of retail rates in our analysis, even if long-term planning processes do not always fully consider the direct impact of retail rates.[1]

In summary, we find that the complexity of the electric grid and interdependence of its components pose some challenges for analyzing its evolution. Recent research has generally focused on a (1) subset of the entire power system (e.g., distribution versus transmission); (2) limited set of potential impacts such as voltage regulation or power purchase costs; and (3) centralized decision-making paradigm. This paper addresses these gaps by focusing more broadly on the entire electricity system (Area 7 of Figure 2.1); evaluating a range of physical and economic metrics (e.g., line losses, reliability constraints,

[1] IRP activities often include the impact of rates indirectly through price elasticities, but these are generally simplified to the response of demand to a single volumetric rate level and not to more complex (or varied) rate structures.

wholesale prices, infrastructure costs); and ultimately assessing the economic value that would result from different decision-making frameworks (e.g., centralized utility planning versus decentralized decisions by end-use customers) on an empirical representation of a U.S utility.

3. Methods

In this section, we introduce the GAP model employed to assess the differences between centralized and decentralized decision-making paradigms. The original GAP model implements a centralized decision-making paradigm for investment and operation of the power system. For this paper, the model is modified to emulate a decentralized decision-making paradigm by splitting the customer (behind the meter) decisions from the utility expansion decisions. These two model versions are then used to simulate a set of scenarios and compare the outcomes of each paradigm.

3.1 GAP Model Description

GAP is a joint capacity expansion and production cost model that determines the least-cost investment and dispatch decisions to operate a power system over a long-term time horizon, subject to numerous constraints that ensure that results are both possible and reasonable. GAP is based on the SWITCH model, an open source generation-transmission expansion model that was developed at the University of California, Berkeley and has been employed in expansion pathways studies across the world [38–41].

GAP is a deterministic linear program whose objective function is to minimize the net present value (NPV) of investment, operation, and maintenance of the generation and storage units, transmission lines, distribution network, and DER technologies in a power system (see equation (1)). The model meets residential, commercial, and industrial demand at every node in every sampled hour by dispatching the available utility-scale and DER generation and storage units and transmission and distribution lines. Utility-scale generation is split into baseload, flexible, variable, and "peaker" technologies such as natural gas-fired simple cycle combustion turbines, recognizing the operational constraints of each technology type including its capacity to provide spinning and non-spinning reserve and ramping, among others. Several "conservation" constraints assure that basic power system physical balancing is met. A detailed mathematical representation of the GAP model adapted from Carvallo et al. (2019) is included in Appendix A (see that Appendix for a nomenclature table).

$$\min(\text{total cost} = \text{NPV}(\text{I}_G + \text{I}_T + \text{I}_D + \text{I}_R + \text{O\&M}_G + \text{O\&M}_T + \text{O\&M}_D + \text{O\&M}_R + \text{F}_G + \text{F}_R)) \quad (1)$$

where NPV is the net present value function; I_G, I_T, I_D, and I_R are the annuities of generation, transmission, distribution, and DER investment, respectively; $O\&M_G$, $O\&M_T$, $O\&M_D$, and $O\&M_R$ are the non-fuel operation and maintenance costs, and F_G, F_R are fuel costs for utility scale and DER generation.

GAP was developed with the objective of assessing the tradeoff between investment and operation of distributed versus utility-scale resources. For this purpose, GAP represents generation units, transmission and distribution lines, and distributed resources with explicit temporal and spatial resolution.

Temporally, GAP uses two levels to represent operation and investment decisions. The model samples chronologically related hours—called *timepoints*—to simulate dispatch decisions on representative peak and median load days throughout the year. The model makes investment decisions in investment periods, which usually encompass one or more years. There is a set of representative timepoints in each investment period, and the set of investment periods constitutes the simulation horizon. Each timepoint has a weight that is proportional to the number of hours in the investment period that the timepoint represents. The specific model calibration for spatial and temporal resolution used in this paper is reported in Section 4.

Spatially, GAP uses two levels of aggregation to represent the transmission and distribution systems. The bulk transmission system is divided into load zones, which represent the most important transmission nodes. Within a load zone there is no transmission congestion; the transmission of power between load zones is modeled with a transshipment or transportation model. Within each load zone there is a simplified representative distribution system consisting of dozens to hundreds of load nodes connected through an existing distribution network, whose investment and dispatch are also simulated using a transportation model. The limitations and consequences of these modeling choices are explained in Appendix B.

The GAP model simulates a basic primary distribution system expansion and operation by solving a network flow problem with variable edge or circuit capacity using a transportation model. These types of models obviate the physical complexity that AC optimal power flow (OPF) and DC OPF approaches can represent. However, the choice of a transportation model is necessary to make the model computationally tractable, especially to solve the centralized problem. Even though transportation models are simplified, research has shown that these representations are reasonable approximations for distribution and transmission network capacity expansion modeling [42,43].

It is important to note that the intended use for the GAP model is as a high-level planning tool by regulatory staff and utility planners who seek to understand the interactions between distributed and utility-scale resources over time and space. The model is not intended to produce investment decisions related to the procurement of actual resources.

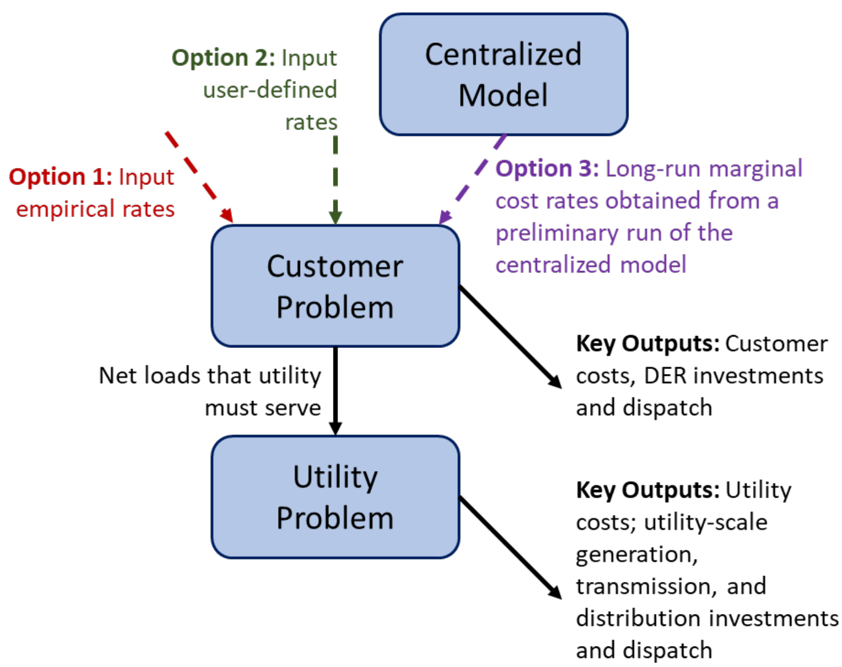
3.2 Decentralized Decision-making Model Implementation

The GAP model is based on the perspective of a centralized planner who controls all decisions about investing in and operating its power system. This single planner optimizes the entire integrated system, from utility-scale power plants to transmission expansion to residential-scale DER. However, in reality, DER are typically deployed and operated behind the meter by customers following their own incentives to minimize electricity bills or maximize profits. Consequently, it is unlikely that customers would choose to implement the same DER investment and operation decisions that are featured in the least-cost integrated power system expansion. Therefore, the optimal decisions determined by the original, centralized GAP model may have limited practical value despite providing a helpful representation of an "ideal" power system. Its results do not project how customers will invest in and operate DER based on their own objectives, and it cannot shed light on optimal utility-scale decisions with respect to customer-driven DER deployment. We decompose the centralized GAP model into customer and utility problems that together define a resource planning framework with decentralized decision-making to assess the effects of potentially conflicting utility and customer objectives.

In the customer problem, customers decide between investing in and operating DER, and purchasing electricity from the utility to minimize the total net present cost of satisfying their demands for electricity. DER deployment is allowed for residential and commercial customers, but in this implementation we do not allow industrial loads to deploy these resources. The customer problem assumes that customers can purchase any amount of electricity from the utility under a known rate structure. The differences between customer electricity demands and DER generation levels in the optimal solution to the customer problem are passed to the utility problem as net loads. The utility is forced to satisfy these net loads by using its existing assets and expanding its utility-scale generation, transmission, and distribution systems. A flowchart that illustrates this solution procedure for the decentralized decision-making paradigm is presented in Figure 3.1.

In the utility problem, the utility determines the least-cost pathway for satisfying these net loads—which is consistent with traditional IRP modeling processes—but it also includes distribution system expansion. Table 3.1 provides an overview of the originally centralized and the decentralized GAP model as modified for this analysis.

Figure 3.1 Flowchart illustrating the solution procedure for decentralized decision-making scenarios



The customer problem uses the same availability and costs for DER as the centralized model, but also includes an electricity rate structure. Rates are specified exogenously with enough flexibility to represent hourly and node-level rates, if needed. Rates can be calibrated to existing rate structures, specified by the model user to consider alternative rate schemes, or determined via a preliminary run of the centralized model (see Section 4.2 for more detail). In the decentralized framework, the utility problem requires net loads as inputs, which are obtained from the optimal solution to the customer problem after subtracting the contributions of DER from the exogenous demand forecast.

