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by

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Abstract

Solar and wind power are now cheaper than fossil fuels but are intermittent. The extra supply-side variability implies growing benefits of using real-time retail pricing (RTP). We evaluate the potential gains of RTP using a model that jointly solves investment, supply, storage, and demand to obtain a chronologically detailed dynamic equilibrium for the island of Oahu, Hawai'i. We find that RTP reduces costs in high-renewable systems by roughly 6 to 12 times as much as in fossil systems holding demand assumptions fixed, markedly lowering the cost of clean energy integration.

Keywords: Renewable energy, real-time pricing, storage, demand response, optimization.
JEL codes: Q41, Q42, Q53

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1 Introduction

Technical progress has lowered the cost of wind and solar power to make clean, renewable energy competitive with coal and natural gas. Battery storage costs are also falling, which is growing electric vehicle use and could help electric grids transfer energy from times when it is plentiful to times when it is scarce. However, the intermittency of renewables imposes significant challenges, especially over seasonal and other longer-term imbalances that are not easily accommodated using battery storage.

Addressing these challenges efficiently requires a portfolio of generation assets selected optimally in conjunction with potential demand-side adjustments. Real-time retail prices (RTP) that reflect the incremental cost and marginal willingness to pay for electricity are a well-known but rarely implemented solution to incentivize the demand side (Borenstein and Holland 2005, Borenstein 2005, Borenstein and Bushnell 2022).[1] If electricity were priced at its incremental value and cost, there would be new, powerful incentives to efficiently store energy on a distributed basis or otherwise shift or adjust consumption from times and places of relatively scarce renewable supply to times and places of plenty. Automated smart devices acting on customers' behalf are already available and could be refined to aid such responses, but remain rare because incentives are limited (Bollinger and Hartmann 2020). One reason could be that few utilities and regulators are aware of the potential, or perceive potential gains as small, which they seem to be in fossil systems.

In this paper, we develop a model of power supply and demand to examine the extent to which RTP could increase the social benefits of clean power with intermittent renewables. We illustrate this potential by integrating a flexible demand system, one that includes both overall price response and heterogerogenous interhour substitution possibilities, into a long-term planning model that jointly solves for optimal investment and real-time operation of the system. From this holistic model we can see how different aspects of demand response feedback and influence both chronological operation and the portfolio of generation investments, in full, long-run dynamic equilibrium. Holding all else the same, including the demand system, we show how RTP versus flat pricing engenders different investment and more consumer and social benefits in high-renewable systems as compared to fossil systems. Because existing evidence on the degree and nature of demand response is limited, we consider a wide range of assumptions about demand and other assumptions, like technology costs.

To derive these results, we bring together the engineering and economic literatures and improve existing models in several ways. First, we simultaneously solve for investment in

[1] There are a few exceptions. Several states in the US have implemented RTP since early 1990s (Barbose, Goldman and Neenan 2004), and Spain introduced RTP in 2015 (Fabra, Rapson, Reguant and Wang 2021). While RTP did show some early success, others have shown limited participation, possibly due to varying degrees of marketing effort by utilities (Barbose et al. 2004, Goldman, Barbose and Neenan 2006).

generation and storage capacities, real-time operation of the system, and a demand system with different interhour elasticities for different end uses, as well as substitution between electric power and other goods and services. Both supply and demand sides of the model can provide reserves—upside and downside buffers to guard against short-term imbalances in supply and demand. The model, an extension of *Switch 2.0* (Fripp 2012, Johnston, Henriquez-Auba, Maluenda and Fripp 2019) is open source and adaptable to other settings.[2] Finally, it better accounts for the wide range of weather- and time-contingent circumstances by using a strategic sample of days that are modeled in chronological detail. This sampling is critical given both supply and demand are highly weather-dependent in clean-energy systems. Here we introduce a novel two-stage method of selecting the sample days. In the first stage, we cluster days by daily solar radiation, wind, and nominal demand, and select the central day in each cluster. The second stage then identifies the most-difficult-to-serve day over two years (727 days modeled in hourly chronological detail) while holding fixed the capital selected in the initial stage. The most-difficult-to-serve day is then added to the initial sample, and the whole joint system, including capital, is re-solved.

We apply the model to the island of Oahu, Hawai'i, for several reasons.[3] First, its scale is large enough to be emblematic of larger, more complex systems, but small enough to be holistically modeled. Second, given Oahu's isolation and lack of connectivity to other Hawaiian islands, intermittency is an acute problem, since connectivity with other regions is not economically feasible. Third, Hawai'i was among the first to adopt an ambitious renewable portfolio standard—100 percent renewable by 2045—which makes the analysis especially relevant to actual policy implementation. Fourth, Hawai'i depends on oil for its power production, making wind and solar power cheaper than fossil fuels today, so it is early to face an economic crossover that other regions will face in the future, as wind, solar, and storage move toward undercutting coal and natural gas.

The main contributions of the paper are threefold. First, we estimate the costs, benefits, and optimal generation mix of a 100 percent renewable energy system that accords with Hawai'i's renewable portfolio standard (RPS) and compare it to a conventional fossil-fuel power system

[2]Earlier versions of the model, which lack reserves and demand-side integration, have been implemented for California, the Western United States, and other areas (Nelson, Johnston, Mileva, Fripp, Hoffman, Petros-Good, Blanco and Kammen 2012, Mileva, Nelson, Johnston and Kammen 2013, Wei, Nelson, Greenblatt, Mileva, Johnston, Ting, Yang, Jones, McMahon and Kammen 2013, Ponce de Leon Barido, Johnston, Moncada, Callaway and Kammen 2015, Sanchez, Nelson, Johnston, Mileva and Kammen 2015, He, Avrin, Nelson, Johnston, Mileva, Tian and Kammen 2016). Some other recent capacity expansion models better integrate real-time operation of the system and investment decisions, but use simpler accounts of demand response, and can only consider short-run planning horizons for investment (one year at time) (oemof Developer Group 2017, Dorfner 2018, Brown, Hörsch and Schlachtberger 2018, Palmintier and Webster 2015, van Stiphout, Vos and Deconinck 2017, O'Neill, Krall, Hedman and Oren 2013, Jenkins and Sepulveda 2017).

[3]Oahu is the state's most populous island (about 1 million), which comprises roughly two-thirds of the state's population and consumes over three-quarters of the state's power. The island supports a large urban city (Honolulu), plus a substantial tourist industry and several large military bases.

(Fossil) and a least-cost system with no constraints on the generation mix (Unconstrained). The model characterizes a full equilibrium in each case, jointly solving for investment, real-time operations with reserves, and a time-varying price-responsive demand system. To our knowledge, such dynamic equilibrium models have not been solved in the economics or engineering literature.[4] Second, for each kind of system (RPS, Fossil, and Unconstrained), we evaluate the welfare improvement of having real-time marginal-cost pricing that can efficiently mobilize demand-side resources as compared to flat prices, which cannot. Lastly, we evaluate how much gains from RTP are distributed across different types of customers with a different degree of flexibility or interhour substitutability.

Cost assumptions for a wide range of power generation and storage alternatives, from which an optimal portfolio is selected, are based on those in the Power Supply Improvement Plan (PSIP) of the local utility, Hawaiian Electric Company (HECO).[5] We consider scenarios for which costs equal recent-past assumptions (2016), as well as scenarios that use the lower costs projected for renewable and battery technologies in 2045 in the PSIP.[6] The analysis is a single-stage analysis in the sense that each scenario assumes the optimized system is built at one point in time, although pre-existing assets can be retained. We do this to make clear comparisons of high-renewable and fossil systems, and to show how much renewable power would be selected in optimized systems with flat prices versus RTP. In practice, an optimal plan would make investments gradually over time; *Switch* has the capacity to formulate such a long-term plan, although we do not consider it in this paper.

Consistent with earlier studies, we find that RTP of power provides little social benefit in conventional fossil-fuel systems, only 1.5 to 2.5% of baseline annual expenditure depending on technology and fuel costs and interhour substitutability under baseline assumptions. These baseline results assume an overall demand elasticity of 0.1, that 50% of the vehicle fleet is electric (EV), and benefits of smart charging under RTP. However, RTP leads to a much greater social benefit of 8.7 to 19.4% in a 100% clean system with otherwise identical baseline assumptions. We believe these assumptions underlying these estimates are fairly conservative. If, however, we optimistically assume an elastic overall demand of 2, which is not observed in history but *might* arise in a future that is more automated, has more price variability, and prevalent free or near-free electricity, the benefits of RTP are much higher. Specifically, the value of RTP versus flat pricing roughly doubles in the fossil system (up to 4.9% of baseline expenditure) and roughly triples in the 100% clean system (up to 62.7% of baseline expenditure). We also

[4] A working paper by Butters, Dorsey and Gowrisankaran (2021) considers optimal investment and operation of batteries in conjunction with real-time operation of the system, but does not jointly optimize other forms of storage or new generation sources, and they take demand as exogenous.

[5] See https://www.hawaiianelectric.com/about-us/our-vision.

[6] These cost assumptions are generally conservative. At this writing, costs for renewables and storage are closer to 2045 assumptions than to 2016, while fossil fuel prices, projected to rise in the PSIP, are notably higher than 2016.

find greater benefits of RTP in high renewable systems if, in addition to elastic demand, 100% instead of 50% of the vehicle fleet is electric, as EVs comprise a large amount of easy-to-shift demand. Finally, we find that even inflexible demand types normally benefit from RTP, and in some cases, nearly as much as flexible demand types do.

The other main finding is that clean energy systems are generally less expensive than conventional fossil systems. Even with flat pricing, a 100% clean energy system is 30% less expensive than a fossil system and only 5% more costly than a least-cost system that is 90% clean, excluding externality costs. With RTP and optimistic inter-hour flexibility, a 100% clean system is 44% less expensive than a fossil system and only 1.7% more costly than a least-cost system that is 97% clean. If demand is more elastic (elasticity = 0.5 instead of 0.1), the social benefit with RTP relative to a fossil system with flat pricing exceeds 60% of expenditure in the fossil system (costs fall while consumption benefits rise substantially), and 100% clean is least-cost, not even counting externalities. Thus, as we transition from fossil-based to clean-energy electricity systems, the benefits of RTP grow by roughly an order of magnitude (6 to 12 times) holding all other assumptions the same, while causing a meaningful reduction in the cost of integrating clean renewable energy.

These numerical results may represent a lower bound on the gains of location-specific RTP, for several reasons. First, we ignore pollution externalities, and since RTP favors clean energy, it procures an external benefit. Second RTP increases the elasticity of residual demand faced by large-scale generators during constrained times, thereby limiting market power (Borenstein, Bushnell and Wolak 2002a). Thirdly, it implicitly creates free entry into the energy storage market, enhancing competition. And finally, RTP will provide alternatives to, and ease evaluation of, expensive grid upgrades normally financed by rate-of-return regulation. Explicit analysis of these auxiliary benefits of RTP is beyond the scope of this analysis.

The rest of the paper is organized as follows: Section 2 explains conceptually how the value of RTP differs in conventional and high-renewable power systems; Section 3 characterizes the demand system and how we calibrate it; Section 4 reviews *Switch* which optimizes investment and operations, as well as a Dantzig-Wolf algorithm used to equilibrate supply and demand and thereby optimize the joint system; Section 5 summarizes capital and input cost assumptions and the wide range of scenarios we consider; Section 6 summarizes the results; and Section 7 concludes with a discussion about the various reasons we find clean energy systems to be more affordable than other have, how reasonable assumptions about potential demand flexibility may be, how the results may extend to larger, continent-scale systems with more inter-regional connectivity, as well as some of the practical obstacles to optimal portfolio selection and implementing RTP.

2 Real-Time Pricing in Conventional and High-Renewable Power Systems

Recent research shows that intermittency combined with the high cost of storage can increase the cost of renewable energy from a system perspective (Gowrisankaran, Reynolds and Samano 2016, Bushnell and Novan 2021), while transferring rents from incumbent producers to renewable-energy generators and consumers (Liski and Vehviläinen 2020). A challenge for intermittent renewables is that modern infrastructure has been built around systems with centralized and easily controllable generation. Electric grids operate through balancing authorities that adjust electricity generation on timescales ranging from seconds to years, to perfectly balance supply with presumably inelastic, time-varying demand. Although marginal generation costs vary over time in a conventional system, regulated retail prices tend to be flat, giving rise to well-known inefficiencies (Borenstein and Holland 2005, Borenstein 2005, Borenstein and Bushnell 2022). Incremental costs, however, do not normally vary that much in conventional systems, except when demand approaches the capacity constraint and marginal cost rises substantially. A critical concern is the strategic withholding of power during these constrained times, which can cause tremendous spikes in wholesale prices (Borenstein et al. 2002a). RTP or critical peak pricing can help resolve much of the inefficiency that derives from flat retail pricing in conventional systems, curbing peak demand and thereby reducing investment in rarely used peaking power plants, and also reducing market power (Blonz 2016). Foregoing potential demand response creates some deadweight loss in conventional power systems but the loss will be much greater in systems with a large share of intermittent energy. With renewable energy, the value of real-time pricing involves much more than simply curbing peak demand. It involves shifting demand toward renewable supply.

To better appreciate how the potential value of RTP and demand response changes with renewables, it helps to consider the integration process as it has progressed thus far. Ample subsidies have helped to speed adoption of renewables and push down costs via learning-by-doing (Van Benthem, Gillingham and Sweeney 2008). Today, solar and wind power are the cheapest sources of energy on a levelized basis, even without subsidies. Having zero fuel costs and minimal operating costs, almost all costs are fixed, with supply varying only with sunlight and wind speed. When intermittent renewables make up a small to moderate share of total generation, the existing infrastructure accommodates their variability in much the same way it has always managed time-varying demand, by counterbalancing with directed generation from thermal power plants. As larger shares of renewable energy are accommodated using this conventional approach, system-level costs can rise significantly above the levelized costs from any particular source.

Cost accretion happens mainly for two reasons. First, controllable generation must be built or retained to compensate for periods of low renewable power production. These plants may burn either polluting fossil fuels or high-cost biofuels and may have higher marginal cost than coal or nuclear. Providing spinning reserves from thermal power plants—ramping them up and down to compensate for short-term variations in demand or renewable production—requires running these plants at inefficient fractional load levels. Renewable power and spinning reserves also reduce the share of demand that can be served by coal and nuclear "base load" plants that are designed to operate continuously at full capacity. This is a key reason why renewables paired with cheap natural gas have cut severely into the rents gleaned by nuclear and coal power. Second, as more intermittent renewable power is added to the grid, there will be times when supply exceeds demand net of minimum operating capacities of thermal plants. During these times renewable energy must be curtailed (i.e., discarded). California, Hawai'i, Texas, Ireland, and many other places with high renewable penetration already curtail a considerable amount of clean power, even while utility customers can simultaneously pay 30 cents per kWh or more for electricity.[7]

With retail prices far above the incremental cost of generation (zero or negative during curtailment), flat pricing creates substantial marginal inefficiency with flat pricing, even with renewable energy penetration far below eventual decarbonization goals. The value of RTP is thus more multifaceted as compared to the conventional case. It can curb demand during times that are difficult to serve (which may or may not be peaks), while also encouraging greater use, and perhaps engendering new sources of demand, when incremental costs are low or zero. The socially efficient price might even be negative during curtailment if extra clean power consumed during a curtailment event would substitute for polluting energy that would otherwise be consumed at a different point in time.