Table 3.1 Overview of the centralized and decentralized GAP models

Model	Objective	Constraints	Key Inputs
Centralized model (original GAP model):	Minimize total net present cost of power system, inclusive of all investments and operational dispatch	Utility-scale generation constraints, DER constraints, transmission constraints, distribution constraints	Customer electricity demands; performance, cost, and initial installed capacity of utility-scale technologies, DER technologies, transmission, and distribution
Decentralized model (modified GAP model): Customer problem	Minimize total net present customer costs, inclusive of DER deployment and purchases from the utility	DER constraints	Performance, cost, and initial installed capacity of DER technologies; electricity rate structure
Decentralized model (modified GAP model): Utility problem	Minimize total net present utility costs, inclusive of utility-scale generation, transmission, and distribution, but excluding DER	Utility-scale generation constraints, transmission constraints, distribution constraints	Performance, cost, and initial installed capacity of utility-scale technologies, transmission, and distribution; customer net electricity demands from optimal solution to customer problem

The sequential modeling approach for the decentralized scenarios used in this paper implies that the customer first invests in DER under exogenous electricity rates, then the utility must satisfy net loads. The structural distinctions between this approach and an equilibrium model are important to emphasize, as they affect how the model results should be interpreted. Since the rates are exogenous, our approach is not designed to lead to an equilibrium between the marginal costs of power supplied by the utility and power produced behind the meter by customer-controlled DER. Achieving such an equilibrium would require a model that allows for endogenous determination of electricity rates to balance supply and demand. In addition, our model does not attempt to internally calculate the “right” electricity rates. Hence, there is no guarantee that the exogenously assumed rates would generate adequate revenue for the utility to recover its costs. In Section 5.3, we examine the cost recovery implications of various rate structures, which are important in a setting where customers can invest in DER to reduce their grid electricity purchases when rates are high.

On the whole, our decentralized scenarios should be interpreted as “what-if” developments of the electricity system with respect to exogenously defined rate structures. Those rates may be well calibrated, or they may lead to technical or financial problems in the future, depending on how the user defines them. Our model can project that these problems would arise under a given rate structure, but it does not contain a mechanism to endogenously adjust rates during the course of a model run. In this sense, we believe our sequential structure in which customers invest in DER, then the utility satisfies net loads, is a reasonably accurate representation of the current decision-making environment. Especially in the short run, the retail rates facing customers are fixed, and the utility is legally obligated to satisfy their net loads. In the long run, the utility could petition its regulator to adjust rates in order to address revenue adequacy issues that might emerge, but this is not a simple process of equilibration and it is also far from exact.

3.3 Formulation of the Customer Problem

Customers are defined as the collection of either residential or commercial entities at a given node of a load zone who consume electricity, and own and operate DER technologies[2]. We assume the behavior of customers at different nodes are independent in each period. The customers' objective function is to minimize the total net present cost of the electricity required to meet their demands with full reliability.[3] There are no interactions among customers at different nodes because the customer problem assumes that the rate structure is exogenous and that the customers can procure any amount of electricity for these rates. Customers then are not directly subject to utility-scale generation, transmission, and distribution constraints. Therefore, rather than solving thousands of smaller customer problems, we combine the problems faced by customers at all nodes into a single optimization problem faced by a representative customer agent. The composition of the total cost is represented by equation (2):

$$\text{total customer cost} = \text{DER costs} + \text{electricity purchases} - \text{net metering revenues} \quad (2)$$

First, the customer incurs DER investment and operational costs ("DER costs"). Since the customer can purchase an unlimited amount of electricity from the utility at known rates, they will only invest in DER insofar as their costs are offset by reduced electricity purchases or increased net-metering revenues. In this analysis, the customer can deploy and operate either or both of two specific DER technologies: rooftop PV panels for generation and distributed battery storage. Rooftop PV deployment is modeled with an upfront capital cost, a fixed annual operation and maintenance cost, and no fuel costs, with capital costs declining over time. Storage is an emerging technology that could significantly change the way distribution systems operate. We assume that storage technologies have decreasing capital costs over time, following [44]. Furthermore, battery storage is modeled with separate upfront capital costs for discharge capacity (MW) and for energy storage capacity (MWh). Storage operational levels are tracked across successive timepoints, subject to storage capacity and efficiency losses.

Second, the customer purchases electricity from the utility in order to complement DER generation. In our model, the customer must pay for the net electricity consumed at each timepoint. This is a simplification of typical monthly billing cycles, which would require complex tracking and balancing of monthly net demand. The total "bill" for each investment period is calculated as the sum of the

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[2] We assume that industrial customers are connected at the transmission level and hence are not considered part of distribution system load nodes.

[3] Full reliability means meeting all demand in all simulated hours. Given the temporal resolution and deterministic nature of the model, simulating perfect reliability is a conservative way to assure the results comply with resource adequacy requirements.

expenditures in each timepoint weighted by the duration that the timepoint represents (see Section 3.1 for an explanation of the temporal representation).

Third, the customer may earn revenue through a net energy metering (NEM) program, which is represented in the model as a negative cost. With net-metering, the customer can sell excess electricity back to the utility when their PV system generation exceeds end-use demand. As with the "bill" for electricity purchases, the net-metering policy in this model is calculated monthly. If the monthly DER generation exceeds the end-use demand, the excess energy will be purchased by the utility at a surplus electricity price. The surplus electricity price is typically specified in advance either as a flat rate in \$/MWh or as a percentage of a time-varying electricity rate. Customer demand must be satisfied according to the constraint specified in equation (3) below:

$$\text{customer monthly demand} = \text{DER monthly generation} + \text{electricity purchases} - \text{net meteringenergy} \tag{3}$$

From the utility's perspective, it is important that the rate structure be designed in a way that induces customers to make appropriate investments in DER. If rates are too low, then customers will adopt little to no DER and need to acquire more electricity from the utility. This could potentially increase stress on the utility's existing assets and force the utility to make costly investments in its utility-scale generation, transmission, and distribution systems. If rates are too high, then customers will deploy substantial DER and supply a significant amount of their own electricity. This could be a more expensive pathway due to higher per-unit capital costs at the distributed scale, and the utility might struggle to recoup its costs due to dwindling electricity sales. In either case, rates that are too high or too low can result in investments that diverge from the least-cost solution, resulting in a more expensive power system.

The customer problem in our decentralized model has several noteworthy limitations. The most important is the absence of fixed costs such as connection or capacity charges, whose inclusion would turn the customer model into a mixed-integer problem and make it computationally intractable. Second, a node represents a collection of either residential or commercial entities and hence cannot represent household- or commercial facility-level costs such as bi-directional meter installation fees or the annual fee for participating in a net-metering program. Third, our assumption that the customer can purchase any amount of electricity from the utility ignores the short-term rigidity of the generation, transmission, and distribution systems that the utility has to expand to procure that power. Fourth, to ensure that the model can be solved in a reasonable amount of time, we omit elasticity of final demand and economies of scale associated with DER deployment. This assumption could cause the model to underinvest in DER in scenarios with high penetration and decreasing costs. Finally, we assume that the rate structure and net-metering policy are independent and exogenous inputs, such that altering either one does not automatically lead to a change in the other.

4. Case Study and Input Data Creation

The GAP model has been employed previously to study conceptual systems. For this study, however, we deemed it useful to calibrate the model with input data that resemble an existing LSE's generation, transmission, distribution, and customer-sited DER assets. We use an actual utility from the Western

U.S.[4] as a case study for this report, chosen based on its size, existing and potential DER penetration, and vertical integration[5]. These characteristics make the setting interesting, produce a model that is computationally tractable, and lead to results that are potentially applicable. *Utility* also conducts an annual long-term planning process that provides publicly available information to calibrate the supply side of the model, including load and fuel cost projections, existing plan inventory, and a discussion of potential future resources. Data sources are discussed in the subsections below.

As of 2018, *Utility* had approximately 630,000 customers, total sales of nearly 12,000 GWh, and peak demand of ~3,000 MW. *Utility*'s service territory currently has ~190 MW of distributed PV capacity, with growth in PV expected to exceed 500 MW by 2030.

The representation of *Utility* in this paper departs from the actual utility in several ways (see Table 4.1). We are confident that the omissions and adjustments made to *Utility's* real operation do not affect the scenario-based comparisons used in this analysis.

Table 4.1 Main adjustments to *Utility's* representation in this implementation and their reasoning

Characteristic of Utility not Represented in Implementation	Reason for Omission	Potential Impact
Imports: *Utility* purchases about 25% of its peak demand requirements from the wholesale market	Modeling imports would require depicting and modeling areas neighboring Utility, which are outside the scope of this paper.	Low: Market purchases are probably a mix of natural gas and solar/wind generation, which are the same resources used for capacity expansion in the Utility implementation.
Cogeneration: Utility produces about 40% of its power through cogeneration	Modeling cogeneration requires steam demand data, which are not readily available.	Medium: The natural gas plants that Utility uses for cogeneration are simulated, but possibly with higher availability and flexibility compared to real operation conditioned by steam demand.
Actual distribution system	Detailed information on Utility's distribution system is not publicly available and our efforts to obtain it were unsuccessful.	Low: We develop a reasonable approach to recreate a distribution system that should be similar to Utility's (see Section 4.1).
Actual locations of existing DER within the distribution system	The information is not publicly available.	Low: Low for a whole-system analysis, but impact could be

[4] Representatives from a Western U.S. utility, which served as a case study for this analysis, provided constructive comments on this manuscript. Utility staff requested a desire to remain anonymous. Accordingly, for the remainder of this paper, we refer to this LSE simply as "Utility."

[5] This paper does not seek to recreate the utility's investment recommendations from its IRP or to provide alternative expansion options for the utility. As discussed earlier, this analysis employs a substantially different modeling approach by integrating deployment decisions for utility-scale *and* distributed resources within the same model framework.

Characteristic of Utility not Represented in Implementation	Reason for Omission	Potential Impact
		higher if the actual feeder topology were employed.
Transmission system capacity	The information is not publicly available.	Low. We estimate existing transmission capacity based on voltage levels. Transmission capacity can be expanded as needed.

4.1 Input Data Creation

This subsection explains the methods, data sources, and assumptions used to create the input data for the *Utility* case study analysis. More specifically, we discuss assumptions related to the transmission and distribution networks; peak demand and model simulation; existing and new utility-scale resources; and existing and new distributed resources.

Spatial components: transmission and distribution networks

GAP represents the transmission network by grouping actual load centers into "load zones." The load zones represent nodes in the transmission system among which transmission capacity constraints and expansion decisions are modeled.

In this implementation, load zones are created by clustering buildings in the *Utility* service area. We obtain a database of buildings from the OpenStreet project [45]. Buildings are clustered into 21 load zones using a k-means clustering algorithm (see blue polygons in Figure 4.1). Transmission capacity between load zones is estimated by overlaying existing substations and transmission lines above 66 kV with the load zones. We then identify the lines that link specific load zones and aggregate those to produce a simplified transmission network (see red lines in Figure 4.1).

Unfortunately, we do not have access to any distribution network data from *Utility*. Accordingly, we implement the following procedure to produce a proxy distribution system based loosely on *Utility*[6]:

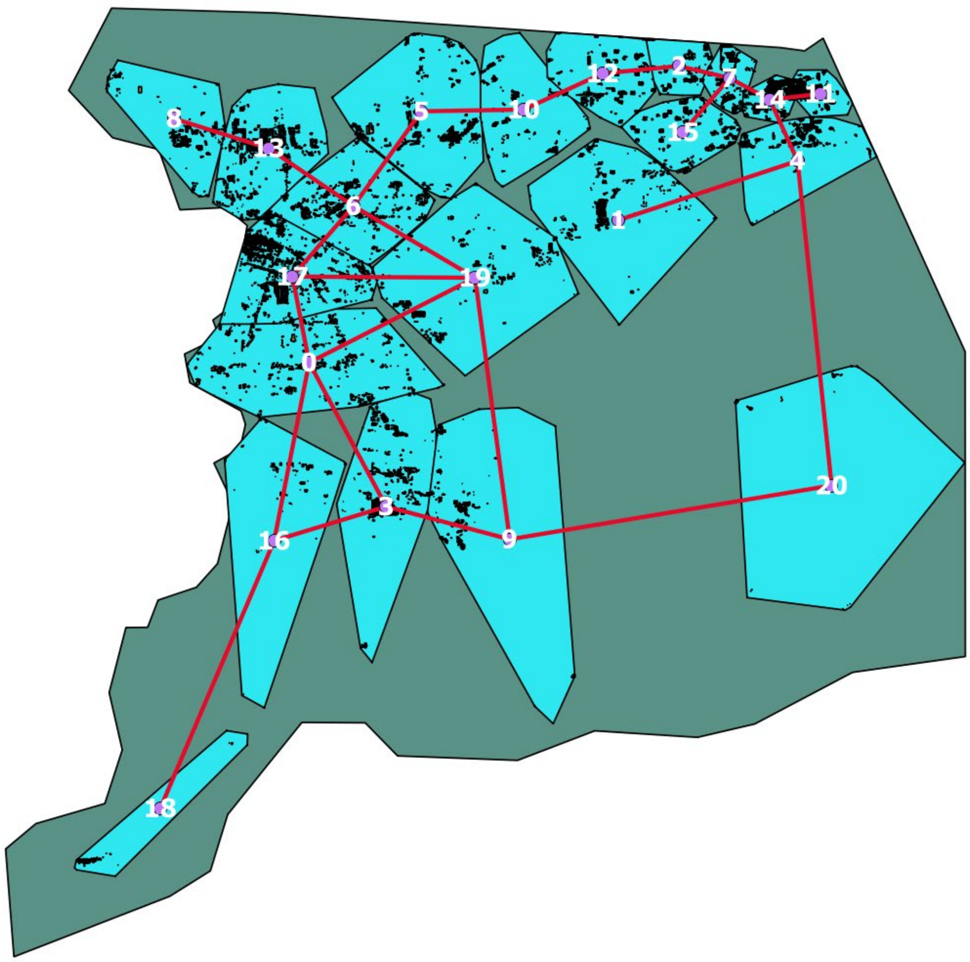
1. We leverage the "taxonomy of feeders" work developed by the Pacific Northwest National Laboratory (PNNL) and commissioned by the U.S. Department of Energy [46]. In this work, PNNL analyzed 575 distribution feeders across the country and produced a taxonomy of 24 prototypical feeders associated with five climate regions.
2. These prototypical feeders were made publicly available in Grid Lab-D format. The information available includes poles, transformers, overhead and underground lines, customers, and operation equipment. NREL complemented this dataset with an estimation of a year (8,760 hours) of hourly load data for each customer connected to a feeder [47].
3. The five feeders in the climate region where *Utility* resides are used to represent its feeders.

[6] Additional information on the techniques discussed in this section can be found in Appendix C.

Four of those five feeders have load data: a moderate suburban and light rural; a small urban center; a heavy suburban; and a light rural feeder.

4. Each load zone is assigned a representative feeder based on its building density per unit area. For example, load zones 20, 17, and 4 (Figure 4.1) are assigned light rural, urban center, and moderate suburban feeders, respectively.

Figure 4.1 Load zones and simplified transmission network we develop for the Utility service area



The feeders assigned to each load zone have varying numbers of nodes, ranging from 52 nodes in the small urban downtown feeder to 337 in the moderate suburban feeder. The final *Utility* model has 3,524 load nodes and 6,330 total nodes. In each one of these nodes, the model meets demand in every simulated hour by using a combination of DER PV, DER battery storage, and utility-scale power flowing through the transmission and distribution networks.

Temporal components: load and simulation resolution and horizon

The hourly demand at each feeder load node is scaled by a factor proportional to its building density to make the aggregate peak demand match Utility's actual peak demand. This scaling process is undertaken for two reasons. First, it ensures that load zone demand is consistent across load zones given the lack of spatially explicit load data. This consistency is important because it matches location-specific resources with demand requirements and allows potential mismatches in resource location and demand to drive transmission and distribution capacity investments (if needed). Second, the scaling process also ensures that aggregate distribution system demand is consistent with existing transmission and generation capacity.

The hourly load profiles in the taxonomy feeders distinguish between commercial and residential nodes. Aggregate demand is split into residential, commercial, and industrial segments based on customer segment data reported in *Utility's* 2018 Annual Report. Next, residential and commercial demands are allocated to load zones using the scaling factor, and then allocated to residential and commercial nodes using their actual peak demands. About 1,320 MW are designated as industrial demand and assigned to the head nodes of each feeder (i.e., this demand does not require use of the distribution network). Residential and commercial load grows 1.23% per year following the average annual growth reported in *Utility's* 2017 planning report. We hold industrial load growth constant over time due to a lack of information on the growth rate for this type of end-use customer.

GAP operates according to two different time steps for investment and dispatch:

- *Investment*: The simulation for this analysis is conducted for three investment periods: 2020–2024, 2025–2029, and 2030–2034. We use five-year increments—instead of annual—to ensure that the model is able to solve in a reasonable amount of time.
- *Dispatch*: GAP samples 12 chronological hours in a day (every other hour) for two days in the month: the peak demand day and a median demand day. We choose one month per quarter to capture any seasonality in demand and renewable resources. This results in 96 simulated hours per investment period, for 288 total simulated hours. Least-cost system dispatch (centralized or decentralized) is performed on each of these 288 hours at the generation, transmission, distribution, and DER levels.

Existing utility-scale resources

We extract *Utility's* existing supply-side resources from the Energy Information Administration's Forms 861 and 923 [48], in addition to *Utility's* 2018 resource planning report. A summary of *Utility's* generation mix is presented in Table 4.2.

Generation capacities listed in Table 4.2 include projects that are currently operational or have been committed with a known in-service year. Plants operating inside the *Utility* service territory are assigned to load zones based on their actual location. Plants located outside the Utility footprint are assigned to a load zone based on proximity and an appropriate interconnection cost is assessed based on their distance. The supply side mix includes three 500 MW CCGTs identified as "Market Purchases" (1,500 MW in Table 4.2) that emulate *Utility's* market purchases. We employ CCGTs because it is likely to be the marginal generation technology for market purchases.

Table 4.2 Capacity of *Utility's* existing generation resources

Technology	Nameplate Capacity (MW)

Biogas	72
Combined Cycle Gas Turbine (CCGT)	940
Geothermal	51
Hydro Reservoir	607
Hydro Run-of-River (RoR)	475
Market Purchases	1,500
PV	301
Simple Cycle Combustion Turbine (SCCT)	72
Wind	392

Monthly capacity factors for hydropower plants are estimated using historical data. Variable capacity factors for run-of-river hydro plants are estimated as the ratios between average monthly generation and nominal capacities in three years of operating data. For simplicity, these capacity factors are held constant in all future periods.

Hourly capacity factors for existing wind and solar plants are obtained from the data developed by [41] for a capacity expansion model for the Western U.S. Wind turbine output comes from the 3TIER dataset used in the Wind and Solar Integration Study [49]. Solar PV output is based on gridded solar insolation data developed by the State University of New York [50] merged with gridded weather data developed by the National Center for Environmental Prediction [51], processed with NREL's System Advisor Model. These datasets contain thousands of sites that are identified by their coordinates; we select sites close to existing *Utility* wind and solar PV farms to create input data consistent with them.

New utility-scale resources

The GAP model is supplied with a set of proposed projects from which the model selects the types of technologies and capacity size to invest in, subject to limits on some technologies that are resource constrained. The portfolio of new resources is based on the technologies suggested in *Utility's* 2018 planning report, with the following setup:

- SCCTs of 150 MW of maximum capacity are proposed in the same load zones as existing CCGTs or SCCTs.
- Wind sites are proposed only outside *Utility's* service area. *Utility's* planning documents suggests 1,200 MW of potential in CA and 900 MW in the Western U.S. (WY and NM). We include fourteen 150 MW proposed wind farms: eight in CA, four in WY, and two in NM. We calculate linear distances from each site to the utility service area and use this distance to estimate a transmission cost adder for each proposed project.
- Solar sites are proposed both inside *Utility's* service area and outside. The IRP suggests 1,000 MW of potential in domestic solar resources, 110 GW in CA, and 70 GW in the Western U.S. For simplicity, we define one project per load zone and distribute their capacities proportional to their areas.
- Battery storage projects with 150 MW maximum discharge capacity are proposed in each of the

21 load zones. The energy storage size—the number of hours of storage at full discharge capacity—is a decision variable for the model.

Capacity factors for new wind and solar PV projects are calculated following the same procedure described above for existing resources, using the appropriate locations. It is important to note that the model does not make discrete or "bulky" decisions on new project deployment. For every project, the model decides on a continuous investment in capacity per period ranging from zero to either a maximum capacity (if available) or whatever capacity is technically and economically cost-effective.