High-cost critical peaks will also occur at different times and have a different character. Peak demand normally occurs during sunny and sometimes windy summer days that tend to have ample supply from renewables, and thus could be among the easiest to serve in a high-renewable system. Instead, the most costly times to serve will be when renewable supply is unusually low relative to demand for an extended period of time.[8] More generally, demand response can effectively substitute for centralized storage, by shifting use from one time to another, using demand-side thermal storage or strategic automated timing of flexible demands,

[7] Indeed, as documented by Borenstein and Bushnell (2022) and (Reguant 2019), retail prices generally exceed marginal cost because substantial fixed costs are typically recovered using volumetric rates, exacerbated by block pricing. During curtailment, this inefficiency becomes especially stark.

[8] At this writing, in early Summer 2022, Texas is experiencing record heat and demand for electricity and their system is handling it easily due to high production of wind and solar energy (see `https://www.cnn.com/2022/06/14/us/texas-energy-record-solar-wind-climate/index.html`). In the future with far more solar power, net production risk will be even smaller during such times. In the model we present here, the most difficult day to serve in a high-renewable system over 727 days of high-resolution benchmark weather and demand data is November 22, 2008, which was very cloudy with little wind, but below-average demand.

like electric vehicle charging and appliance use, by developing new flexible sources of demand, or by indulging or sacrificing comfort or convenience during especially low- or high-priced times. Much of these responses could be automated using smart systems, with or without direct connectivity to the control room of the balancing authority. These kinds of demand responses could reduce the costs of storage and/or costs associated with fractional operation of thermal power plants, in addition to limiting costs of rarely-used peaking power plants and reducing market power.

The interplay between demand-side adjustments and the optimal portfolio of generation and storage investments is fairly complex. On the supply side, the available generation technologies from which to select a portfolio matters, as does the cost of storage. Real-time operations depend on the weather, history-dependent system status, and expectations about the future, as these will govern the management of storage and spinning reserves. On the demand side, the time-of-day, day-of-week, and weather-specific factors matter, both for the general level of demand, and the degree of potential responsiveness and intertemporal substitution. The novelty of this paper is that we consider all of these factors simultaneously in order to discern the potential value of RTP in both conventional and high-renewable systems, all in an effort to shed light on the importance of retail pricing reform to decarbonization efforts.

3 Demand

A key novelty of this paper is its integration of a fully-specified interhour demand system with *Switch*, a state-of-the-art planning model that jointly optimizes investment and chronological, hourly operation of a power system. We, therefore, begin by describing the structure of the demand system and how we calibrate it. The structure of the demand system, and the range of assumptions we consider, is intended to encompass a wide scope around what might be possible in a future with real-time pricing and automated response. The idea is to see how much more valuable RTP is in clean, renewable systems versus fossil systems across this range of possible demand systems.

3.1 A Nested-CES Demand System

The demand system is comprised as the sum of three nested, constant elasticity of substitution (CES) utility functions that represent different types of demand. The outer layer of each utility function assumes just two goods, electricity and all other goods, with a constant elasticity of substitution θ, which represents overall demand for electricity. The nested layer considers electricity demand in each hour within each 24-hour day, with an interhour elasticity of substitution σ. Aggregate demand in any given day is comprised as the weighted sum of three representative pseudo-customers with different σ values, *flexible* ($\sigma_f = 10$), *medium flexibility* ($\sigma_m = 1$), and *low flexibility* ($\sigma_l = 0.1$). This means, holding average price within a day constant, a relative price difference of 5% between hours within a day will cause about 50 percent, 5 percent, or 0.5 percent share baseline demand to be shifted from the high-priced hour to the low-priced hour, depending on the pseudo-customer type.

This demand system can embody a wide range of demand responses. If one were to assign all load share to low-flexibility pseudo customers, the demand system would nearly collapse to a simple demand system that lacks interhour substitutability, prevalent in earlier studies of RTP. If, however, we can identify sources of demand that may be easily rescheduled to different times at minimal cost or disutility, the flexible demand component is well suited, as the interhour elasticity of 10 implies little implicit cost to such rescheduling.[9] The medium-flexibility pseudo customers capture shiftability between these two extremes. By attaching different load shares to different pseudo-customers, one can reasonably approximate almost any degree of load-shifting potential. Note that, these inter-hour elasticity parameters pertain only to shiftability of demand from one hour to another within a 24-hour period, not to the overall amount of electricity consumed, which is captured by the outer elasticity (θ).[10] By varying the outer elasticity and shares of load attached to each type of pseudo-customer, we can assess how much flexibility and overall responsiveness matter in conventional versus high-renewable systems. Nevertheless, the functional form is approximate/heuristic; existing evidence cannot yet inform the actual potential of demand response at a large scale, even if early experimental evidence is encouraging (Bollinger and Hartmann 2020).

In the computational model, we partition a baseline load profile, drawn from actual historical hourly demand, into these three pseudo-customers. The pseudo-customers thus differ with regard to their budget and with regard to their calibrated share parameters (β_h), because their load profiles differ. The calibrated share parameters also differ by hour of day, and day of year, to account for time-of-day and weather. We explain how implement this partition after formally characterizing demand.

To formalize this demand system, denote the calibrated load shares on day d and pseudo-customer i by β^{id} and income by $M^{id} = \frac{E^{id}}{s}$, where E^{id} is the baseline expenditure of pseudo-customer i on day d, and s is the share of baseline state income spent on electricity. Thus, define the demand for a pseudo-customer i on day d in hour h as $x_h(p|\bar{p}, \sigma_i, \beta^{id}, M^{id})$, using the definition in equation 3. Aggregate demand on day d and hour h is given by the sum of the demands from the three pseudo-customers:

$$x_h^d(p|\bar{p}) = x_h(p|\bar{p}, \sigma_l, \beta^{ld}, M^{ld}) + x_h(p|\bar{p}, \sigma_m, \beta^{md}, M^{md}) + x_h(p|\bar{p}, \sigma_f, \beta^{fd}, M^{fd}) \qquad (1)$$

[9] Some engineering studies simplify consideration of such demand response by explicitly rescheduling such demands as if the grid operator were making these decisions, rather than solving for equilibrium as we do here.

[10] Of course one could build an even more flexible demand system by assuming different overall demand elasticities to different customer types or uses.

The complete specification and derivation of the demand system is provided in the Online Appendix.

While this demand system provides an intuitive and relatively simple way to embody a range of heterogenous demand responses and inter-temporal substitutability that vary over hours of day, seasons, and weather-related circumstances, it may under- or over-estimate actual technical possibilities. For example, it assumes the same degree of substitutability between any two hours within the same day. At least for some kinds of demand, substitutability may be greater for hours nearer in time. It may also be an imperfect characterization of demand-side storage, where the cost of shifting pertains to a loss of energy (e.g., heat loss or gain from thermal storage) as opposed to a cost of utility and/or capital expenditure. At the same time, the demand system assumes zero substitutability between days, when in reality substitution between late in one day and early in the next may be fairly elastic. While this later assumption may under-estimate the overall degree of flexibility, the structure makes it easy to scale up a sample of representative days throughout the year to parsimoniously represent a portfolio of days with weather and demand that are chronologically matched with supply.

3.2 Shares of Flexible Demand

This section describes how we estimate baseline loads for each kind of pseudo-customer. We use hourly aggregate demand data for Oahu from the Federal Energy Regulatory Commission to calibrate hourly load shares that are coincident with solar and wind data used in modeling the supply side. This calibration accounts for the covariances between intermittent supplies of each potential wind and solar project and aggregate demand. However, because some kinds of demand are likely to be more time shiftable than others, we develop alternative interhour flexibility scenarios based on estimated load shares that are known to be shiftable using current technologies: air conditioning, water pumping and water heating.

Air conditioning demand is shiftable using ice storage, wherein ice is generated when electricity prices are low, and used for cooling instead of running the compressor when electricity prices are high. These systems can be retrofitted onto existing air-conditioning systems. A number of companies already market this technology to reduce *demand charges*[11], to respond to real-time variation in prices, or provide contingency or regulating reserves to the balancing authority.[12] Such systems may only require different, smarter controllers and network connectivity. A considerable amount of flexible power is also used to pump water from aquifers to

[11] Demand charges, which are common for commercial electricity customers, link monthly bills to the highest kW draw, typically averaged over a 15-minute period, from each commercial customer during the month or year. However, because peak demand by an individual customer is unlikely to coincide with the system peak, demand charges may do little to improve efficiency relative to real-time pricing (Borenstein, Jaske and Rosenfeld 2002b).

[12] *Regulating reserves* balance the electricity system in real time as demand fluctuates from moment to moment while *contingency reserves* keep the system stable in response to larger disruptions, such as a power plant unexpectedly falling off line.

storage reservoirs and tanks on hillsides; water is then gravity fed to homes and businesses. Currently, most water pumping is done at night, because the water municipality receives a slight discount under current time-of-use pricing. There should be a considerable amount of flexibility in when pumping could occur, a flexibility that is mainly constrained by the capacity of water storage. A number of companies have also developed smart water heaters, which can heat proactively in relation to power availability (or prices) and typical use patterns instead of reactively to hot water use. All of these systems embody an implicit form of storage that may be less expensive than batteries, compressed air, pumped-water hydroelectricity or other means. These systems can also provide a source of reserves to help maintain system stability in the face of unexpected load fluctuations.

By considering loads only from these three principle sources, we believe our estimates of demand-response potential should be conservative, because other kinds of electricity demand for which we could not obtain estimates, or for which current technologies do not exist, may nevertheless prove shiftable if appropriate incentives and technologies were to be made available. For example, refrigerator/freezers and swimming pool pumps likely have large, time-shiftable loads, but we do not explicitly consider them in this study because we were unable to obtain data on their real-time use.

Another consideration is that over 70 percent of total demand on Oahu derives from commercial customers, some of which have electricity already metered at 15 minute intervals or less to accommodate demand charges specified in commercial tariffs. Commercial customers have proven a willingness to participate in RTP when the tariff is well-marketed to customers (see (Barbose et al. 2004), especially the case of Georgia Power). The utility has also begun to install smart meters for other customers. Even without smart meters, integrators could implement a wide range of demand-response services, including reserve provision, by using other forms of network connectivity to control power consumption of certain designated devices. Alternatively, devices could be programmed to forecast and respond to price signals automatically.

Estimates of shiftable load in each hour of each month are drawn from Navigant Consulting (2015), a private consulting report commissioned by Hawaiian Electric, a copy of which was submitted to the Public Utility Commission. Although much of the report is redacted, obscuring the methods used to estimate load shares from alternative uses, it is the only available load share data, specific to Oahu, that we have been able to obtain. The starting point for our estimates is a graph in the report depicting September 2025 projected end-use loads by hour of the day. We measured the bars in the graphs by hand to estimate load shares in each hour for this month, and summed those for air conditioning, water heating and water pumping to obtain an estimate for the mid-September share of potentially shiftable load. Because loads vary over time, and tend to be higher when it is warmer, presumably due to greater use of air conditioning, we adjusted load shares for other months to account for this seasonality. We made this adjustment using hourly load estimates provided in the Navigant report for February, May, August and November of 2014, but were not partitioned by end use. These hourly loads were regressed against a polynomial of hour-of-day and average temperature in each month.

$$Load_{mh} = \beta_0 + \beta_1 h + \beta_2 h^2 + \beta_3 h^3 + \beta_4 PV_{mh} + \beta_5 T_{mh}.$$

where $Load_{mh}$ is demand in hour h of month m, h hour of the day, PV_{mh} is distributed generation from photovoltaic solar (which may be associated with temperature), and T is temperature. We attribute temperature-sensitive load to air conditioning, and then using load shares given for September 2025 as a baseline, we infer the air conditioning share for the other months, linearly interpolating between February, May, August and November. Load shares in each hour attributable to water pumping and water heating is assumed to be same across all months of the year.

We consider three different scenarios (optimistic, moderate, pessimistic), each of which assigns different shares of the potentially-flexible and other load to pseudo-customers with different interhour substitutability. The assumptions for each scenario are reported in Table 1. In figures 1 we plot the implied shares of highly flexible, moderately flexible, and inflexible demand in total and by hour and month for each of the three scenarios.

In the end, we cannot know in advance how much demand is truly flexible or the appropriate elasticities to use, nor anticipate how customers will choose to engage with a well-designed RTP program. Evidence on demand response remains limited, mostly focused on residential customers, and has not yet benefited from widespread automated price response. We anticipate that commercial customers would comprise the bulk of participating flexible demand, at least initially. Because commercial customers comprise over 70% of Oahu's demand and commercial demand tends to have a large share of potentially-shiftable load, the optimistic scenarios assume that a large majority, but not all, of commercial customers with shiftable load would actively participate in a demand response program, and zero participation by residential customers. That optimistic scenario might be justified by the historically high participation of commercial customers in RTP programs like the one in Georgia (Barbose et al. 2004). We anticipate that participation could be even greater in future Hawai'i, since price variation will be far greater than Georgia and advanced computing technologies could make participation convenient and economic.

We do not explicitly account for the capital cost of enabling equipment, such as ice or hot water storage and smart controllers, which might enable some kinds of demand response, nor do we account for the thermal energy loss that may accompany some of these systems.[13] Some measure of these costs is implicit in the elasticities of substitution. The challenge with explicit

[13] Thermal loss appears to be modest over the daily timescale considered here (about 5%), far less than with battery storage, for example (Heine, Tabares-Velasco and Deru 2021)

account of costs is that they tend to be building specific. The estimated gains to customers from RTP provide an an upper bound for costs that would be economic.

Table 1: Assumptions about flexible demand and demand-side reserves

	Shares (%)						Hourly demand (MWh)		
	Potentially flexible load			Remaining load			Mean (std. dev.)		
Scenario	High $\sigma_f = 10$ (1)	Mid $\sigma_m = 1$ (2)	Inflex $\sigma_l = 0.1$ (3)	High $\sigma_f = 10$ (4)	Mid $\sigma_m = 1$ (5)	Inflex $\sigma_l = 0.1$ (6)	High $\sigma_f = 10$ (7) (1)+(4)	Mid $\sigma_m = 1$ (8) (2)+(5)	Inflex $\sigma_l = 0.1$ (9) (3)+(6)
Optimistic	67%	5%	28%	15%	5%	80%	323 (62)	43 (6)	497 (56)
Moderate	33%	5	62%	8%	5%	88%	160 (31)	43 (6)	661 (85)
Pessimistic	15%	5%	80%	0%	5%	95%	56 (13)	43 (6)	765 (103)
Demand-side reserves							Yes	No	No

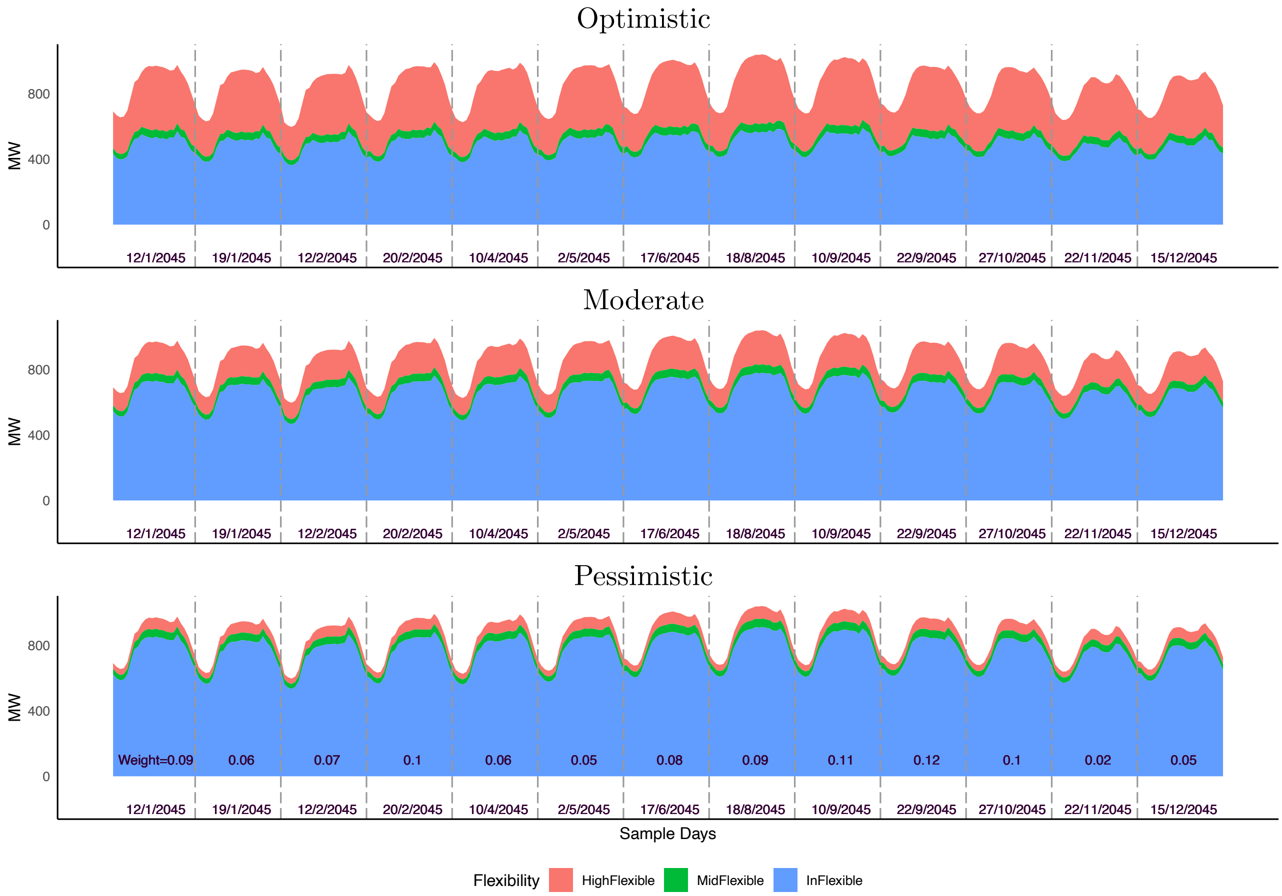
Notes: The table reports assumed shares of flexible, mid-flexible, and inflexible demand in each of the three scenarios. σ denotes the within-day interhour elasticity of substitution. Column 7 is the sum of columns 1 and 4 multiplied by hourly load and weighted by the size of the cluster represented by the sample day (see section 4.3); columns 8 and 9 similarly aggregate columns 2 and 5 and columns 3 and 6. Standard deviations of the loads across hours are in parentheses.

3.3 Demand-Side Reserves

Up reserves normally refer to residual capacity by dispatchable generators that can ramp up in the event that a power plant drops offline, wind or solar energy generation unexpectedly falls, or demand suddenly surges. Reserves can also be provided by the demand side, and this is typically what power engineers call *demand response*, while economists normally connect the term to the more general idea of price-sensitive demand. Historically, demand-side up reserves have involved contracts between the balancing authority (e.g., utility or ISO) and large-scale users of electricity that give the balancing authority the ability and right, in exchange for a rate reduction, to remotely reduce or terminate power supply to participating customers during certain critical events (note that “up” reserves are specified from a generation perspective, so they correspond to *reducing* load). In Hawai'i, residential customers have also participated in a program that gives residential customers a $3 monthly discount in exchange for allowing the utility to suspend power supply to water heaters during critical events. Similarly, *down reserves* correspond to the option of quickly ramping down a power plant or increasing energy use in the event of a net supply surge, which might result from a sudden falloff of demand or supply surge from intermittent solar or wind.

The model presented here includes demand-side participation in reserve markets for both up and down reserves, with only highly-flexible demand types assumed to participate. Reserves can also be supplied by the supply side, either from batteries or dispatchable generators. On the demand side, we incorporate reserve provision into flexible-type demand by applying a net

Figure 1: Demand flexibility scenarios by hour and month



The graphs show three scenarios for interhour demand flexibility, optimistic, moderate, pessimistic, respectively. Note that all demand types are assumed to have the same overall demand elasticity for electricity (0.1 in the baseline case). Flexible, midflex and inflexible loads are assumed to have within-day interhour elasticities of substitution equal to 10, 1 and 0.1 respectively. Each sample day is assigned to different weight for representativeness, indicated at the bottom of the pessimistic panel. See Section 4.3 for an explanation of how we selected days and assigned weights.

cost that includes sale of up and down reserves and purchase of energy, all at real-time prices. We define these as follows:

$$x_h^u = x_h^* \tag{2}$$

$$x_h^d = \max(x_h) - x_h^* \tag{3}$$

where x_h^* is energy use in hour h, x_h^u is demand-side up-reserves provision (option to decrease demand) in hour h, x_h^d is demand-side down-reserves provision (option to increase demand) in hour h, $\max(x_h)$ is the maximum electricity demand when price equals an imposed minimum ($1 per MWh). The minimum price limits demand that could otherwise rise to infinite levels given the constant-elasticity structure of the demand system. The flexible pseudo-customer chooses x_h^* (and implicitly x_h^u and x_h^d), resulting in a net cost given as follows:

$$\begin{aligned}
\text{Net Cost} &= p_h^* x_h^* + p_h^u x_h^u + p_h^d x_h^d && (4)\\
&= p_h^* x_h^* + p_h^u x_h^* + p_h^d \cdot (\max(x_h) - x_h^*) && (5)\\
&= x_h^* \cdot (p_h^* + p_h^u - p_h^d) + p_h^d \max(x_h), && (6)
\end{aligned}$$

i.e., the incremental cost per unit of consumption is $p_h^* + p_h^u - p_h^d$.

3.4 Calibration of Hourly Demand Shares

We calibrate demand scenarios by estimating the share of aggregate load in each hour and each sample day used for three potentially shiftable loads: water heating, water pumping and air conditioning. Typically these uses of power can be shifted many hours at relatively low cost using existing technologies. Then, as summarized in Table 1, we suppose optimistic (67%), moderate (33%) and pessimistic (15%) scenarios, each of which assumes a different share of these potentially-shiftable loads will actually have high interhour substitutability within a day (elasticity = 10). Across all scenarios we assume just 5% of baseline demand has moderate substitutability between hours (elasticity = 1). We assume that 80-95% of remaining load (not for water heating, water pumping or air conditioning) is highly inelastic between hours (elasticity = 0.1). The optimistic scenario could be achieved with widespread adoption of real-time pricing, thermal storage, and automated demand-response systems by commercial customers and little or no adoption by residential customers.

We use a baseline model that assumes an overall demand for energy (capturing substitution between electricity and all other goods) that is highly inelastic (elasticity = 0.1), which is consistent with a recent estimate with a strong study design and relatively similar climate and marginal price profile (Ito 2014). Looking over a longer horizon, a more recent study by Deryugina, MacKay and Reif (2020) shows compelling evidence of a higher elasticity of 0.3, so we believe our baseline is conservative. While some studies find even larger demand elasticities, they tend to be based on poorer study designs and we believe it is important to have a baseline model that is reasonably conservative. Within our model, this outer elasticity accounts for overall consumption response to the price level, which is more akin to a longer-run response. This kind of responsiveness helps with seasonal imbalance and long-duration weather events, and adjusts overall scale of demand modestly depending on average prices. However, because it seems possible that new technologies and energy demands might arise in a world with highly variable (and often free or nearly free) electricity, we also consider scenarios with larger demand overall elasticities (0.5 and 2.0). In our view, an elasticity of 0.5 is highly plausible, and 2.0 is much less likely, but conceivable with widely varying prices, large stretches of free or nearly-free energy, and induced innovation.

3.5 Electric Vehicles

An important consideration for modeling future power systems with high-penetration renewables is the potential growth of electric vehicles. Electric vehicles represent a new source of power demand and, given their large and growing battery sizes, a new source of power storage or interhour flexibility that might also provide reserves. Like demand-side flexibility, it is highly uncertain how quickly electric vehicles may grow as a share of the vehicle fleet. Given the unique nature of power demand from electric vehicles, plus the fact that they comprise a small share of historical loads used to calibrate the demand functions described above, we treat them separately. We also consider scenarios with a wide range of electric vehicle adoption, 0.5% (the share around 2016), 50% and 100%. In variable pricing environments we assume that vehicle charging is optimally scheduled to least-cost times in each day, and thus makes high-penetration renewable systems easier to achieve, but do not allow for any interday substitution of charging (which will likely be feasible). In fixed-price environments we assume vehicle charging normally occurs as soon as vehicles arrive at home or work, based on trip inventories from the National Household Travel Survey (Fripp 2017, Das and Fripp 2015, FHA 2009). This shifts up the evening peak more than other times, and makes high-penetration renewable systems more costly.

4 Generation Cost, Weather Assumptions, and Equilibrium

Our analysis uses and extends *Switch 2.0*[14] (Fripp 2012, Johnston et al. 2019), an open-source power planning software that uses mixed-integer linear programming to minimize the net present value of the cost of electricity production subject to operation and policy constraints. The main decision variables are generation capacities at each candidate project site and the amount of power to produce or store at each project site during each hour of the planning period. Constraints require adequate power to satisfy demand plus reserves during all hours, and satisfaction of any exogenous policy constraints, such as a renewable portfolio standard (RPS). Exogenous factors include high-resolution weather data paired with each candidate project site to indicate generation in each hour for any chosen level of installed capacity, plus technology and fuel costs.

Switch combines an operational model, similar in detail to commercial production cost models such as GE MAPS or Plexos, and a long-term capacity expansion model, similar to Ventyx Strategist or PowerSimm Planner. Commercial capacity planning models typically consider the distribution of loads exogenously imposed on a system, neglecting price response by customers.

[14] http://www.switch-model.org

Moreover, conventional planning or expansion models generally use unordered sets of time steps, and thus do not have enough temporal detail to model the operation of power systems with a large share of time-varying renewables or storage. Such power sources may need to be curtailed or be balanced by interhour load shifting or energy storage, which can only be modeled accurately with chronological time steps. In contrast to conventional capacity planning models, conventional production cost models can optimize chronological management, but assume fixed generation portfolios that must be selected by other means. Efficient integration of renewables can be greatly enhanced by simultaneously considering both capacity and chronological operation decisions, as does *Switch* (Fripp 2012, Johnston et al. 2019, Nweke, Leanez, Drayton and Kolhe 2012, Sullivan, Eurek and Margolis 2014). The supplement to this paper provides the main equations and constraints used in *Switch*.

4.0.1 Utility-Scale Solar

Land available for utility-scale solar was restricted to parcels zoned for agricultural or country use, excluding Class A agricultural land per Hawai'i statute. This excludes a significant amount military land, and the military plans to install a considerable amount of solar. We also exclude land with a slope greater than 10%, land within 50 meters of street centerlines, and parcels with any directional dimension less than 60 meters. These areas are indicated in gold in Figure 2. We assume that the photovoltaic installations use single-axis tracking and require 7.5 acres of land per MW (AC) of capacity. This is roughly in the lower quartile of the national statistics indicated by the National Renewable Energy Laboratory (NREL)[15] and is 15% higher than the 6.5 acres/MW reported by Oahu developers for recent projects. We assume the systems have a ground cover ratio of 0.45. These assumptions affect the capacity factor when the sun is low. We then use NREL's PV Watts tool to calculate hourly output for each 4 km cell using 2007-08 irradiance data from the National Solar Radiation Database (NSRDB) (Sengupta, Xie, Lopez, Habte, Maclaurin and Shelby 2018, Akar, Beiter, Cole, Feldman, Kurup, Lantz, Margolis, Oladosu, Stehly, Rhodes et al. 2020).