Existing and new distributed resources

Utility reports about 200 MW of existing DER PV and no DER storage in its operational area. However, there is no information on the location of these resources within the system. We address this limitation with the following procedure:

1. We use LBNL's Tracking the Sun dataset to estimate installed capacity by ZIP code for residential and commercial customers [52].
2. We develop a mapping of ZIP codes to load zones in GIS and weight each ZIP code's capacity by the fraction of its footprint that falls in each load zone. This method assumes an even distribution of PV deployment across each ZIP code. However, since ZIP code level capacity is aggregated to a larger geographic unit, this simplification will not significantly skew the estimate of load zone capacity.
3. Each load zone contains nodes that represent sites of residential and commercial facilities. For each node, we calculate its share of residential and commercial annual zonal load. Then, by assuming that PV deployment scales directly with load, we use the shares to weight load zone-level residential and commercial installed capacity to estimate node-level capacity.

For new DER, the model can install PV and battery storage DER on any of the 6,330 nodes in the system, including adding DER PV to nodes with existing capacity. There is no *a priori* limitation on DER deployment such as a hosting capacity limit for feeders, because the utility can adapt to optimal DER deployment by expanding its network.

Finally, we develop capacity factors for residential-sited and commercial-sited PV in each load zone. Using the same insolation input data for the utility scale—but limited to insolation inside the utility's footprint—we use NREL's System Advisor Model to estimate PV generation for fixed-roof systems for 14 cities in *Utility's* territory that fall within or overlap with each of our 20 load zones. The hourly generation is divided by the system DC capacity to create annual capacity factors.

Technology costs

GAP model results depend on the assumed capital costs of DER and generation technologies, their fuel, non-fuel O&M, and fixed costs, and expansion costs of the transmission and distribution networks. See Appendix B for a detailed account of the cost assumptions used in this analysis. In this subsection, we highlight the capital costs for key technologies, fuels, and infrastructure. All costs are expressed in real 2018 dollars unless otherwise noted.

Renewable resources including PV and wind are expected to continue their capital cost reduction trends from the last decade [53]. The pace and extent of these reductions will have an important impact on decisions that are based on least-cost dispatch. We use data from NREL's 2018 Annual Technology Baseline (ATB) report, which documents a realistic set of input assumptions and their evolution (e.g., capital costs, fuel costs) to inform electricity sector analysis in the U.S. [53]. Based on this data, utility-scale PV costs are expected to decline from 0.92 $/W in 2020 to 0.71 $/W in 2035 and rooftop PV is expected to decline from 2.01 $/W in 2020 to 1.32 $/W in 2035. In addition, onshore wind power costs are expected to decrease from 1.67 $/W in 2020 to 1.33 $/W in 2035.

The evolution of battery storage costs is particularly hard to predict given the relative immaturity of this technology in the market. The ATB relies on a study by [44], which projects that utility-scale battery storage costs will decrease from 488 $/MWh at present to 192 $/MWh by 2035. There is no known information on future capital costs of distributed storage. However, the modular nature of batteries suggests that there may not be substantial economies of scale for utility-scale deployments when compared to widespread adoption at the distributed scale. We assume a 10% cost adder for DER storage and use a cost of 537 $/MWh at present decreasing to 211 $/MWh by 2035.

The most important fuel cost assumption for the *Utility's* case study is natural gas. We use two sources of information to define a base case price forecast for natural gas: (1) the projections included in *Utility's* 2018 planning reports and (2) an average of Western U.S. LSEs' base case or reference natural gas forecasts extracted from their latest IRPs through the Berkeley Lab's Resource Planning Portal.[7] *Utility's* forecast was roughly 10–15% lower than the average of the other forecasts, with no obvious explanation for this difference. We decided to use the average of Western U.S. IRPs as the natural gas fuel price as a more conservative parameter.

Transmission and distribution system expansion costs are simplified and normalized using a single dollar per capacity-length value, expressed in $/MW-km. Transmission costs are assessed at 5,000 $/MW-km based on an estimation of length and capacity of *Utility's* transmission lines and the infrastructure cost reported in its annual report. Distribution costs are assessed using a similar approach and yield 25,000 $/MW-km. It is important to note that the value of existing infrastructure is similar to the actual investment value reported by *Utility*. However, these average values may be lower than the marginal costs of expanding both systems, given the impacts of interrupting service and the technical complexities of expanding distribution and transmission circuits and substations, especially in urban areas. This caveat is particularly relevant for distribution systems, whose expansion costs may affect DER adoption directly. We address this limitation by running a sensitivity centralized decision-making scenario with distribution costs ten times higher based on a distribution expansion analysis to accommodate DER [2].

4.2 Scenarios

We analyze several scenarios to study the impact of centralized versus decentralized decision-making paradigms on expansion strategies and the deployment of DER. The scenarios are used to model different decentralized decision-making problems, because their outcomes depend on the rates and

[7] See http://resourceplanning.lbl.gov.

incentives available to customers. It follows that a thorough analysis requires simulating different rate structures and levels. For simplicity, we perform a single run for the centralized model, which is used as a benchmark to evaluate the optimal integrated solution from a social planner perspective. Then, we consider three decentralized decision-making cases:

1. A series of flat volumetric rate scenarios to assess how the balance between utility-scale and distributed generation changes as the rate varies. We use arbitrary rates of 10, 12, 14, 16, and 20 ¢/kWh, which span most rate levels offered by U.S. electric utilities. For simplicity, we report results for the extreme flat rates of 10 and 20 ¢/kWh, and the median rate at 14 ¢/kWh.
2. A time-of-use (TOU) rate structure based on the one currently implemented by Utility. This rate has summer and non-summer seasons, with three pricing blocks in the former and two in the latter (see details in Table B-4 in Appendix B).
3. A NEM policy scenario, in which consumption and DER generation are net-metered monthly using a flat retail rate structure.

In the final core scenario, we evaluate how a utility could strategically establish its rate structure to induce customers to adopt DER at levels consistent with those in the true, system-wide optimal solution from the centralized model. This is accomplished by the utility setting its time- and node-specific rates equal to the shadow prices of the supply and demand balance constraints from the centralized model run. It follows that these shadow prices reflect the full marginal costs of satisfying demand across time and space. Table 4.3 summarizes the scenarios considered in this analysis.

Finally, three sensitivity scenarios are tested to better understand the impacts of key variables: a low DER PV cost scenario (10% reduction compared to BAU), a low DER storage scenario (15% reduction compared to BAU), and a centralized scenario with higher distribution expansion costs (ten times more expensive than BAU). The first two sensitivity scenarios are applied to both the centralized scenario and the decentralized TOU scenario. The higher distribution expansion costs sensitivity is only applied to the centralized BAU scenario.

Table 4.3 High-level summary of scenarios

Scenario Procedure	Scheme Description	Rate Structure	Scenario Name
Centralized	Single decision maker controls all decisions as a social planner.	No concept of rates under the centralized model scheme	Centralized
Customer → Utility	Customer optimizes DER under exogenous rates; then utility must satisfy net loads.	**Flat Rate:** single exogenous volumetric rate for all nodes and times (including sensitivity analysis on this rate)	Decentr Flat rate 10 ¢/kWh Decentr Flat rate 12 ¢/kWh Decentr Flat rate 14 ¢/kWh Decentr Flat rate 16 ¢/kWh Decentr Flat rate 20 ¢/kWh
		TOU Rates: apply the actual rate structure currently implemented by Utility	Decentralized TOU
		Flat Rate with NEM: same as Flat Rate, but with net-metering implemented in the customer problem	Decentr Flat NM 10 ¢/kWh Decentr Flat NM 12 ¢/kWh Decentr Flat NM 14 ¢/kWh Decentr Flat NM 16 ¢/kWh Decentr Flat NM 20 ¢/kWh
Centralized → Customer → Utility	The additional first centralized step allows the utility to apply rates set to steer the customers toward DER decisions that are close to those in the optimal solution to the centralized model.	**Marginal Cost Rates:** the utility applies rates that are strategically set equal to the shadow prices of the supply and demand balance constraints in the preliminary centralized model run, to steer customers toward optimal DER decisions that are aligned with the true least-cost power system	Decentralized Marg