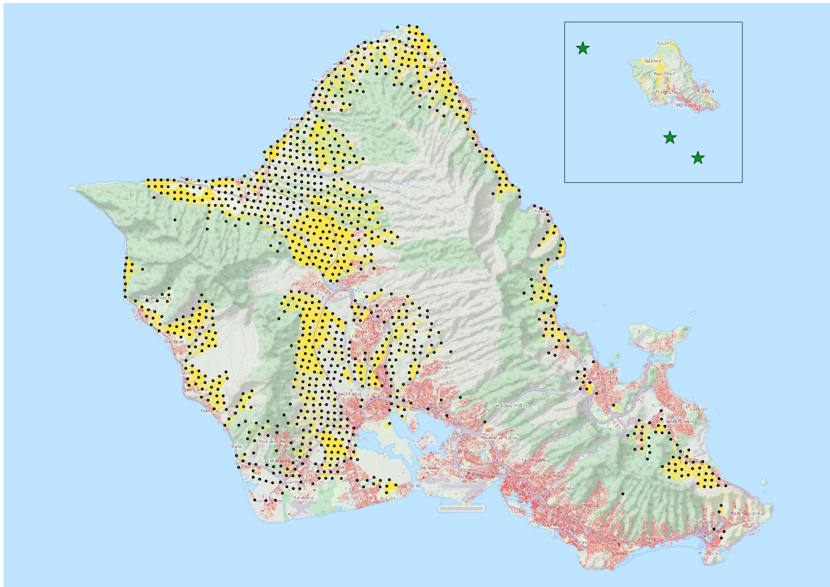
4.1 Rooftop Solar

The potential quantity of rooftop solar on Oahu and the amount oriented in each direction (flat roofs or North-, East-, South-, or West-facing roofs) was calculated from the Google Project Sunroof (`https://sunroof.withgoogle.com/accessed10/1/2019`). Rooftop locations were calculated from Google Map images.[16].Visual review of many roofs and statistical comparison of census tract population and roof coverage indicate accurate identification. We assume that panels on sloped roofs are tilted at 25 degrees and panels on flat roofs are tilted at 5 degrees,

[15]See `http://www.nrel.gov/docs/fy13osti/56290.pdf`.

[16]See Google Maps Static API, `https://developers.google.com/maps/documentation/maps-static/`, accessed 10/1/2019

Figure 2: Solar and Wind Resources



This map summarizes solar and wind resources on Oahu from which Switch selects sites to build. Potential build sites for solar are indicated in gold, rooftop solar in red, possible onshore wind turbine sites in black dots, and offshore wind farms by stars in the inset. Total capacities available in terms are MWh are summarized in Figure 3. Sources: see text.

matching assumptions in the National Renewable Energy Laboratory's Annual Technology Baseline (ATB) (Akar et al. 2020). Hourly generation profiles of photovoltaic systems are modeled using parameters from the ATB and solar data from the National Solar Radiation Database for 2007–08 (Sengupta et al. 2018).

4.2 Wind Potential

On shore wind potential was estimated using a screening of available land similar to solar. Only land zoned for agriculture or country and not within 300 meters of other zones was considered. Slopes were restricted to 20 percent grade or less, and not within 30 meters of steep slopes, to eliminate narrow ridge tops and valleys (Das, Chermakani and Fripp 2016). A map of potentially developable locations for wind turbines is shown in figure 2, together with solar resources. We considered wind turbine density of 8.8 megawatts (MW) per square kilometer (km^2), which is conservatively less dense than the current Kahuku wind farm already installed on the island (12.9 MW/km^2), but on the high end of 5-8 MW/km^2 that is estimated by Denholm, Hand, Jackson and Ong (2009). Potential turbines were clustered by region into separate scalable projects. Hourly behavior of each potential project—its coincident potential capacity—is calculated based on historical meteorological modeling conducted for the Oahu Wind Integration and Transmission Study (Corbus, Schuerger, Roose, Strickler, Surles, Manz, Burlingame and Woodford 2010). For all practical purposes, there is an unlimited supply of off-shore wind potential with a high capacity factor of an estimated 43 percent, which enters the model as a single scalable resource.

4.3 Sample Days and Investment Decisions

The model solves for a 30-year planning horizon using 12 representative days in each investment period, plus a 13$^{\text{th}}$ day that represents the most-difficult-to-serve day over a 727-day period of baseline weather and demand (based on years 2007 and 2008). Each selected day is modeled chronologically with hourly resolution of demand and generation. The twelve representative days were selected using k-means clustering of three historical variables—mean daily demand, mean daily solar radiation, and mean daily wind—assuming a full build out of potential solar and wind capacities. The central day of each cluster (k=12) was selected, with each day weighted in accordance with the number of days in its associated cluster, and then the model was solved for the optimal portfolio of assets over the planning horizon. This initial solve assumed fixed, perfectly inelastic demand. Then, holding the selected portfolio of generation and storage assets fixed, we solved a chronological operation model over all 727 days (17448 hours), imposing a penalty of $10 per kilowatt hour for any demand that went unserved. The most costly day from this operation model was assigned as the 13$^{\text{th}}$ sample day (derived from November 22, 2008). This day was not exceptionally high demand, but was exceptionally cloudy and not especially windy. We then recalculated the clusters and weights using the final set of 13 sample days; that is, we assigned each historical date to the nearest sample date (in terms of solar radiation, wind, and demand), then weighted each sample date based on the number of historical days that were closest to it. We then re-solved for the optimal portfolio of assets, which generally resulted in no instances of unserved load under perfectly inelastic demand when the system was tested against the full 2-year chronology. We held the sample days and weights fixed at these values for all scenarios.[17] Note that this sampling strategy is somewhat conservative because it assumes several days each year (2%) that are as difficult to serve as the most difficult day over a two-year horizon.

The analysis here is a single-stage analysis in the sense that each scenario assumes all new assets are built at one point in time (i.e., 2045). *Switch* is designed to consider a series of investment windows so as to optimize a long-run plan or transition. However, because our focus in this paper is on the value of RTP, we chose to simplify this part of the problem so

[17]In an earlier version of the paper we sampled the 15$^{\text{th}}$ day of each month of the year and assigned equal weights, which can miss especially difficult-to-serve days. Since demand response is more valuable on difficult days, or when days are more varied, we underestimated the value of real-time-pricing by a remarkably large margin, a point that was gently pointed out by an anonymous referee. We considered a few cluster-based sampling strategies besides this one, including k-means clustering based on hourly (not daily) wind, solar, and demand, or minimizing differences between the full and sample empirical cumulative distributions of wind, solar, and demand (Kolmogorov-Smirnov statistics). These approaches were slightly inferior in that they led to a slightly more costly system under perfectly inelastic demand.

as to provide more clarity about the long-run tradeoffs of this critical policy choice. It is also possible to add more sample days to gain a fuller representation of the joint distributions of time, weather, supply, and demand; this does not appear to change our results in a substantial way, but may be useful for fine-tuning an actual resource plan.

4.4 Equilibrium: Merging *Switch* with Demand

Iterations between *Switch* and the demand system were completed as follows. First, we solve *Switch* for a baseline load profile, which is connected to either actual 2007 loads or projected loads for 2045 (differences are discussed below). Tentative prices are derived as marginal costs (shadow values of the constraints specified in the Online Appendix), and these are offered as prices to the demand system. The demand system returns optimal quantities given these prices, and also reports Marshallian consumer surplus minus a fixed offset – i.e., the line integral of demand taken from baseline prices to offered prices. [18] Switch then minimizes the cost of serving the new quantities, sending new prices based on marginal costs. During successive iterations, *Switch* constructs a linearized demand system from the convex hull of demand and associated willingness to pay (consumer surplus plus total expenditure). In other words, it approximates total willingness to pay as a convex combination of willingness to pay from prior iterations (i.e., any linear combination of prior bids with total weight of 100%). During each iteration, *Switch* chooses a new system design to maximize welfare (willingness to pay minus cost) and offers new prices. This cycle repeats until there is no further improvement in total surplus from having new prices offered and receiving new quantity bids.

This method is a Dantzig-Wolfe decomposition of the joint supply-demand problem (Dantzig and Wolfe 1960). With this method, solutions from the supply problem, in which consumers are given quantities based on the linearized demand function, represent a lower bound on surplus; solutions from the demand problem, in which consumers can choose any amount they want without changing prices, provide an upper bound on surplus. We stop iterating when the difference between these two measures is less than 1 percent of baseline electricity expenditure.[19]

[18] To find the correct competitive equilibrium in this iterative manner requires that we use Marshallian surplus rather than compensating or equivalent variation. Because nested-CES utility is well behaved, this high-dimension integral is not path dependent (Takayama 1982). And because income effects are small, owing to the fact that electricity expenditure is a small share of income, this measure of surplus is also very similar to compensating and equivalent variation or money-metric utility. For this reason, we report only Marshallian consumer surplus.

[19] As an aside, note that this algorithm might be used to coordinate supply and arbitrary non-linear demand to aid price discovery in a power system. Such coordination could be challenging if a large share of demand is highly flexible, as we anticipate it will be (e.g., EV charging and some kinds of thermal storage). As the elasticity of intertemporal substitution approaches infinity, some sources of demand would need to be explicitly scheduled, and this algorithm can effectively achieve this in a decentralized manner (Callaway and Hiskens 2010).

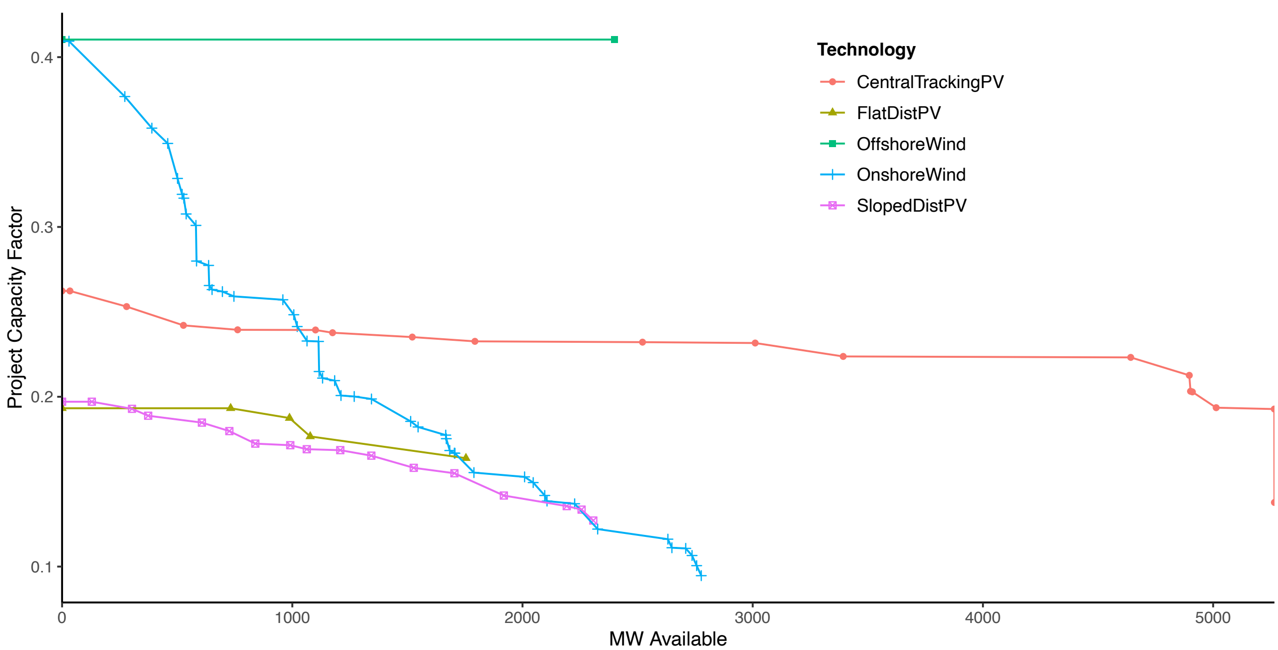
5 Cost assumptions and scenarios

5.1 Cost Assumptions

The inputs for the *Switch* model are based on Hawaiian Electric Company's Power Supply Improvement Plan (PSIP) and are summarized in Table **??** and Table **??**. The report lays out projected costs each year from 2016 through 2045, and we consider models with costs at each endpoint to show sensitivity of results to cost assumptions.

We summarize average capacity factors (normalized production potential) for the renewable sources in figure 3. In the optimization model, capacity factors for each project vary by hour. While projects with higher average capacity factors are more likely to be selected from the optimization routine, the timing of output relative to demand and other projects also matters.

Figure 3: Average output and potential capacity of renewable energy sources on Oahu



The graph shows the resource capacity of different potential sources of renewable energy, each ordered from highest average output (capacity factor) to lowest. For perspective, peak demand on Oahu is about 1000 MW. A project with a 0.25 capacity factor would produce an average of 25% of its nameplate capacity throughout the year.

5.2 Scenarios

We solve the full model under a number of scenarios to explore sensitivity of results to different assumptions. The scenarios span combinations of the following sets of assumptions. Solving many scenarios also allows us to check internal consistency of the results, which builds confidence that the models converged correctly, as each is solved independently.

Most of the different sets of assumptions have been detailed above. Overall demand is likely inelastic, so we focus mainly on results with an overall demand elasticity for electricity of 0.1 (the elasticity of substitution between electricity and all other goods); this assumption is somewhat conservative given compelling recent evidence that demand is more elastic over the longer run (Deryugina et al. 2020). However, we do consider scenarios with larger elasticities, partly because some scholars may find these more plausible, but mainly because broader implementation of RTP combined with automation could cause demand elasticities to grow larger. Indeed, new uses for electricity could arise to make use of free or very inexpensive electricity, which will be prevalent for significant stretches of time under high-renewable scenarios (e.g., times of curtailment), and these new intermittent demand sources may be more elastic. While higher-elasticity scenarios are speculative, they help to demonstrate the upside potential with renewable energy integration.[20]

The two load profiles, actual 2007 and projected 2045, differ mainly in their degree of variability, including seasonality. The 2045 projection for demand reshapes the 2007 profile to match Hawaiian Electric Company's projected peak and average load for that year holding prices fixed. Because Hawaiian Electric Company (HECO) reports a projected peak load of 1065 MW and average of 861.4, but the historical peak and average were 1249 and 955 (in 2007), the profile is flatter for 2045 than it is for 2007.[21] Because seasonal variability may be more costly to manage than intraday variability, comparison of these scenarios provides some sense of this cost of seasonality.[22]

Much of our discussion focuses on cost differences between flat and variable, marginal-cost pricing (RTP), and how these differences vary across other sets of assumptions. Considering all combinations of the above scenarios yields $3 \times 2 \times 3 \times 3 \times 3 \times 2 \times 2 = 648$ scenarios. In addition to these scenarios, we solved models along a path wherein we constrain the percent renewable to a range of values between the least cost (unconstrained) portfolio and 100% clean, holding all else the same. This allows us to trace out the social cost (loss in producer plus consumer surplus) of additional renewable energy under each set of assumptions. Note that we *do not* consider the external cost of pollution emissions. Reduced pollution externalities ought to be weighed against these cost curves; the point is focus squarely on the shape of this cost function and how RTP influences it.[23] This exercise added over a thousand additional

[20] We thank Stephen Holland for suggesting that we consider more elastic demand.

[21] To reshape historical load to HECO's projection, we multiplied baseline demand by multiplying the historical loads by 0.693 and adding 200 MW, which reduces both seasonal and intraday variability by about 30 percent.

[22] We do not know how HECO projected future peak and average loads. It could be that they assume a substantial share of residential demand, which comprises much of the peak, is assumed to self-generate. Moreover, the numbers reported in the PSIP do not appear consistent with what was used in their own modelling and that of their consultants during the planning process. Thus, it is not clear whether HECO really believes that seasonal demand variability will decline.

[23] We also omit consideration of innovation and learning by doing, which can also reduce costs.

scenarios. Computing time required to solve a single scenario can range from less than an hour for flat-price scenarios, to several days for some of the dynamic scenarios with more elastic demand, where many different resources and demand profiles are on the margin. We used the University of Hawai'i's high performance computing facility with thousands of state-of-the-art cores to solve many models simultaneously. Although space constrains us from reporting all individual scenarios, we have characterized many of them here, and have developed a website with drop-down menus that will allow readers to explore details of any particular scenario (http://www2.hawaii.edu/~mjrobert/power_production/).

Welfare calculations consider changes in Marshallian consumer surplus (CS), producer surplus (PS), and charging costs for electrical vehicles (EV), which are treated separately but included in total CS. We also calculated CS for each type of pseudo-customer, each having different interhour flexibility and base load profiles. CS changes are similar to CV and EV, given the relatively small share of expenditure, so we do not report them. Producer surplus is the change in revenue minus total cost. Note that these calculations do not include fixed customer charges or rebates, which could be used to change the overall balance of welfare between customers and producers. For this reason, it may be more meaningful to focus on changes in total surplus and differences across pseudo-customers. Also note that we do not explicitly account for fuel savings that may derive from greater EV use. Comparison of low versus high EV scenarios are meant to show how EVs could change the value of variable versus fixed pricing, since EVs embody a potentially large block of flexible demand.

6 Results

To ease comparison of scenarios, results are reported as the difference between a particular scenario and a baseline scenario.[24] In most cases, the baseline scenario, indicated by the bold-faced sets of assumptions in Table 4, assumes fossil-based generation, future 2045 costs and projected load profile, flat pricing, and an overall demand elasticity for electricity of 0.1 (the elasticity of substitution between electricity and all other goods). Note that under flat pricing scenarios, interhour demand flexibility has no bearing on the outcome. We choose this scenario as the baseline because we presume that it is the future that utilities would have envisioned in the absence of clean energy, particularly wind and solar. To make welfare calculations easy to interpret, we report these as percent differences from the baseline level of total expenditure on electricity.

[24] There are practical as well as interpretative challenges with using total surplus as a basis for comparison. Technically, it is difficult to numerically integrate price to infinity, especially with CES utility. In addition, electricity expenditure is a small share of overall expenditure, even at baseline prices.

6.1 Main Results: The Value of RTP and Cost of Clean Power

Table 5 reports a subset of the main results for scenarios with an overall demand elasticity of 0.1 and 50% EV penetration. The table stratifies scenarios across four characteristics (1) Policy objective (fossil-based or 100% clean generation mixes); (2) Technology cost (2016 or projected 2045); (3) Demand flexibility (optimistic or pessimistic); and (4) Pricing (flat or RTP). A fuller set of results, including unconstrained scenarios (a surplus-maximizing generation mix, excluding externalities) is reported in the Online Appendix. Comparing different rows from this table, one can infer the essential findings. The value of RTP, holding all else the same, is given by comparing two adjacent rows. Outcomes reported for each scenario include the share of renewable energy, average price, average quantity (MW of load), the standard-deviation of price, and the change in total surplus measured as a percent of baseline expenditure (future fossil-based system with flat prices). The last column gives the change in total surplus from using RTP versus flat pricing, holding all else the same.[25]In Table 6 we break out components of the total surplus changes reported in column 8 of Table 5. Note that the change in consumer surplus (Δ CS) includes cost reductions from optimally scheduling EV changing, which is why it can differ from some weighted average of CS changes for different demand types (highly flexible, medium flexible, and inflexible).

Several findings can be parsed from this table, including the central point: while real-time pricing has relatively little value in a conventional fossil-dominated systems (1.5 to 2.5 percent of baseline expenditure), the value is considerably larger in a 100 percent renewable system (8.7 to 19.4 percent of baseline expenditure). The other key finding is the remarkable affordability of clean power systems under projected future costs. Compared to a conventional fossil system in 2045, a 100 percent renewable system is projected to increase total surplus by 30.4 to 44.1 percent of baseline electricity expenditure, mainly depending on whether flat pricing or RTP is employed. These gains are only slightly less than the unconstrained optima which increase surplus by 35.0 to 45.8 percent, especially with RTP (unconstrained scenarios are reported in the Online Appendix). Indeed, the unconstrained optima with RTP has 97 percent renewable energy in 2045, and the cost of increasing renewable share beyond this level is modest. We elaborate upon and refine this point below.

We present a larger set of results in figures 4 and 5. Figure 4 shows the value of RTP in comparison to flat pricing, all else the same, classified across a few dimensions: (i) fossil-based, 100-percent renewable, or unconstrained build portfolios (columns); (ii) current (2016) or future (2045) costs (rows); (iii) degree of interhour flexibility (the bars); (iv) higher or lower EV vehicle penetration (the whiskers); and (v) 2007 baseline load profiles, which have more inter- and intra-day demand variability. The graph shows that higher EV penetration and actual 2007 demand

[25]The fossil scenarios include a fixed amount of clean energy that is preexisting. The clean share changes slightly across scenarios because the total amount of energy changes.

profile make RTP more valuable. The value of RTP in the unconstrained model is more similar to the fossil-based system with 2016 costs and more similar to the 100-percent-renewable case with future costs. This result is not surprising given the unconstrained model selects a more modest clean energy portfolio under 2016 costs (39-57%), wherein balancing is achieved mostly through ramping of fossil plants as with a conventional system, and chooses a near-100% clean energy portfolio under 2045 costs (89-97%).

The second graph (Figure 5) shows the same results from from a different vantage point; it shows the social cost of a 100% clean system (negative change in producer plus consumer surplus) relative to fossil and unconstrained systems, holding all else the same. It is important to emphasize that these social costs exclude external costs of pollution. Under 2016 costs, a 100% clean system is roughly 30% more expensive than a fossil system with flat pricing, but just 15% to 20% more expensive than fossil with RTP. The cost of a 100% clean system relative to an unconstrained (least cost) system are visibly indistinguishable from the fossil baseline under 2016 costs. Under projected 2045 costs, however, a 100 percent renewable system is almost 30% *less* costly than a fossil-based system that allows no further building of renewables, and just 5% more expensive than an unconstrained optimum under flat pricing, and again half to two-thirds this amount under RTP.

Figure 6 shows how the social cost of renewable energy rises as the share of renewable energy increases from the optimal portfolio (greatest surplus, excluding pollution externalities) to 100 percent renewable. The graphs juxtapose how costs rise with flat vs RTP, with both pessimistic and optimistic interhour flexibility, while also illustrating the influence of electric vehicles, overall demand elasticity, and 2016 versus 2045 technology. Costs displayed are all less than 100% of the baseline, indicating that a clean system is less expensive than a fossil system at projected 2045 prices. While costs increase as the share of renewable energy rises above the least-cost share, and markedly so with flat pricing under 2016 costs, it is apparent that the cost curves rise much less under 2045 input costs and under RTP.

Table 2: Generation Equipment and Maintenance Costs

Technology	Generators	Year Built	Capital Cost ($/KW)	Fixed O&M ($/Year)	Variable O&M ($/MWh)	Useable Life (Years)	Outage Rate
Biomass	H-Power	1989	2042.05		18	61	0.41
Fossil-fueled	Airport_DSG	2013	585.67		37.46	61	
Fossil-fueled	CC_152	2045	1667.97	19.08	4.49	30	0.05
Fossil-fueled	CIP_CT	2009	585.67		40.76	61	
Fossil-fueled	IC_Barge	2045	1460.71	38.04	20.96	30	0.02
Fossil-fueled	IC_MCBH	2045	3152.36	38.04	20.96	30	0.02
Fossil-fueled	IC_Schofield	2018	2706.48	38.04	20.96	30	0.02
Fossil-fueled	IC_Schofield	2045	2473.99	38.04	20.96	30	0.02
Fossil-fueled	Kalaeloa_CC1	1989	2042.05		6	61	
Fossil-fueled	Kalaeloa_CC2	1991	2042.05		6	61	
Fossil-fueled	Kalaeloa_CC3	1991	2042.05		6	61	
Fossil-fueled	Waiau	1973	585.67		3.46	77	
Solar PV	CentralTrackingPV	2012	3218.61			30	v
Solar PV	CentralTrackingPV	2016	3218.61			30	v
Solar PV	CentralTrackingPV	2019	1934.12	13.96		30	v
Solar PV	CentralTrackingPV	2045	1279.93	9.24		30	v
Solar PV	FlatDistPV	2016	4644.52			30	v
Solar PV	FlatDistPV	2045	1885.54	11.48		30	v
Solar PV	SlopedDistPV	2016	6762.96			30	v
Solar PV	SlopedDistPV	2045	1890.26	9.33		30	v
Storage	HydrogenElectrolyzer	2045	769.37	46.93	19.92	40	
Storage	HydrogenFuelCell	2045	583.68	26.9	0.02	26	
Storage	HydrogenLiquifier	2045	47.46	0	0.01	30	
Storage	Battery_Bulk	2045	408.40	17.73		15	
Storage	Battery_Conting	2045	470.79	17.73		15	
Storage	Battery_Reg	2045	533.19	17.73		15	
Storage	DistBattery	2045	408.40	17.73		15	
Wind	OffshoreWind	2045	3128.11	42.3		30	v
Wind	OnshoreWind	2011	2417.55			30	v
Wind	OnshoreWind	2012	2417.55			30	v
Wind	OnshoreWind	2045	1522.49	37.23		30	v

Notes: Cost assumptions are derived from Hawaiian Electric Company's Power Supply Improvement Plan from December 2016. IC and CC stand for Internal Combustion and Combined Cycle, respectively. CIP_CT, Waiau, Airport_DSG, Schofield, IC_Barge, IC_MCBH, Kalaeloa are all multi-fuel and will automatically convert to biodiesel in 2045. The letter "v" on renewable generation indicates variable capacity factors determined from weather data at selected site locations on the sample days.

Table 3: Fuel Costs

Fuel	Year	Unit cost ($/MMBtu)
Biodiesel	2045	33.95
Coal	2045	4.18
Diesel	2045	24.31
LNG	2045	14.89
LSFO	2045	18.88
Motor_Diesel	2045	36.33
Motor_Gasoline	2045	33.43
Pellet-Biomass	2045	14.53

Table 4: Summary of Scenarios

Scenario Characteristic	Number	Constituents
Interhour demand flexibility	3	**Pessimistic, Moderate, Optimistic**
Costs	2	HECO PSIP 2016, **HECO PSIP 2045**
Overall electricity demand	3	Elasticity = **0.1**, 0.5, 2.0
Electric vehicle share	3	0.5%, **50%**, 100%
Policy Objective	3	**Fossil**, 100% Clean, Unconstrained.
Baseline demand	2	**Projected 2045**, Actual 2007
Pricing	2	**Flat pricing**, RTP

Notes: We solved for all combinations of characteristics, which amounts to ($3 \times 2 \times \times 3 \times 3 \times 3 \times 2 \times 2 = 648$) scenarios. Assumptions in boldface indicates the baseline. Under flat pricing, interhour substitution has no influence on the outcome. Electricity expenditure in the baseline scenario is used for welfare and cost comparisons.

Table 5: Main Results - Total Surplus and Value of RTP

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) Price ($/MWh)	(6) Mean Q (MWh/hr.)	(7) SD of Price ($/MWh)	(8) Δ TS (%)	(9) Δ TS RTP (%)
Fossil	2016	Optimistic	Flat	90	930	0	37.2	2.5
			Dynamic	82	952	21	39.7	
		Pessimistic	Flat	90	930	0	37.1	2.2
			Dynamic	94	939	41	39.3	
	2045	Optimistic	Flat	158	870	0	Baseline	2.3
			Dynamic	148	884	87	2.3	
		Pessimistic	Flat	158	870	0	Baseline	1.5
			Dynamic	150	869	81	1.5	
100% Clean	2016	Optimistic	Flat	150	876	0	4.2	19.4
			Dynamic	158	1,006	153	23.6	
		Pessimistic	Flat	147	878	0	4.2	11.4
			Dynamic	189	984	197	15.6	
	2045	Optimistic	Flat	105	914	0	30.4	13.7
			Dynamic	123	1,062	133	44.1	
		Pessimistic	Flat	105	914	0	30.4	8.7
			Dynamic	119	1,054	125	39.1	