5. Results Analysis and Discussion

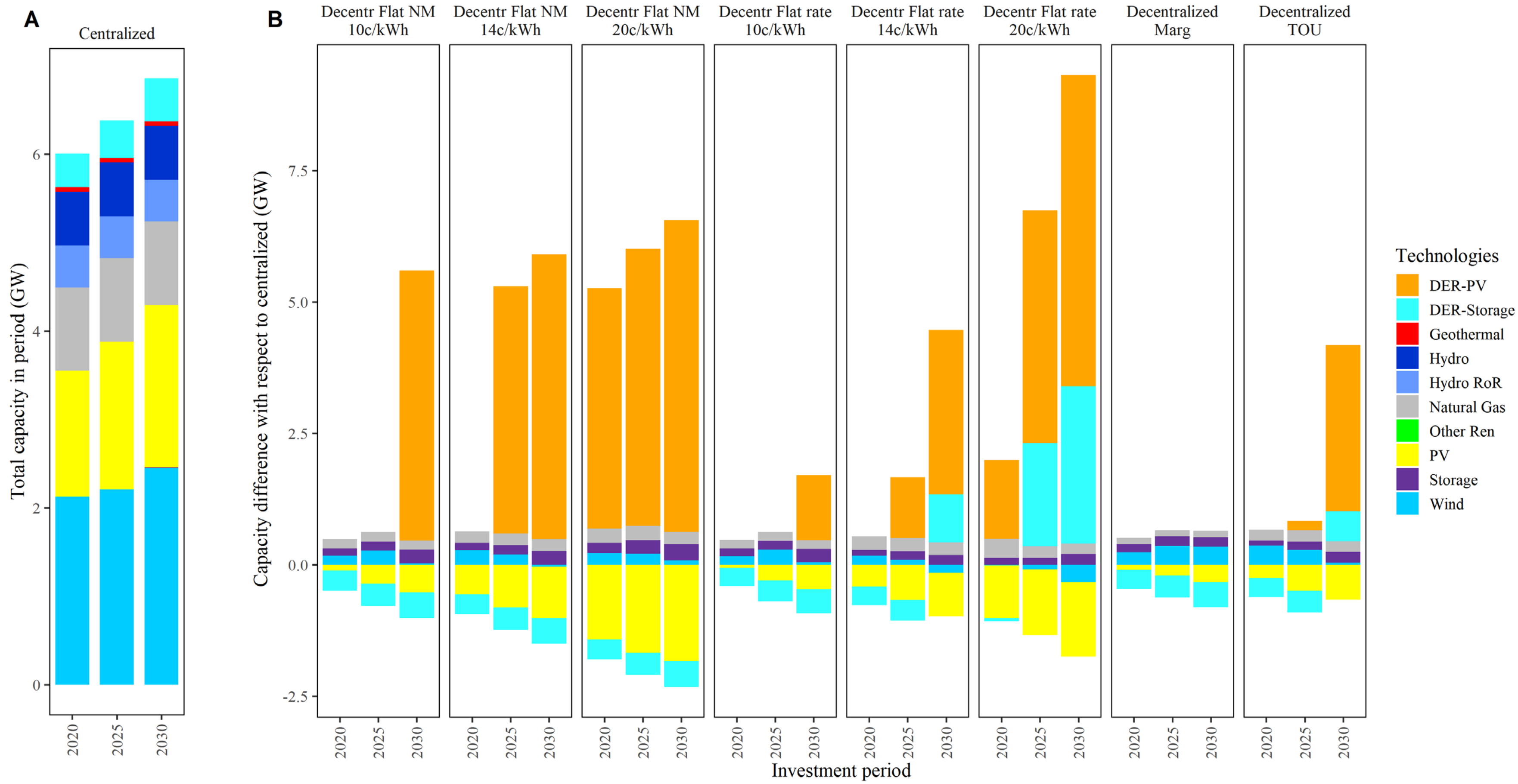
This results section is organized in the following manner. First, we report how centralized and decentralized decision-making outcomes differ in technology and location choices as well as operational decisions. Second, we detail the differences in costs between scenarios. Third, we show the impact of different rate structures on DER adoption for both decision-making paradigms. Finally, given cost-effective DER, we introduce the concept of *price elasticity of net load* as a metric that could complement the traditional metric of price elasticity of final electricity demand.

5.1 Technology Choices

This subsection reports the differences between generation technology investment and dispatch decisions under centralized and decentralized decision-making paradigms. These differences arise in the balance between utility-scale and distributed resources, as well as the composition of the utility-scale capacity and generation mixes.

Figure 5.1 illustrates the evolving total installed capacity mix in the centralized scenario, and it shows the differences between this scenario and selected decentralized cases. Centralized decision-making would generally lead to substantially lower DER PV adoption, but higher DER storage adoption, compared to the decentralized scenarios. This is not always true, however, for distributed storage, which undergoes a spike in adoption in 2030 under the 14 ¢/kWh flat rate and TOU decentralized scenarios. There is evidence that high electricity price signals and expected capital cost declines for battery storage are sufficient to induce strong residential battery uptake by 2030 in decentralized scenarios. The customer makes these behind-the-meter decisions to minimize their electricity bill, but these decisions may not be optimal at the system level.

Figure 5.1 The evolving total installed capacity mix in the centralized scenario and differences that emerge in selected decentralized scenarios



In almost all decentralized scenarios, the utility responds to behind-the-meter DER decisions by deploying less utility-scale solar compared to the fully centralized solution. The tendency for distributed and utility-scale PV to substitute for one another has important implications for utility planning to satisfy renewable resource standards and mitigate the environmental impacts of electricity. Interestingly, distributed storage is the preferred mode of storage investment in the centralized solution, which contrasts with PV generation where the utility-scale mode is preferred. This likely reflects the smaller differences in relative capital cost between distributed and utility-scale battery storage, and the ability of DER storage to defer investments in the distribution network. Consistent with the logic behind their construction, the long-run marginal cost rates result in decentralized investment decisions being much more similar to those featured in the centralized solution, as evidenced by the smaller differences for this case in Figure 5.1.

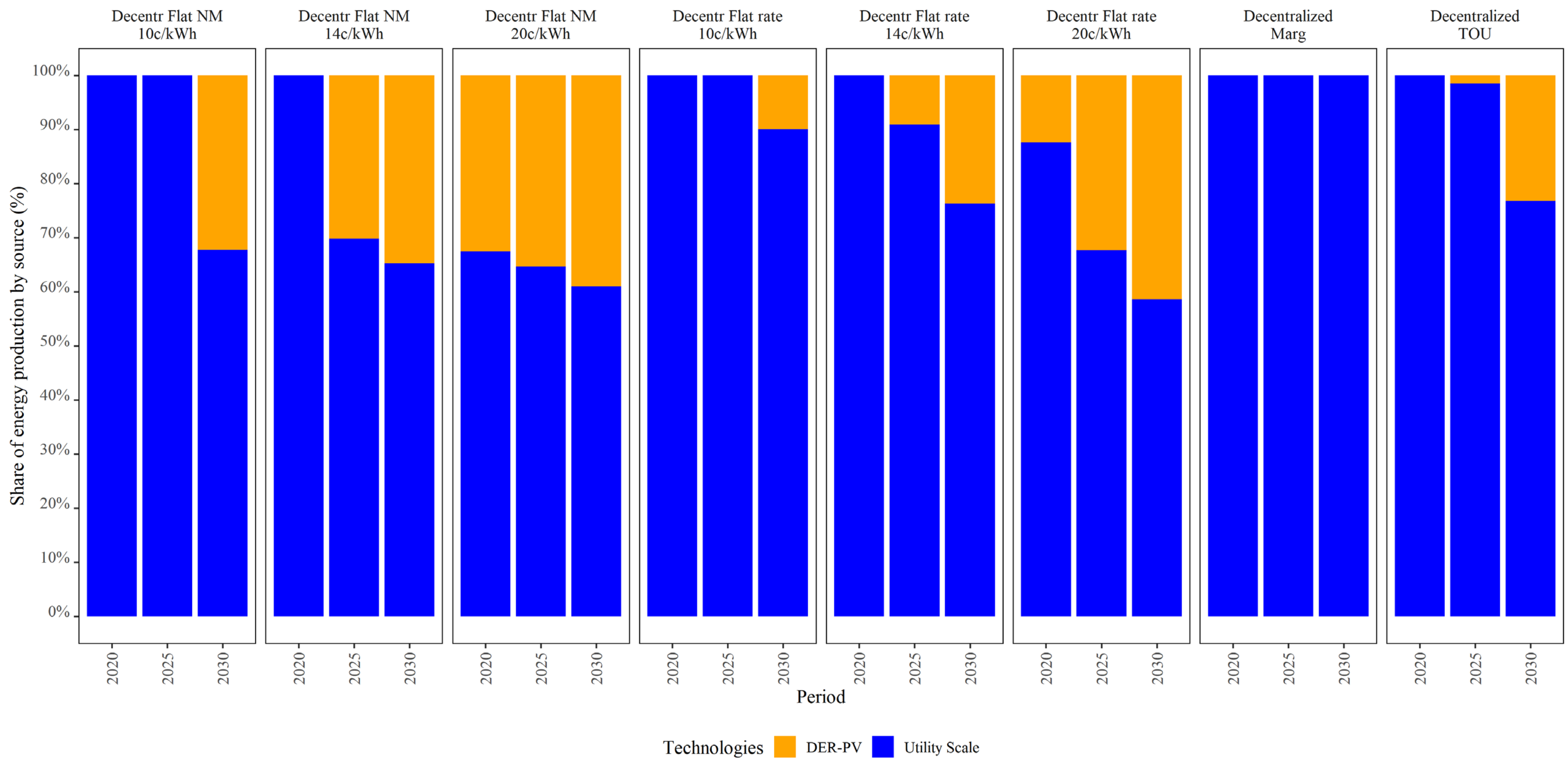
Decentralized model results reflect the expected decline in distributed PV capital cost over time. Noticeable differences appear only in period 2030, but higher rates stimulate higher adoption to period 2025, as more expensive utility-scale electricity makes DER PV investment attractive at a higher capital cost that will be reached earlier. For this case study, a flat rate of 14 ¢/kWh[8] drives 1.2 GW of DER PV adoption by 2025 and 3.1 GW by 2030 without a net-metering policy. The relative importance of DER PV costs and electricity rates for PV adoption is more evident in the decentralized scenario with *Utility's* TOU rates. The average annual mid-day rate—coincident with peak PV output—is about 12 ¢/kWh, whereas the peak rate of 25 ¢/kWh takes effect at 5pm when PV output is much lower. DER PV costs falling below 1.5 $/W by 2030 are necessary to spur behind-the-meter adoption.

Compared to the scenarios without net-metering, a monthly NEM scenario completely eliminates investments in distributed storage. Since high PV production in peak hours can compensate for hours with low PV production, distributed storage is much less valuable for customers if a monthly net-metering balance is available. Similarly, the availability of NEM drives earlier and larger adoption of DER PV compared to scenarios where it is not available. While DER PV adoption is contingent on rate levels, for a given rate level a NEM policy can drive two to three times more DER PV adoption compared to a non-NEM case. This is in part due to customers investing in DER storage in non-NEM cases, and also due to the economic incentives provided by the NEM policy.

The shares of distributed and utility-scale generation resources in the overall generation mix are reported in Figure 5.2. This representation captures only production technologies (no storage). We find that substantial customer PV adoption occurs in many of the decentralized scenarios as DER PV becomes more affordable. Increasing DER PV adoption proportionally reduces utility net loads and displaces utility-scale generation. Approximately 10–15% of demand is met using DER PV by 2030 with lower flat electricity rates, which increases to 40% with higher flat electricity rates in the 20 ¢/kWh range.

[8] A reminder that dollar values are in $2018. A 14 ¢/kWh rate corresponds to a nominal cost of 16.4 ¢/kWh in 2025 and 18.4 ¢/kWh in 2030 assuming a 2.3% average annual inflation rate.