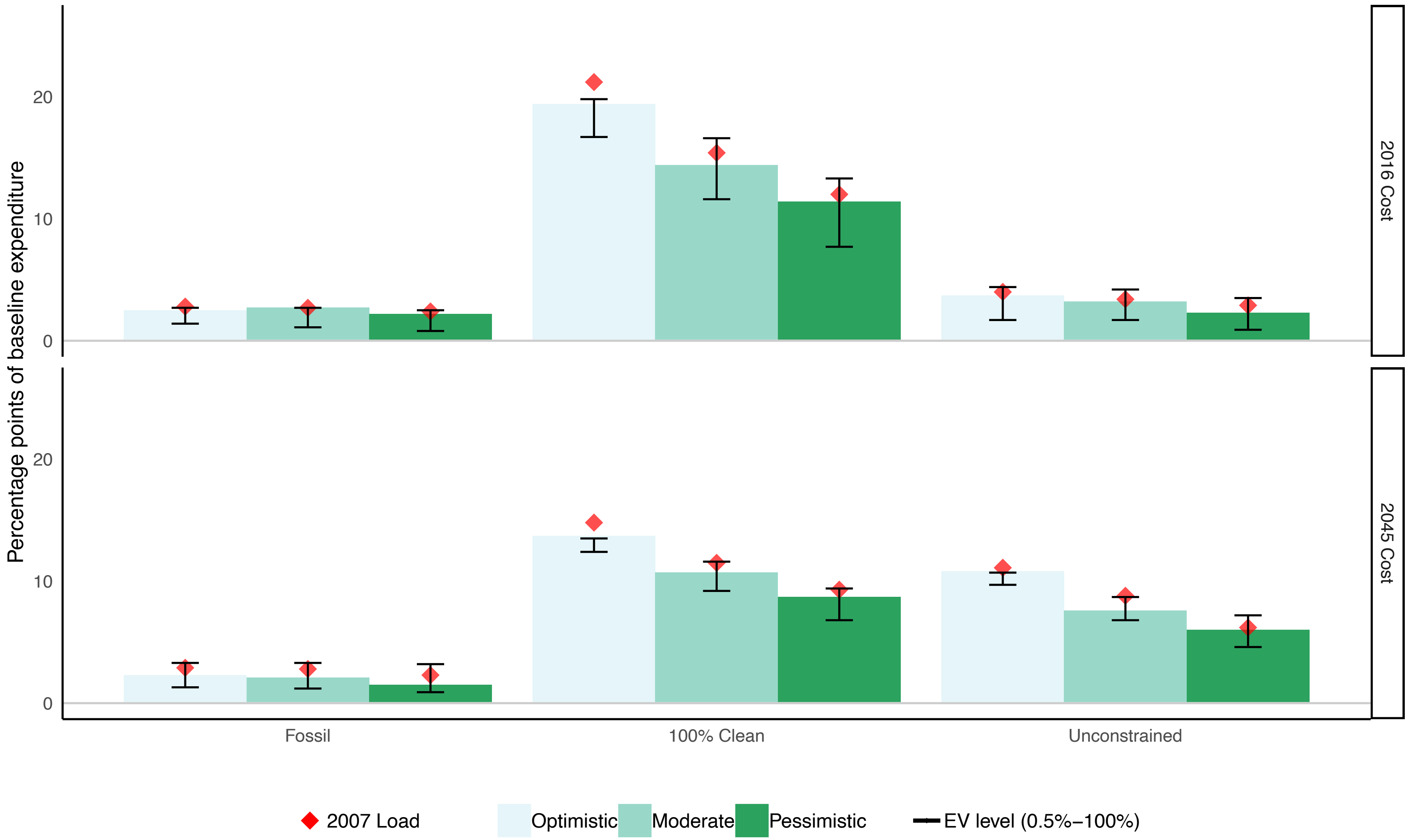
Notes: This table reports a subset of results for the baseline set of scenarios with an overall demand elasticity equal $\theta = 0.1$, a vehicle fleet that is 50 percent EV, and a projected 2045 load profile. Δ TS gives total surplus measured as the difference from the baseline scenario (2045 Fossil with flat pricing) measured as a percent of baseline expenditure, and includes changes in consumer surplus, producer surplus, and EV charging costs. Δ TS RTP gives the value of RTP versus flat pricing as a percent of baseline expenditure holding all else the same. A full set of results that includes additional outcome metrics and an unconstrained (surplus maximizing) policy objective is given in the Online Appendix, together with full results from other sets of assumptions ($\theta \in \{0.5, 2\}$ different EV shares, and an actual 2007/2008 load profile).

Table 6: Main Results - Distribution of Total Surplus

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) Δ CS (%.)	(6) Δ PS (%)	(7) Δ CS Highflex (%)	(8) Δ CS Midflex (%)	(9) Δ CS Inflex (%)
Fossil	2016	Optimistic	Flat	48.3	-11.1	37.2	37.2	37.2
			Dynamic	53	-13.3	44.4	42.6	42.4
		Pessimistic	Flat	44.3	-7.2	37.2	37.2	37.2
			Dynamic	45.5	-6.2	41.7	36.8	34.7
	2045	Optimistic	Flat	Baseline				
			Dynamic	12.5	-10.2	8.9	8	7
		Pessimistic	Flat	Baseline				
			Dynamic	9.3	-7.8	9.5	7.5	5.4
100% Clean	2016	Optimistic	Flat	7.6	-3.4	4.3	4.3	4.3
			Dynamic	27.5	-4	35.8	20.5	9.1
		Pessimistic	Flat	2.3	1.9	5.9	5.9	5.9
			Dynamic	14	1.6	35.5	21.7	5.2
	2045	Optimistic	Flat	37.2	-6.8	28.9	28.9	28.9
			Dynamic	52.2	-8.1	51.7	42	35.9
		Pessimistic	Flat	34.6	-4.2	28.8	28.8	28.8
			Dynamic	44.2	-5.1	54.3	44.4	34.3

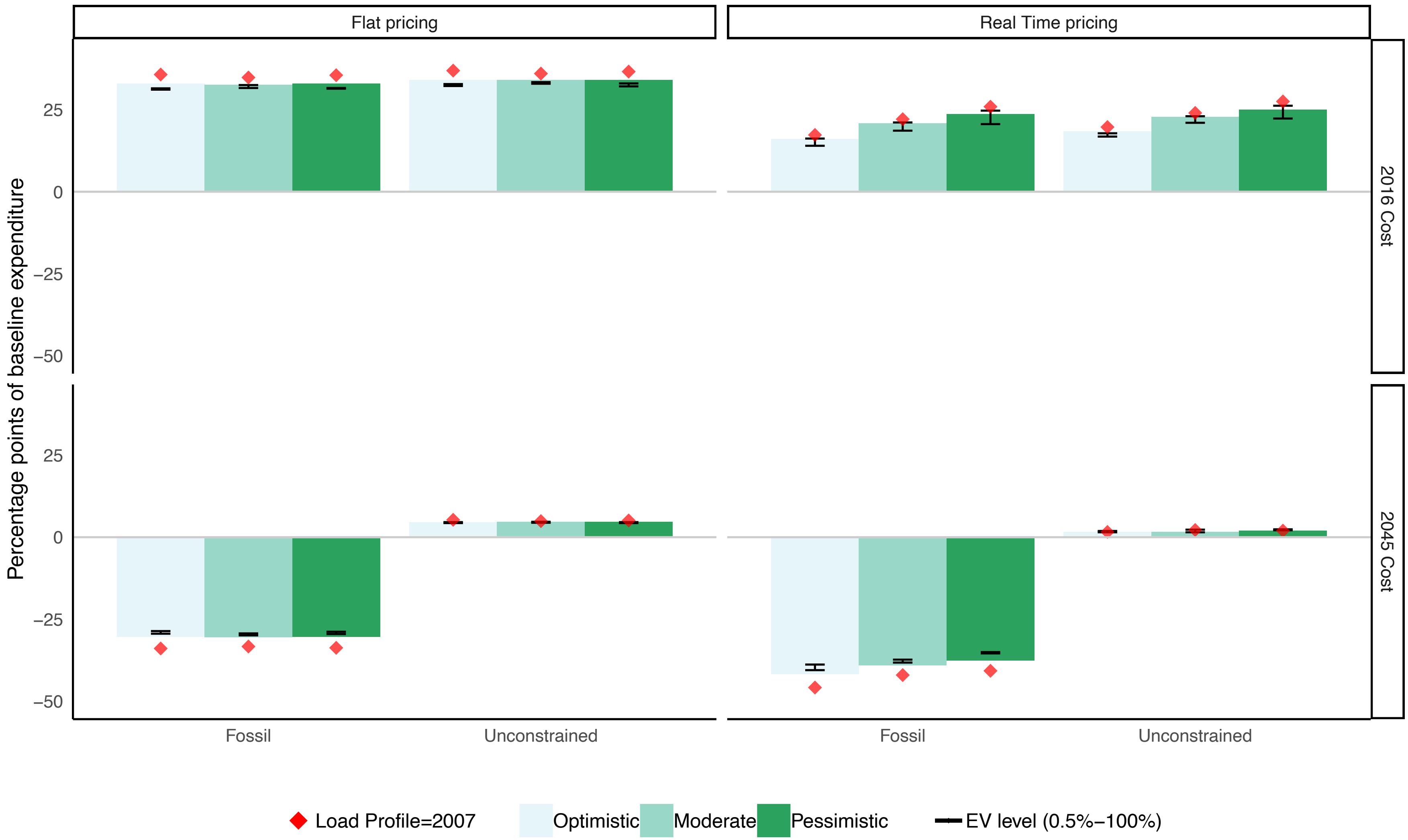
Notes: This table breaks out total surplus (TS) from Table 5 into its components, consumer surplus (CS) and producer surplus (PS). The table also reports changes for different demand types with more and less flexibility. Note that CS includes EV charging costs, which is why CS can differ from any weighted sum of flexibility types.

Figure 4: Surplus gain from real time pricing under different policy, cost and demand flexibility scenarios.



The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.1; results for larger overall elasticities are shown in the appendix. The top row shows the value of RTP under current costs; the bottom row shows the value of RTP under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% clean or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of RTP.

Figure 5: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios.



The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.1; results for larger overall elasticities are shown in the appendix. The top row shows the value of RTP under current costs; the bottom row shows the value of RTP under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% clean or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of RTP.

Under 2045 technology and fuel costs, the least-cost share of renewables always exceeds 80 percent and costs rise little as the share increases above the least-cost share. Electric vehicles reduce the overall cost curve by about 5-10 percentage points under flat pricing and a bit more under RTP, since EV charging is a particularly flexible load. Note that the baseline changes with more EVs, as we add the required demand for charging them to the 2045 technology/fuel costs, flat-price, and predominantly fossil scenario.

Increasing the overall elasticity of demand from 0.1 to 2 has a more dramatic impact. Under elastic demand ($\theta = 2$), a 100% clean system is optimal under RTP and astonishingly welfare improving—more than 100% of baseline expenditure. (Note that we must change the scale of the graphs to illustrate high-elasticity cases in the bottom panels of Figure 6). The cost is slightly lower with 100% electric vehicles instead of 50% as displayed. Real-time pricing is also considerably more valuable with more elastic demand, equal 62% of baseline expenditure, holding all else the same. While an elasticity of 2 is quite optimistic, an overall elasticity of 0.1 is likely very conservative. These two scenarios bound the most plausible range.

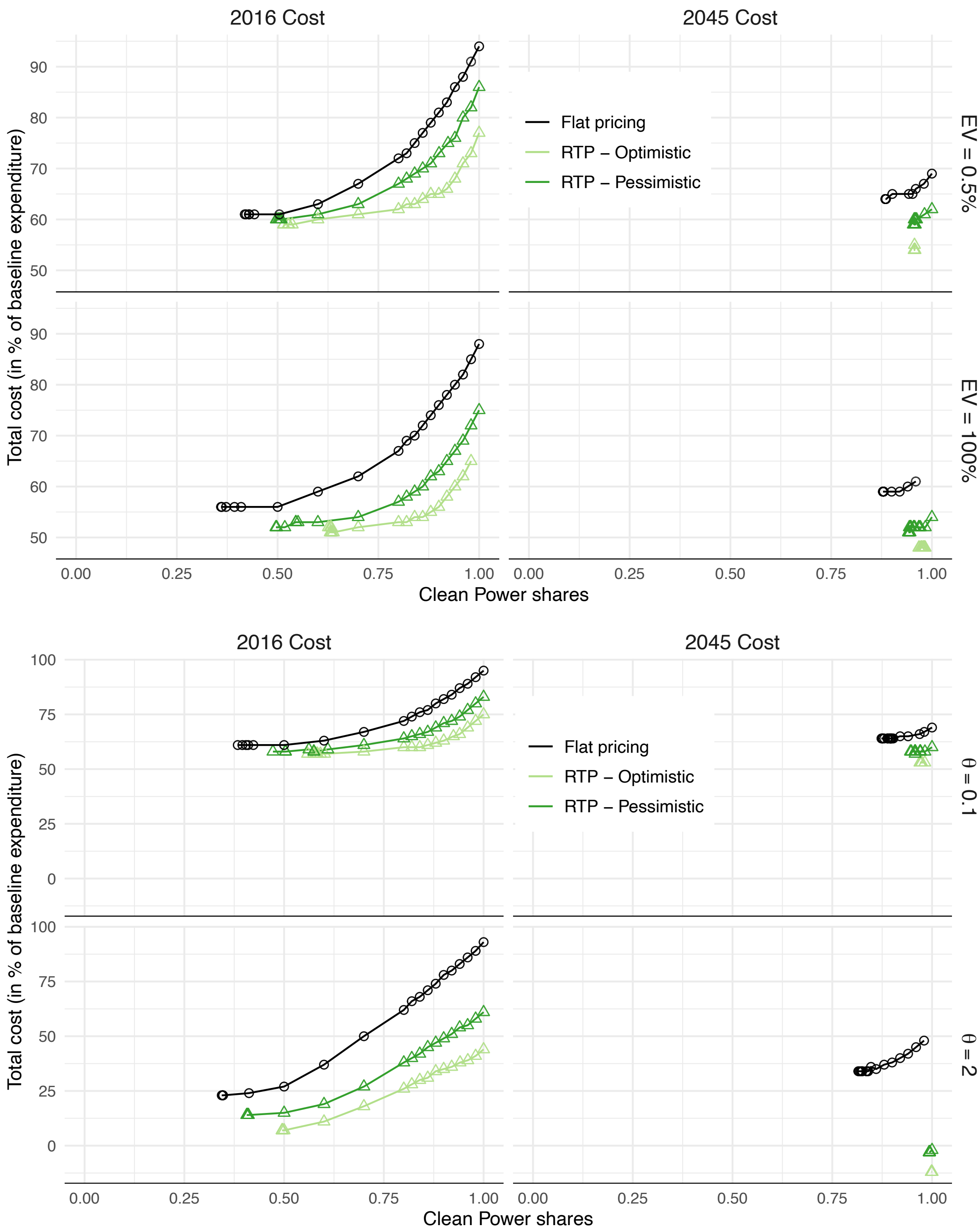
Another clear implication of these results is that while interhour flexibility is valuable, there are strong diminishing returns to the share of load that is highly flexible. The optimistic flexibility scenarios assume nearly six times as much highly-flexible demand ($\sigma = 10$) than the pessimistic scenarios, but less-than-double the benefits of RTP.

6.2 Equilibrium Prices and Quantities

We show the full distributions of equilibrium quantities and prices for a few scenarios in Figure 7. These graphs show striking differences between the influence of RTP in fossil and high-renewable systems. Where RTP slightly reduces the spread of quantities in the fossil system, it greatly *increases* the spread of quantities in high-renewable systems and (future) unconstrained systems. In the high-renewable case, peak quantity under RTP roughly doubles compared to the fossil and flat-price scenarios. Price variation under RTP also differs, with more variation in high-renewable cases relative to the fossil scenario, in which prices hardly vary except for critical peaks. The high-renewable cases also show *lower* and *less* variable prices during high-quantity equilibria.[26] These are times when renewable energy is plentiful and there may be curtailment and zero or near-zero prices. In the Online Appendix we report the share of hours in each scenario with marginal cost less than 5 cents or 1 cent per kilowatt hour. Although RTP reduces this share relative to flat-pricing scenarios, it remains quite high, even in optimized RTP scenarios with ample flexibility. Thus, RTP is especially valuable in high-renewable systems because encourages considerably greater power consumption when it is unusually plentiful and cheap, not just reduced consumption when power is especially scarce.

[26] Note that the critical peaks in the fossil scenario tend to occur at lower quantities, which happen to occur during scheduled or unscheduled power plant outages.