Figure 5.2 Balance between utility-scale and distributed generation resources in the overall generation mix



Three sensitivity scenarios are tested to better understand the impacts of key variables: a low DER PV cost scenario (10% reduction compared to BAU), a low DER storage scenario (15% reduction compared to BAU), and a centralized scenario with higher distribution expansion costs (ten times more expensive than BAU). Results show that lower DER PV costs have minimal impact on its adoption in the centralized scenario (Figure B-2, SI). This suggests that very aggressive cost reductions would be needed to make DER PV adoption cost-effective under a centralized decision-making paradigm. In contrast, lower DER storage costs would drive about 100 MW more adoption of this resource in the centralized scenario, enabling the adoption of about 150-200 additional MW of utility-scale solar PV and displacing wind capacity (Figure B-2, SI).

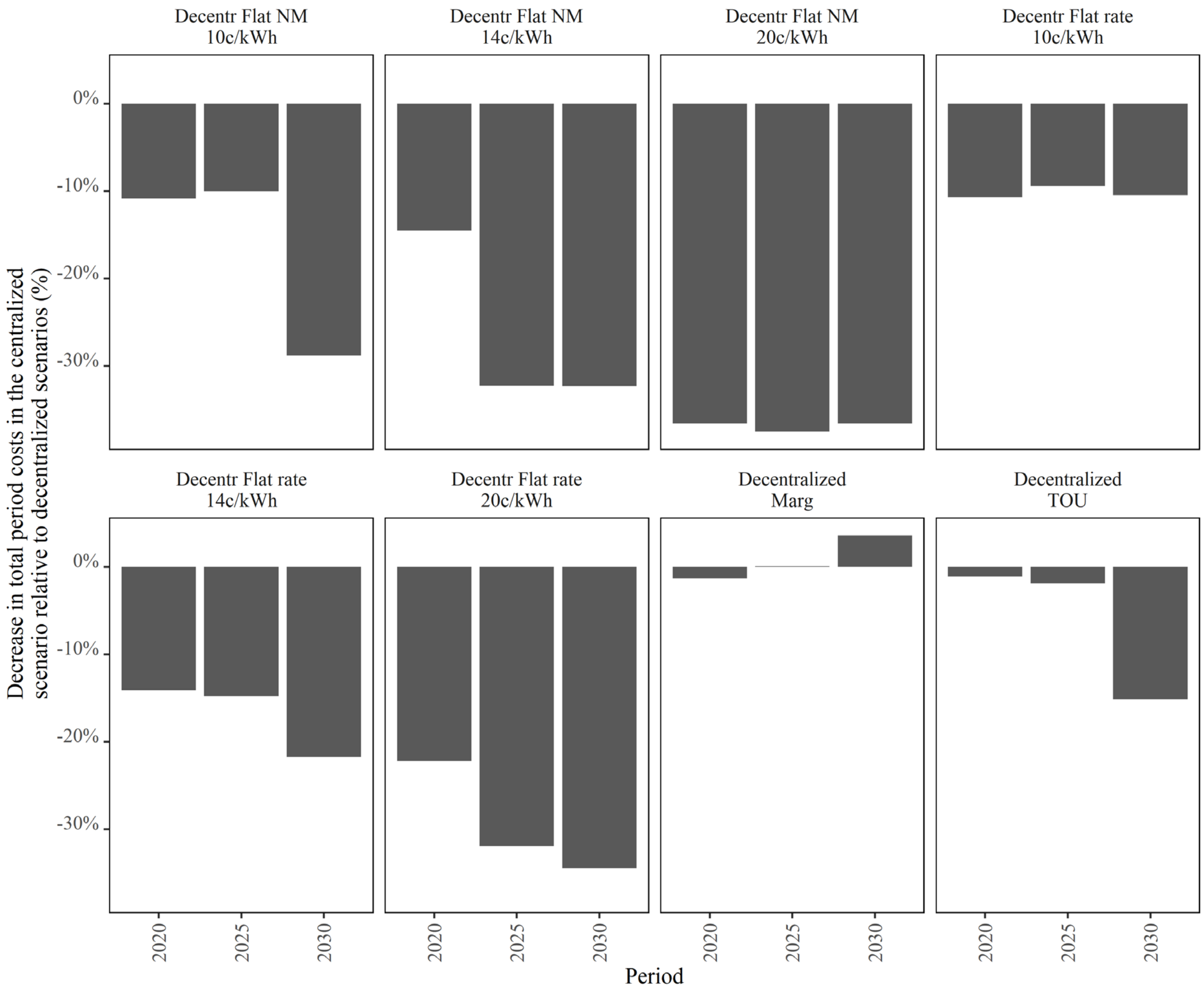
In the sensitivity results for the decentralized TOU scenario, lower PV costs trigger earlier adoption of the resource of ~1.5 GW in 2025 and an additional 0.7 GW in 2030 for a ~3.5 GW total in this period (Figure B-3, SI). Lower PV costs also drive adoption of about 0.5 GW additional DER storage compared to the original decentralized TOU scenario. In contrast, lower DER storage costs do not affect capacity deployment decisions in 2020 and 2025, but would trigger about 300 MW of DER storage and DER PV adoption in 2030. In general, the lower DER costs have modest impact on resource adoption across scenarios, with the exception of lower DER PV costs in the TOU scenario. Finally, higher distribution expansion costs do not impact resource adoption decisions, since the centralized model is already choosing a minimal amount of DER as cost-effective. The logic is that higher distribution costs may drive higher investment in DER as a non-wires alternative, but the low load growth for *Utility* makes this driver irrelevant.

In the decentralized scenarios, *Utility* cannot take advantage of the lower utility-scale PV costs that are correlated with DER PV cost declines, because the decentralized model follows a specific decision sequence with the customer deciding first and the utility following. The value of utility-scale PV drops with DER PV adoption given the high temporal correlation of their outputs. This may produce substantial cost inefficiencies, which we examine in the next subsection.

5.2 Economic Value of DER Integration

The first measure of economic value is calculated by comparing the costs of the decentralized solutions against the centralized decision-making optimum, viewed as a benchmark for comparison. Figure 5.3 reports how much less expensive the centralized scenario is compared to the decentralized scenarios, by period. In other words, the figure reports the percent savings of the total power system costs that would accrue should a centralized decision-making framework be adopted. We use this reporting scheme because the centralized scenarios are the “business-as-usual,” whereas the centralized scenario is the counterfactual.

Figure 5.3 Percentage decrease in total period costs in the centralized scenario relative to decentralized scenarios



The TOU decentralized scenario is constructed to reflect the case study's current residential rate structure. This scenario has very similar costs compared to the centralized scenario in the first two periods, but there are significant savings by the centralized approach in the last period (-15% cost difference). This cost difference occurs because DER PV and battery storage costs drop enough to become attractive to customers by 2030, and hence are heavily adopted in that period (see Figure 5.1). However, the same renewable resource cost trend makes utility-scale wind and PV more cost-effective over time compared to other distributed and utility-scale technologies. The centralized model serves demand more cost-effectively using utility-scale resources instead of DER PV. The centralized model has an NPV of about 7% less than the decentralized model with a TOU retail rate and up to 30% less than the highest flat rate cases (Table 5.1).

Table 5.1 Difference in net present value (NPV) of centralized scenario against decentralized scenarios

Scenario	Centralized Scenario Difference in NPV (%)
Decentr Flat rate 10¢/kWh	-10%
Decentr Flat rate 12¢/kWh	-12%

Decentr Flat rate 14¢/kWh	-17%
Decentr Flat rate 16¢/kWh	-24%
Decentr Flat rate 20¢/kWh	-30%
Decentr Flat NM 10¢/kWh	-18%
Decentr Flat NM 12¢/kWh	-23%
Decentr Flat NM 14¢/kWh	-27%
Decentr Flat NM 16¢/kWh	-32%
Decentr Flat NM 20¢/kWh	-37%
Decentralized Marg	1%
Decentralized TOU	-7%

The cost structures of both paradigms are consistent with their differences in investment choices. By 2030, the decentralized model produces a utility that has a much smaller distribution system because around one third of power is generated behind the meter. The TOU scenario does not significantly expand the distribution system. However, the centralized scenario expands the capacity of the distribution system by 50% to accommodate the native demand growth with little to no DER adoption.

Among the flat rate decentralized scenarios, we choose the 10 ¢/kWh case to compare against the centralized scenario because this is closer to the levelized cost of electricity in the centralized solution. The centralized solution has 7–19% lower costs than this decentralized flat rate. One explanation for this difference is that the centralized model deploys DER battery storage, whereas the decentralized model deploys utility-scale storage (see Figure 5.1). This is because it is generally not attractive for flat rate customers to adopt storage, particularly with a low electricity rate of 10 ¢/kWh. Since the customers do not adopt much DER storage, the utility plans around this by deploying less utility-scale PV and more wind and natural gas. By tailoring its utility-scale investments to the suboptimal (from the utility perspective) DER deployment decisions implemented by customers, the utility can only partially offset the loss of economic value stemming from behind-the-meter DER investments that diverge from those in the centralized solution for the whole power system.

The marginal cost decentralized scenario behaves as expected, with minimal cost differences compared to the centralized decision-making paradigm. In the marginal cost scenario, the customer faces rates that properly reflect the long-term marginal cost of the utility supplying power to that node on an hourly basis. It is worth noting that the decentralized solution based on marginal cost rates does not exactly match the results of the centralized scenario. Slight differences arise because the marginal costs computed during the preliminary run of the centralized model do not remain precisely accurate once the customer problem adds DER at some of the nodes. Essentially, the addition of DER can alter the marginal cost of supplying utility-scale power to each node at each timepoint, but the differences are minor enough that the marginal cost rates from the preliminary model run still induce a decentralized solution that comes quite close to the centralized optimum. In principle, TOU and critical peak pricing rate structures are implemented to at least roughly capture the temporal differences in the marginal cost of providing electricity at different times. However, it should be noted the marginal cost rates exhibit greater temporal variation as well as differences in rates across space. Marginal costs are such that customers would face a price exceeding 200 ¢/kWh on peak hours of the year, a rate that may be politically challenging to impose.