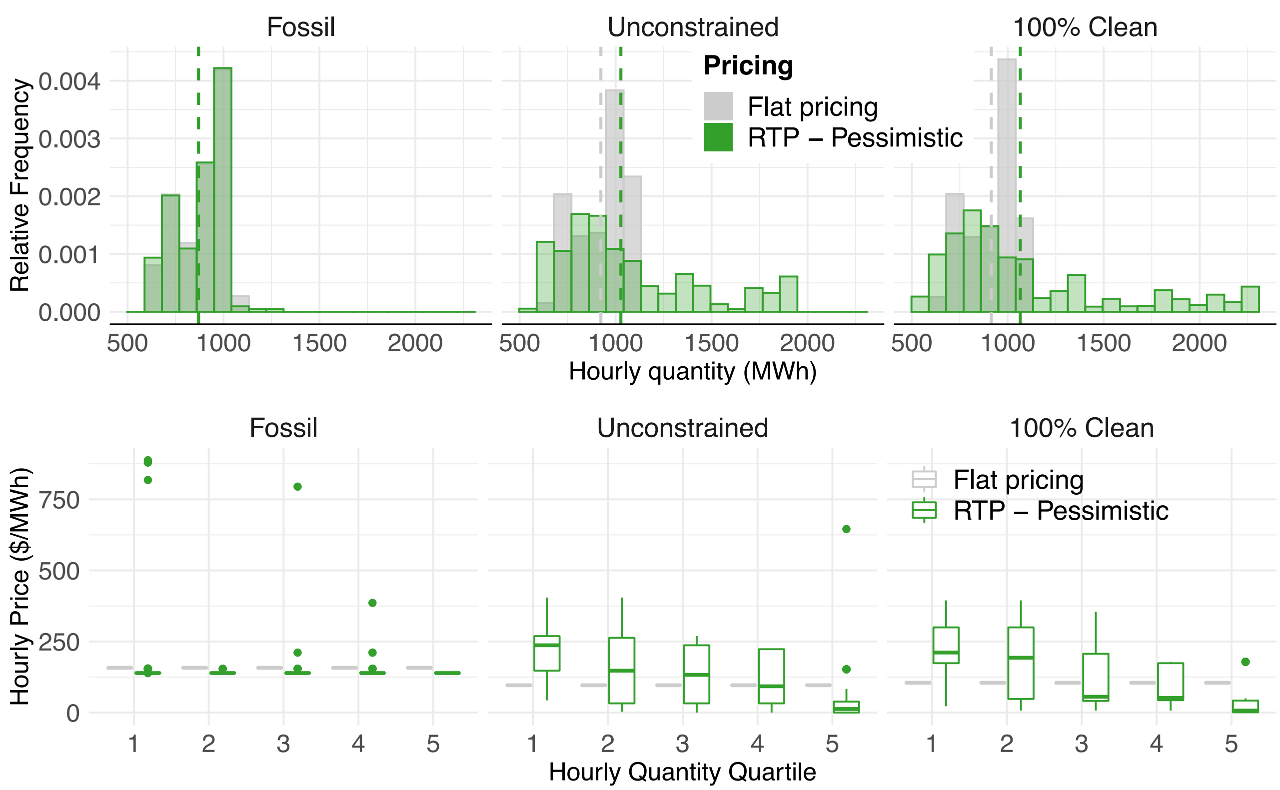
Figure 6: The social cost of clean power relative to a fossil future with flat pricing.



Notes: Each line shows the social cost—the loss in total economic surplus (PS + CS)—as the share of clean electricity rises above the surplus-maximizing share, holding all else the same. Social cost is measured as a percent of expenditure (excluding externalities) in the baseline scenario, which is a predominantly fossil system with flat pricing. Graphs on the left assume current (2016) costs, while graphs on the right assume projected future (2045) costs. A comparison of the top two rows shows the influence of electric vehicles (EV), contrasting the 2016 fleet share of 0.5 percent EV with 100 percent EV. In the top two rows, the overall demand elasticity is fixed at the benchmark $\theta = 0.1$. A comparison of the bottom two rows shows the influence of a more elastic demand ($\theta = 2$ versus $\theta = 0.1$), while holding the EV share fixed at 50 percent. Note the larger scale on bottom two rows (-15 to 100% instead of 45 to 100%). In all graphs, black lines show the social cost with flat prices, the dark-green line shows the social cost with RTP and pessimistic interhour substitutability, and the light-green line shows the social cost with RTP and optimistic interhour substitutability.

The scenarios depicted in Figure 7 show 50% EV, 2045 technology and fuel costs, pessimistic flexibility, and an overall demand elasticity of 0.1. When demand is more elastic, flexibility is more optimistic, and/or there more EVs, the contrast between fossil and high-renewable systems with RTP are similar but larger in magnitude. [27]

Figure 7: Distributions of prices and quantities.



Notes: These graphs show quantity and price distributions under flat pricing and RTP assuming 2045 projected costs, an overall demand elasticity of 0.1, and pessimistic demand flexibility. The top row shows histograms of hourly quantities (in MWh) with dashed lines to indicate the mean quantity for each scenario (RTP or flat prices). Box plots in the bottom row show the distributions of hourly RTP prices (in $/MWh) and grey lines to indicate the corresponding flat-price scenario.

6.3 Chronological Operation

In Figure 8 we show hourly generation, storage, and use profiles for three sample days in a few scenarios. Fossil, 100% clean, and unconstrained models are compared, each with flat prices and RTP. The sample days include a day with a moderately low weight (0.05), a high weight (0.09), and the most-difficult-to-serve day with the lowest weight (0.02). The scenarios depicted

[27]For this figure and some others, it is useful to keep in mind that the weights on the high-price days are considerably smaller than those on the low-price days (shown in Figure 1); the plotted distributions take these weights into account. More detail on the frequency of especially low-priced times are shown in the online appendix.

are for 2045 technology and fuel costs, and pessimistic demand flexibility.[28] The "supply source" panels show the scale and timing of solar and wind generation, when battery discharging occurs, thermal generation using diesel, biodiesel, low-sulfur fuel oil (LSFO), and fuel cell generation from hydrogen. The "demand use" panels show consumption (all flexibilities), battery charging, and production of hydrogen (electrolysis and liquefaction). Nominal demand, derived from benchmark sample days in 2007 and 2008, are shown using a black dotted line, labelled as *Base load*. Nominal demand is pinned to the average generation cost during these benchmark years. Since these benchmark years were high-priced (about 18 cents per kWh due to the high cost of oil fuel), even the flat-price scenarios show higher demand than the benchmark. The "supply source" graphs also show the *benchmark price* (depicted with black dashed lines) and *final price* (red dashed lines), with the scale depicted on the right.

A number of interesting lessons can be gleaned from careful study of these chronological graphs. A few highlights include:

- Fossil systems (with no additional renewable energy) use stationary batteries in 2045 to help satisfy evening peak demand, but most batteries are eliminated under RTP, because electric vehicle charging and flexible demand can be strategically timed to avoid this cost. Prices vary little, however, even in RTP pricing systems. Note, however, that the difficult day pertains to high-renewable scenarios; the most-difficult day for the fossil system is not shown.

- The unconstrained and 100% clean systems look similar, dominated by wind and solar generation, with battery discharging shifting excess midday supply to nighttime and early morning. The main difference is on the difficult-to-serve day, which is satisfied by LSFO and diesel in the unconstrained scenario and biodiesel in the 100% clean case. The 100% clean scenario also makes use of hydrogen for long-run storage.

- With flat prices, both unconstrained and 100% clean systems have significant curtailment of solar on the high-weight day (the middle day shown). In the RTP scenarios, the price falls to zero or nearly so on this day, and extra demand is shifted into these hours.[29]

- There is noticeably less hydrogen production under RTP than under flat prices in the 100% clean case.

[28] We show only three days in order to make the graphs large enough to interpret. For high-resolution depictions of all sample days for all 648 scenarios, see the interactive website at: `http://www2.hawaii.edu/~mjrobert/power_production/`, which allows users to select desired scenarios from a series of drop-down menus, and to download PDF files of each one.

[29] With CES demand, quantity can grow arbitrarily high as prices approach zero, but when demand is highly inelastic, there is little welfare benefit from much of this extra demand.

- Although prices vary widely in the high-renewable RTP scenarios, they vary much more *between* days than *within* days. In both unconstrained and 100% clean scenarios (bottom and middle rows, respectively), the high-renewable days (which are common) have zero or negative prices all day long, not just during the sunny times. On the most-difficult-to-serve day, prices are high (about 35 cents per kWh) all day long, not just during peak demand. The pattern emerges because ample battery installations do not near capacity constraints on most days. On some days, however, there can be spikes in prices around the evening peak (see the first day in the unconstrained model with RTP, for example).

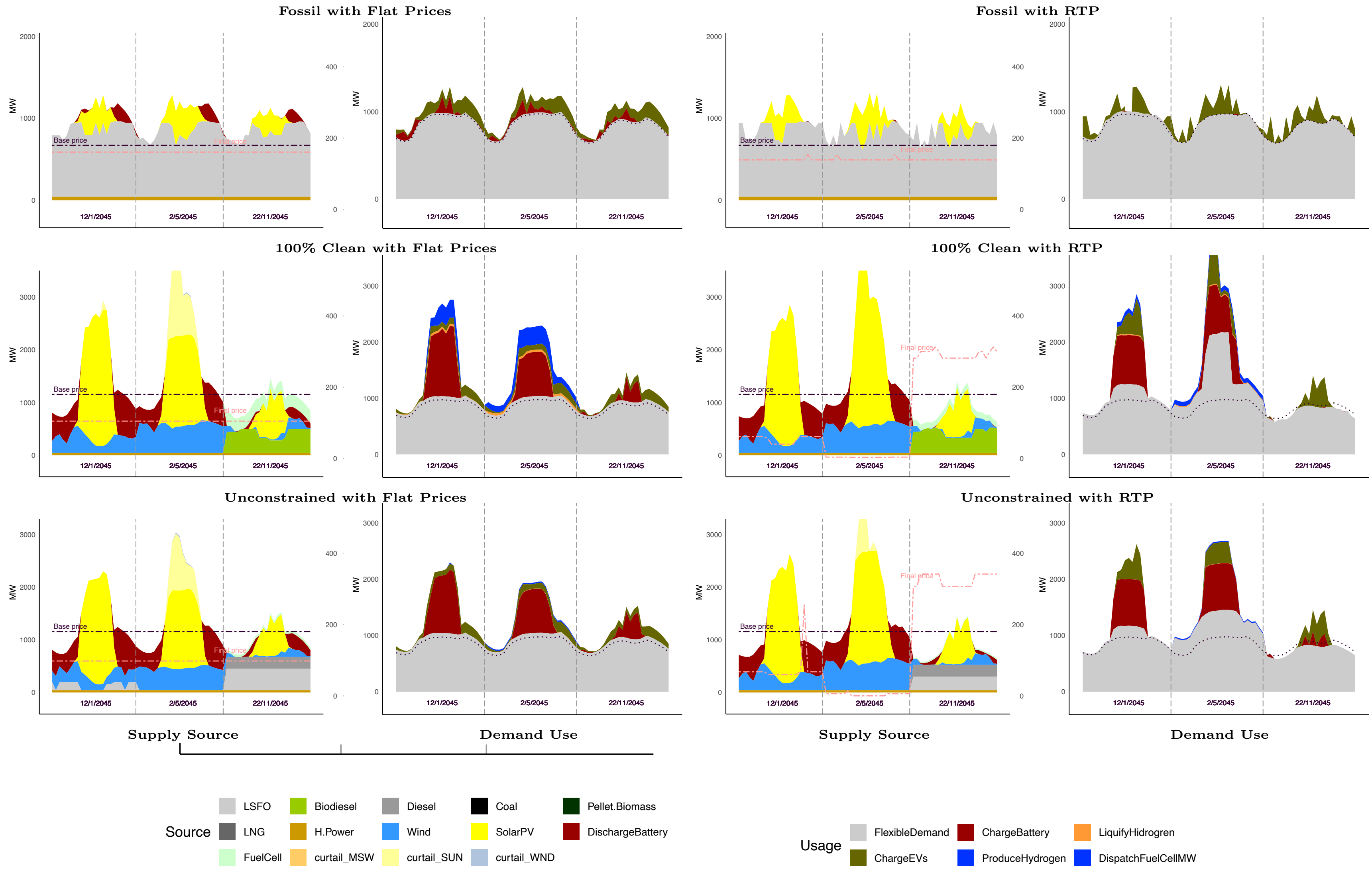
One factor not evident in the graphs or tables concerns the cost and prices associated with provision of reverses. While adequate reserves and equilibrium prices for them are a part of the model, in most scenarios they turn out to be an uninteresting one. There is generally enough storage and/or demand response to provide adequate regulating reserves at zero marginal cost. In other words, regulating reserves effectively become a co-product to storage and demand shifting.

In the Online Appendix we present chronological profiles for all thirteen sample days and explain some of the finer details of how the model resolves start/stop, minimum operating levels, and ramping constraints of thermal generators.