Finally, we develop a back of the envelope calculation to extrapolate these results to all DER PV installed across the U.S. This estimate involves first calculating the difference of DER PV capacity deployment and total system cost between the centralized and decentralized scenarios. Second, we divide these values to estimate cost savings per unit of DER PV capacity. Applying this ratio to existing U.S. DER PV capacity gives a rough estimate of the costs that could have been saved had a centralized framework guided investment and operation of these resources. Based on this simple approach, we find savings of $0.5 to $1.6 per watt of DER PV installed, which is 25% to 75% of current DER PV costs. We used data from the EIA's Electric Power Monthly [54] to estimate $500 million to $2.2 billion in annual savings nationally had existing DERs been centrally dispatched. This national-level estimate is relatively small compared to current utility revenues, because of relatively modest existing DER adoption in the U.S. It can be inferred that additional market penetration of DER technologies—as is expected—will lead to much larger costs than what is reported here unless this deployment follows a centralized decision making paradigm.

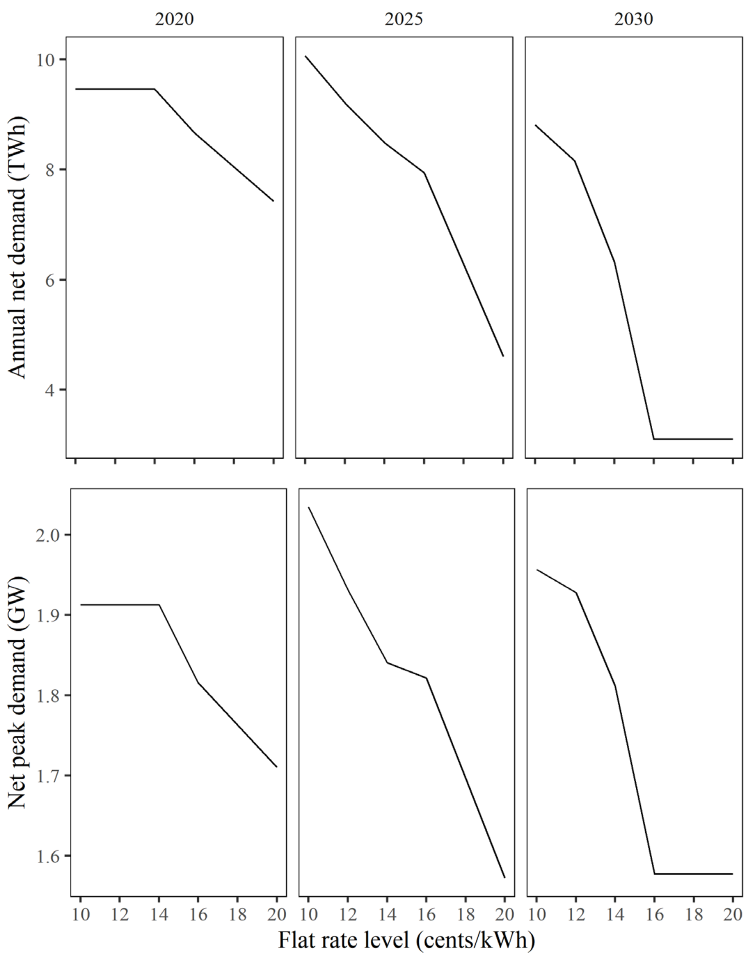
5.3 Price Elasticity of Net Load

The literature that focuses on how resource planning is addressing DER adoption finds that some utilities are devoting considerable effort to refining forecasts of distributed resource adoption (e.g. [4]). Key deployment drivers considered in forecasts include public policy, customer preferences, macroeconomic drivers, and DER economics. The latter driver includes DER capital costs, incentives, electricity prices, and rate design.

However, treating DER adoption as an exogenously forecasted input or consideration through scenario-based analysis misses an important causal linkage between utility electricity rates and DER adoption. To evaluate this causal relationship, we introduce the concept of the *price elasticity of net load* and use the GAP model case study to demonstrate its application. The price elasticity of net load connects the electricity rate to the net load the utility serves by capturing the effect of the rate on DER adoption and the effect of DER adoption on customers' demand for electricity supplied by the utility. As a consequence of decentralized DER decision-making, even if the final demands for electricity are fixed (as is the case in our modeling exercise), the residential and commercial demand served by the utility (rather than met using DER) depends on the rate structure due to behind-the-meter DER adoption that is rate-sensitive.

Figure 5.4 shows how the net energy demand (top) and net peak demand (bottom) vary with the flat electricity rate in each modeled period, for residential and commercial loads. Industrial loads are not included because DER deployment for this type of customer is restricted in the model, and hence their adoption is perfectly inelastic to rate levels by design. The net energy demand is calculated by subtracting the DER generation and net storage from the native demand, for each hour, and summing the weighted hourly samples to produce total annual net energy demand. The net peak demand is calculated by determining the hourly net energy demand for the whole system, and then selecting the maximum value in each investment period. We simulate the system expansion for a decentralized scenario using flat rates at 10, 12, 14, 16, and 20 ¢/kWh and then plot the net energy and net peak demand for each simulation-period combination. This method allows estimating a long-run price elasticity of net demand, as both variable and capital costs respond to the price changes. The simulation does not suffer from the identification issues in empirical studies because the variation in rate is entirely exogenous [55].

Figure 5.4 Net energy demand and net peak demand by period as a function of the flat rate level



The slope of the annual net energy demand decreases at an increasing rate over time, most likely as a reflection of the decreasing capital costs of DER. In 2020, net energy demand is roughly 98% of the native demand for lower rates and it decreases to 77% of native demand with a 20 ¢/kWh rate. However, by 2030 even the lowest rate produces a system whose net energy demand is 81% of the native demand, declining to a plateauing level of 29% at 16 ¢/kWh. The 2025 period serves as a good example of how elastic net energy demand is to changes in flat rates: net energy demand for residential and commercial sales decreases from 10.1 TWh at 10 ¢/kWh to 4.6 TWh at 20 ¢/kWh, a 54% reduction. Using the 2025 period, which does not have the boundary issues of periods 2020 and 2030, we use ordinary least squares (OLS) regression and find a price elasticity of net energy demand of -1.05. In other words, a 1% increase in retail rates correlates with a 1.05% decrease in net energy demand. This value is relevant for two reasons. First, it is similar to other values for long-run elasticities reported in the literature that lie in the -0.7 to -1.0 range [56–58]. Second, net demand is price elastic (elasticities are elastic above 1 in absolute value) and higher than prevailing studies on native demand that are largely based on historical billing data with little DER adoption. The elastic demand may indicate that higher levels of DER adoption could have a larger than expected effect on net demand.

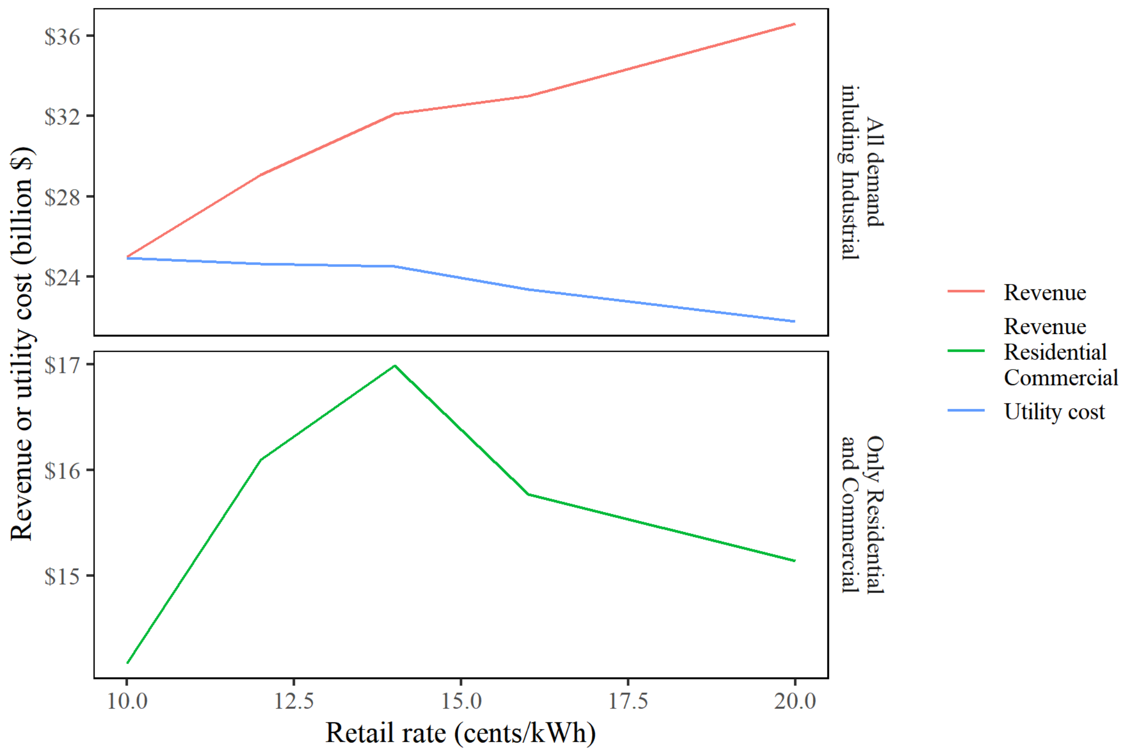
The dynamic for net peak demand is very different from that for net energy demand (Figure 5.4, bottom panel). Net peak demand decreases by around 10% across the range of flat rates studied, from 2.1 GW at 10 ¢/kWh to about 1.6 GW at 20 ¢/kWh for the period 2025. The changes in net peak demand across prices follow a similar pattern as the net energy demand, but with a much smaller overall effect. The main explanation for this result is that the price signal that customers receive in this scenario—a flat volumetric rate—does not reflect the true costs of peak demand. This flat rate does not induce DER investment decisions targeted to reduce peak demand, and hence net peak demand is relatively inelastic. Indeed, an OLS regression of net peak demand against price results in a -0.35 value, three times smaller than the elasticity of net energy demand. There are two additional explanations for the lower elasticity of net peak demand. First, peak demand for the *Utility* case study occurs in the evening hours when the value of DER PV is relatively low compared to its value during high insolation hours in the middle of the day. Second, in the absence of widespread DER storage or net-metering policies, customers have little incentive to oversize their systems to shave higher portions of peak demand.

The price elasticity of net load is relevant for utility resource planning because it connects electricity prices to utility net loads via the mechanism of customer-driven DER investment. The typical demand forecasts rarely account for the impact that higher rates have on DER adoption and, by extension, on net energy or peak demand. These results suggest that this shortcoming of traditional methods for incorporating DER into resource planning will become more problematic and pressing as DER costs decline and adoption expands. In addition, the contrasting elasticities of net energy demand and net peak demand suggest that widespread DER adoption may have a large impact on utility revenue recovery, but not on utility resource adequacy.

We use the decentralized scenario results to estimate utility revenue recovery and revenue requirements (i.e., utility costs). Revenue requirements are commonly used in regulatory planning frameworks as the metric to choose a preferred least-cost, risk-managed portfolio. Figure 5.5 shows how the utility revenue requirements and recovery change across the flat retail rate range of 10 ¢/kWh to 20 ¢/kWh over the entire simulation horizon. The utility cost or revenue requirement decreases as volumetric retail rates increase, following the same pattern as net demand shown in Figure 5.4. As customers adopt more DER, the utility incurs lower capital costs and fuel costs for utility-scale generation. Utility costs or revenue requirements decrease from $25 billion at the lowest rate to $22 billion at the highest rate. Simultaneously, the reduction in net demand translates to changes in physical sales, whose revenue outcome is mediated by the retail rate. In this case study, revenue increases roughly from $25 billion with a 10 ¢/kWh rate to $36 billion with a 20 ¢/kWh rate. Note that revenue increases only 50% with a doubling in the flat rate. This is because, as seen in the bottom panel in Figure 5.5, residential and commercial customers substitute grid power with DER power, reducing their contribution to utility revenue as rates increase.

The aggregate results mask the important inter-temporal differences that occur due to higher uptake of DER in the last period of the simulation. For all the flat retail rate levels, the utility revenue recovery is insufficient to cover utility costs in the 2030 period. The shortfall is approximately 10–20% at the lower retail rate levels but increases to 30–40% at the higher rate levels.

Figure 5.5 Utility cost and revenue for decentralized flat rate scenarios



These results have important implications for utilities that are not vertically integrated. A distribution-only utility will lose sales due to declining net demand, but it will not be able to internalize the cost reductions that are driven upstream in the generation segment. Conversely, utilities that are vertically integrated should be able to balance costs internally between the distribution and generation segments, although this is contingent on the regulatory framework to set rates and determine revenue recovery. In all cases, however, vertical integration may not be enough for utilities to be financially sustainable in cases where DER costs decrease in a manner similar to what was assumed for this study.

6. Conclusion

Electric utilities have traditionally relied on least-cost capacity expansion models with a single decision maker to support their resource planning processes and identify the most cost-effective generation and transmission investments to meet expected load. However, this approach is not well suited to incorporate behind-the-meter distributed resources, which in reality are installed and operated by customers attempting to minimize their own electricity bills or maximize profits rather than make the distributed energy resource decisions that are optimal for the power system as a whole. As the costs of distributed resources continue to decline and more customers adopt these technologies, it is important for utilities to understand the impacts of their own decisions on distributed resource adoption, and to tailor their utility-scale investments to DER deployment scenarios that customers are likely to pursue. Simultaneously, it is important for regulators to set rates that more closely approximate the true long-run marginal cost for the system, in order to drive customers to make socially optimal distributed resource adoption decisions [59].

6.1 Summary

In this paper, we adapted the GAP model for integrated generation, transmission, and distribution system expansion to analyze scenarios with a decentralized decision-making paradigm. This was accomplished by splitting the centralized decision-maker GAP model into a joint decision-making paradigm: a customer problem and a utility problem, which are solved sequentially in that order. In the customer problem, a representative customer agent minimizes the cost of satisfying all customer electricity demands by purchasing electricity from the utility at known rates and investing in distributed PV and battery storage. The electricity purchased from the utility—determined from the optimal solution to the customer problem—is used as an input to the utility problem, where these customer purchases define the net or remaining load that the utility must satisfy. Finally, the utility determines the least-cost generation, transmission, and distribution investment and dispatch decisions to supply the power demanded by customers. We apply this analysis technique to a case study based on a real utility from the Western U.S. ("*Utility*"), which has significant existing and projected residential PV adoption. We determined the least-cost system expansion using the original, centralized decision-maker GAP model and then compared that result to a number of decentralized decision-making scenarios based on alternative electricity rate structures and policy incentives (e.g., net-metering).

Several findings are relevant to utility planning processes and how these processes might need to evolve under a high DER penetration future. First, the cost reductions resulting from centralized decision-making can be substantial. In the *Utility* case study, the centralized solution that optimizes the entire integrated power system leads to a 23% cost reduction in 2030 compared to the prevailing time-of-use rate structure. It follows that integrating distributed resources into planning processes has significant potential economic benefits. Second, the centralized scenario generally resulted in reduced investment in distributed PV and increased investment in distributed storage compared to the decentralized decision-making solutions. In other words, the least-cost, centralized power system favors utility-scale PV and distributed storage, but behind-the-meter, customer-driven decisions tend to emphasize the opposite. Furthermore, increases in distributed PV adoption tend to displace utility-scale PV investment. The relationship of distributed and utility-scale PV as substitutes has important implications for utilities who are attempting to meet renewable resource requirements or mitigate environmental impacts. This relationship and substitutability are not currently considered in resource planning. Third, the choice of electricity rate structure is a key determinant of distributed resource adoption under the decentralized decision-making paradigm, and thus also the net loads ultimately served by the utility. We introduced the concept of price elasticity of net load to capture this causal chain, which connects rates to electricity demand. Accordingly, it will be increasingly important for utilities to understand the effects of their rates on net loads in order to make appropriately sized investments and ensure adequate revenue. Current planning practices do not generally consider the use of retail rates as a tool for bulk power system planning, even for utilities that are vertically integrated. Finally, we demonstrated how a utility could largely overcome the complications of decentralized distributed resource decision-making by supporting and asking regulators to consider electricity rates equal to time- and location-specific, long-run marginal costs. This approach induces customers to implement distributed investments and dispatch them in a way that is aligned with the overall least-cost pathway under the centralized decision-making paradigm. While these rates may not be feasible to implement at present, the benefits to be gained by transitioning to this rate-setting approach will rise over time.

A case study-based analysis can provide useful generalizations, within the limits of the case study. We discuss the potential generalization of results for the distribution-transmission-generation components, and then the behind-the-meter component. While regulatory framework vary widely across states and countries, the basic functions of the distribution utility are the same, including the jurisdictions with retail choice. In contrast, transmission and generation investment decisions in reality depend heavily on the industrial organization, this is, whether these components are vertically integrated or not. However, both vertically and non-vertically integrated frameworks strive to produce a least-cost and timely set of investment decisions, which is exactly what our model does. Hence, we believe that the relative decisions in investment on distribution, generation, and transmission are well represented in our model and can travel well to jurisdictions with or without vertical integration. It is important to remember that a model like GAP is best used in a "what-if" approach, by comparing a base scenario with multiple variations to understand the relative impact of specific parameters. This is exactly what our model, results, and discussion do, and hence these results should apply well to interconnected power systems across the globe.

Behind-the-meter decisions will vary substantially based on the rate structures and incentives that customer face. However, the rational decision making mindset of a customer that wants to minimize its bills is a generalizable assumption that is implemented in the decentralized scenarios in this paper. Our model implements a plethora of rate structures ranging from traditional flat rates to complex real-time rates (i.e. the long-run marginal cost scenario), to make the results travel to most jurisdictions. This suggests that the set of scenarios analyzed and their results should be applicable to most states and countries around the world where customers face a regulated rate and utilities bill and collect revenue based on those same rates. We believe these assumptions and conditions make the behind-the-meter decisions also generalizable across jurisdictions.

6.2 Future Research Needs

This study is the first attempt to compare centralized and decentralized decision-making paradigms and several aspects of the model and method could be improved.

First, model optimization improvements could be undertaken to set rates exactly equal to long-run marginal costs by making them decision variables chosen by the utility. This alternative formulation is essentially a leader-follower game, where the utility explicitly selects its own rates to minimize overall system costs while anticipating the effects of its rates on customer investment on distributed resources. However, this approach is more computationally challenging than the method implemented in this study.

Another avenue for future research would involve incorporating transmission and distribution infrastructure retirements into the model, which are not currently represented in the modeling framework. As transmission and distribution infrastructure comes to the end of its useful lifespan, it is important to reconsider the relative economics of investing in the utility-scale bulk power system versus behind-the-meter distributed resources.

This study was limited to analyzing the investment and dispatch decisions using the same decision-making model. However, it is possible that consumers will invest in distributed resources and then outsource the dispatch and management of these resources to an aggregator. It is also possible that a third party owns the infrastructure and charges a fee to the consumer, who in-turn dispatches the resource. In the first alternative, the consumer owns the asset(s), but another operator—potentially following a centralized approach—makes the dispatch decisions. In the second alternative, a third party—potentially the utility—owns the resources and lets the consumer make the dispatch decision. These two alternatives could be studied with modest adjustments to the modeling framework.

More generally, further research could explore the capabilities of different rate and incentive structures to induce customers to make distributed resource decisions that are more closely aligned with the true least-cost expansion of the entire electricity system. Setting rates equal to long-run marginal costs is a very effective way to achieve this in principle, but it may not be feasible to implement in reality. Therefore, extensions of this research could consider a broader range of rate structures (e.g., time-of-use, critical peak pricing, tiered rates, demand charges) to compare their potential to properly guide customers toward more optimal resource choices.

Finally, this analysis showed that the centralized solution included less distributed PV deployment, but more distributed storage deployment, relative to the decentralized outcomes. This finding suggests that additional research could evaluate incentives to encourage greater customer uptake of behind-the-meter storage systems. The price elasticity of net load concept shows how the availability of economically competitive DER makes net demands—and therefore, utility revenues—more sensitive to electricity rates. Future work should explore new business models to ensure that utilities can generate sufficient revenues to cover their costs while incentivizing socially-optimal levels of distributed resource adoption.

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