6.4 Generation Mix

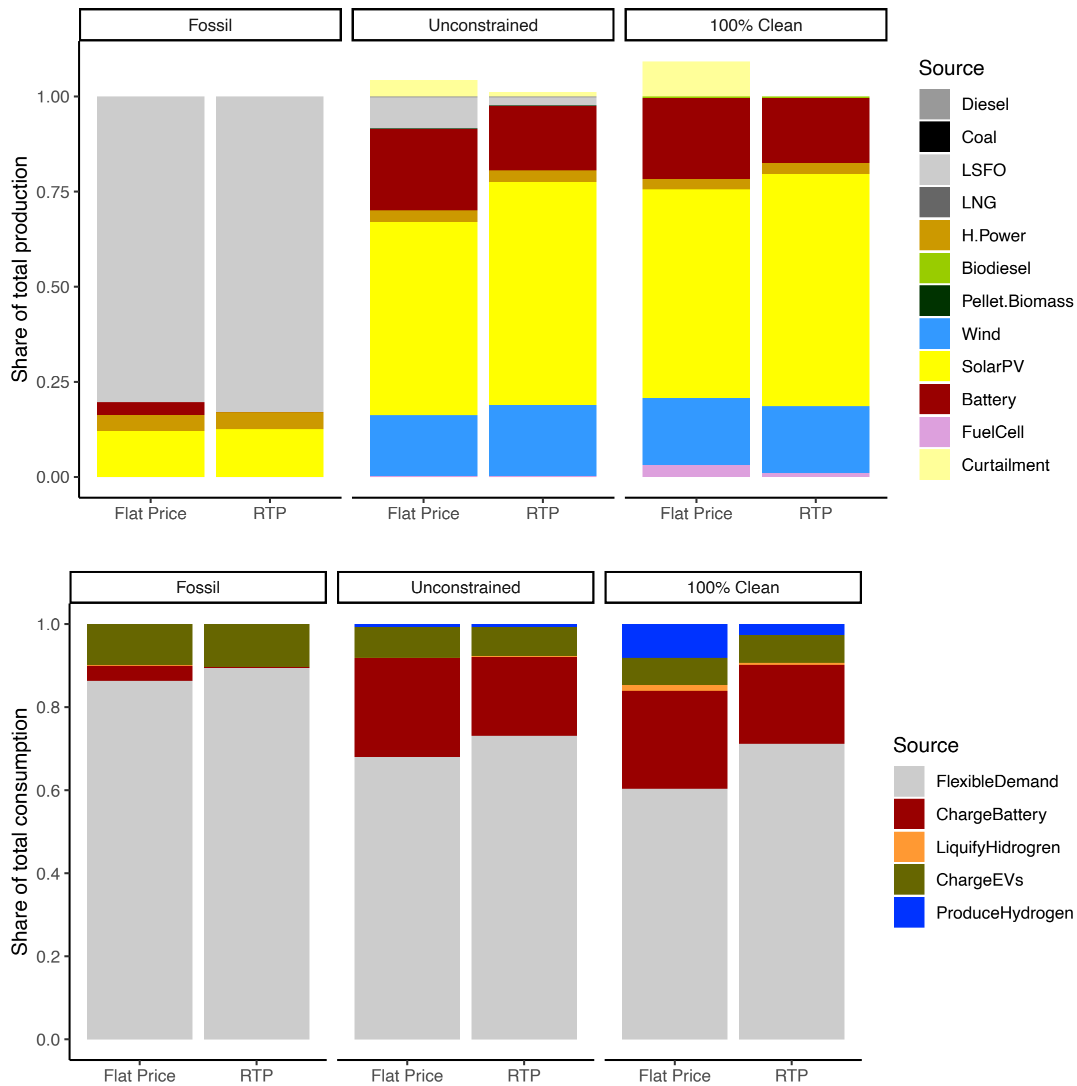
Aggregating across sample days, Figure 9 shows how generation and consumption portfolios differ in RTP versus flat-price environments. In the fossil scenario, we see that RTP nearly eliminates use of batteries overall, not just in the sample days depicted above. In unconstrained and high-renewable systems, RTP increases solar and wind shares of the generation mix while reducing battery use, and there is considerably less use of hydrogen for long-term storage. In all settings, there are also benefits to RTP from better timing of EV charging that are not directly apparent in the generation and consumption shares. There is also greater *overall* electricity use in the RTP scenarios (10-15% greater in 100% Clean scenarios) not directly apparent in the shares. These results are clear in Table 5.

Figure 8: Hourly production and consumption profiles for several scenarios with pessimistic interhour demand flexibility.



These graphs show hourly load balance (supply and demand components) for three sample days under a the scenarios with the pessimistic interhour substitutability of demand, an inelastic overall demand elasticity for electricity equal to 0.1, a baseline demand profile projected for 2045, a vehicle fleet with 50% electric vehicles, and costs of production as projected for 2045 in HECO's Power Supply and Improvement Plan. The first two rows show fossil-fuel systems with flat and dynamic, real-time pricing; the next two rows show 100% clean systems with flat pricing and RTP; and the last two rows show the welfare-maximizing systems (resource unconstrained) with flat pricing and RTP. All 13 sample days are shown in the Appendix.

Figure 9: Production and consumption shares by sources with pessimistic interhour demand flexibility.



The scenario presented assumes the pessimistic interhour substitutability of demand, an inelastic overall demand elasticity for electricity equal to 0.1, a baseline demand profile projected for 2045, a vehicle fleet with 50% electric vehicles, and costs of production as projected for 2045 in HECO's Power Supply and Improvement Plan.

6.5 Gains for Different Demand Types

While RTP benefits flexible demand types more than inflexible demand types, even inflexible demand types normally benefit from RTP, and in some cases, nearly as much as flexible demand types. These results are depicted in Table 6. For example, in the 100% clean, pessimistic flexibility scenario for 2045 with RTP, high-flex customers gain 25.5% (54.3 - 28.8%) in consumers' surplus relative to flat pricing while inflexible customers gain 5.5% (34.3 - 28.8%). Under optimistic flexibility, high-flex customers gain 22.8% while inflexible customers gain 7.0%. Under

2016 technology/cost scenarios and pessimistic flexibility, inflexible types can gain be slightly worse off under RTP versus flat pricing (a loss of 0.7%), but gain under optimistic flexibility.

Many if not most customers probably have both flexible and inflexible demands, as flexibility is likely connected to the specific end use more than customer preferences. Flexibility will also depend on adoption of smart devices that enable automated response, which will likely be heterogeneous. Differences in outcomes across customers will also depend on heterogeneity in baseline load profiles, which we do not consider. Most residential customers, for example, likely have little midday demand and high morning and evening demand, which would be somewhat more costly to serve. The fact that there tends to be more variation in marginal cost between days than within days, however, would appear to mitigate inequity stemming from this kind of demand heterogeneity. Thus, there may less difference in impacts across customers than some might otherwise presume, but those with more potential for demand flexibility (e.g., commercial customers) may see greater benefits than customers less willing or less able to harness demand flexibility.

6.6 Robustness

In the appendix, we report results from scenarios that are like those reported in table 5, except we change individual assumptions that were held constant across all scenarios in the main results. The assumptions we change include: (1) if 2007 loads are used instead of projected loads for 2045 (actual 2007 showed more variable demand within and across days than projections for 2045); (2) if 0.05 or 100% of the vehicle fleet is electric instead of 50%; (3) if the overall demand elasticity is 0.5 or 2 instead of 0.1. We also replicate figures 4 and 5 for different overall demand elasticities. These additional results show that the value of RTP increases modestly if demand varies more within and between days and increases considerably in high-renewable scenarios with a higher overall demand elasticity.

7 Discussion

7.1 Summary of Findings

We developed an integrated model of weather-dependent power supply, nonlinear coincident weather-dependent demand, storage, and reserves to find chronological dynamic equilibria in an electricity market under real-time marginal-cost pricing (RTP), and compare solutions to those with regulated flat retail prices that are currently predominant in practice. We use this model to show how much more valuable RTP is in high-renewable environments as compared to conventional fossil systems. We find that RTP is at least five times more valuable in high-renewable environments as compared to a conventional fossil system, and could easily exceed an order of magnitude more valuable depending on the nature of demand and costs of storage. We also find that a large share of clean energy is currently optimal, that a very high-renewable

(>85%) will soon be optimal, and that the optimal renewable share of power is considerably higher (> 95%) with RTP than it is with flat pricing, even excluding pollution externalities.

The optimized power system with a large share of clean energy uses batteries and/or demand response to cost-effectively manage day-night and other short-term variations in supply. The larger challenge with intermittent renewables concerns seasonality or prolonged shortfalls in power generation. The optimized system manages these variations by striking a balance between overbuilding generation capacity for normal and resource-rich times and, during resource-lean times, using high-cost biofuels in traditional power plants while increasing prices to limit demand. In many scenarios, *Switch* also selects a hydrogen storage option, wherein excess generation produced in resource-rich times is used to make hydrogen from water, which is then liquefied and stored for fuel cell generation during resource-lean times. The scale of this technology is modest in RTP scenarios, as demand response is a more economic substitute, but more substantial in high-renewable scenarios with flat pricing.[30]

Unlike current fossil-based power systems wherein the main benefit of RTP comes from limiting critical peak demand, the benefits of RTP in high-renewable systems are multifaceted, lowering the cost of day-night balance, helping to limit generation capacity by staving off demand during resource-lean times (not necessarily peak demand), while allowing greater social benefit from low prices and higher electricity use during resource-rich times. The last phenomenon—new, flexible uses of low-cost power—is a key source of value from RTP in high-renewable systems, especially if overall demand is more elastic. Although existing empirical studies suggest that demand is inelastic, we speculate that some of the inelasticity stems from the fact that historical retail pricing tends to be flat. It is hard to know how demand could evolve, especially if aided by automation and induced technical change, in an environment with long spells of free or nearly-free energy. With more elastic demand, the potential upside benefits from clean renewables could be extraordinary in conjunction with RTP. With elastic demand, the optimal system under projected future technology costs, is 100% clean under RTP, and has net social benefits relative to a conventional system that exceed 100% of expenditure in that system.

Even with highly inelastic demand, our findings on the feasibility and cost of a zero-emission power system may appear optimistic. Some of the findings derive from assuming more potential flexibility on the demand side than other researchers have been willing to consider, especially air conditioning demand. For example, a recent report by the National Renewable Energy Laboratory (NREL) assessed demand response potential for a large number of end uses and

[30] The model also includes a pumped-water hydropower option that would make use of an existing reservoir, but this is not economic in any of our scenarios. The model does not include consideration of nuclear power because it is unlikely to be economic and does not appear to be under serious consideration in the State of Hawai'i. These and other technologies might be viable components of an optimal generation portfolio in other places.

customer types (Mai, Sun, Jadun, Murphy, Logan, Muratori and Nelson 2020). While that study assumed that a greater share of HVAC demand was shiftable, it assumed that such demand could only be shifted a maximum of one hour earlier or later in the day. A recent report by the National Academy of Sciences that considers alternative decarbonization pathways rests on the NREL report to guide its assumptions about demand side flexibility (Pacala, Cunliff, Deane-Ryan, Haggerty, Hendrickson, Jenkins, Johnson, Lieuwen, Loftness, Miller, Pizer, Rai, Rightor, Gallagher, Takeuchi, Tierney and Wilcox 2021). In contrast, we assume shiftability anytime within each 24 hour period (a 12-23 hour shift, depending on the hour of day). The difference amounts to whether simple thermostat adjustments would be made, which would have limited benefits but be essentially costless, or whether demand-side investments thermal storage or other shifting technologies are employed. These technologies would not be costless, but likely involve greater costs than are implicit in our interhour elasticities of substitution. They are, however, likely much cheaper than batteries, with greater durability, less energy loss per storage cycle, and potential co-benefits, like improved energy efficiency if installed in conjunction with HVAC upgrades, like heat pump cooling and heating.

Still, even in findings for flat-pricing scenarios, clean energy is affordable. Some may wonder if the viability of low-cost, high-penetration renewable energy reflects Hawai'i's unique characteristics: the state is rich in wind and solar resources, but must otherwise import fossil fuels a great distance, making fossil fuels expensive relative to clean alternatives. Hawai'i also has mild seasonal variation in solar capacity, and that variation happens to be correlated with seasonal variation in demand. The unconstrained options also rule out additional installations of new coal-fired power plants. Note, however, that the technology cost assumptions used in this analysis are fairly conservative, especially in light of rapid technological advancement in recent years. By some estimates, such as Bloomberg New Energy Finance and Lazard,[31] current renewable energy and battery technology costs already rival Hawaiian Electric Company's projections for 2045 that we use in this analysis (Lazard 2021). Currently, renewable technology costs are far less, and fossil fuel costs far greater, than those assumed for 2016.

Hawai'i's extreme isolation also creates significant challenges for intermittent solar and wind energy. Oahu is a geographically small place, and therefore has less diversity in solar, wind, and demand flexibility than might be employed in larger regions to smooth differences between supply and demand. Even connecting the individual islands would be cost prohibitive (Woodford 2011). Continental regions, in contrast, have much more scale and connectivity, such that transmission provides another method of managing intermittency, as well as for transferring power from areas rich in renewable resources to those with less. While this fact suggests that demand response may be less valuable in continental regions as compared to Hawai'i, re-

[31] See https://about.bnef.com/blog/ and https://www.lazard.com/perspective/levelized-cost-of-energy-levelized-cost-of-storage-and-levelized-co

cent research suggests that shifting of heating and cooling loads with thermal storage might do more than transmission as a mechanism for flattening existing demand variability across the continental United States (Roberts, Zhang, Yuan, Jones and Fripp 2021). Thus, while the value of demand-side flexibility may differ for larger interconnected regions, its role is likely substantial, and may in some ways complement the benefits of transmission.

While critical high-cost times are rare, low or zero marginal cost times are much more prevalent in all high-renewable scenarios. For example, in the baseline set of clean and unconstrained scenarios with RTP, approximately half of all hours in 2045 have marginal cost less than 5 cents per kWh while 15 to 20% have marginal costs less than 1 cent per kWh. With flat pricing, these shares are considerably higher (top panel of Figure S1 in the online appendix). The reason is clear: among the portfolio of options for managing intermittency, one is to simply overbuild wind and solar such that a reasonably sufficient quantity is available during lean times, which implies a surplus of energy during less-lean times. Because wind and solar are so cheap, all solutions lean heavily on this option, even those with plentiful demand-side flexibility. Much of the additional value from RTP stems from making productive use of energy produced during these sunny and windy days. We expect this pattern to be the case generally. Indeed, most areas likely have more seasonal variation in demand and renewable energy supply than does Hawai'i, which should lead to more overbuilding to satisfy prolonged lean periods, even more excess supply during resource-rich times, and thus even greater value from RTP. Because short-duration battery storage and interhour demand flexibility cannot smooth such long-run imbalances, gains from RTP also tend to be more sensitive to the overall demand elasticity than to interhour flexibility (Figure 6), a result that is likely true in general.

7.2 Modeled Versus Actual Outcomes

Some may wonder if the finely resolved long-run competitive equilibrium prices realistically depict what would occur in actual practice. In practice, there will times with too little generation and storage capital relative to the long-run competitive equilibrium, which would cause higher price spikes and greater volatility. At other times there will too much capital, which would cause prices and price variability to be too low. Capacity markets or other requirements and allowances for investment from public utilities commissions will factor into this overall level of investment. Regardless, RTP will bring about more efficient pricing conditional on the given portfolio of assets at any given time and ought to help facilitate appropriate ongoing capital adjustments. Given the way these decisions have been made historically, however, it seems at least as likely that excess investment will occur as under-investment (Bushnell, Flagg and Mansur 2017). It could be difficult to entice appropriate levels of demand-side investments if customers believe that excess supply-side investment will quell price variability.

Another reason prices can exceed marginal cost is market power, which may be affected by growth of intermittent renewables. Market power will change with changes in the nature and geography of generation, and the resulting times and locations that are most constrained and thus susceptible to strategic withholding from wholesale markets. In the near term, there may be too little storage and flexible demand, which could exacerbate market power during times of reduced renewable energy supply, like when sun sets (Jha and Leslie 2021). Longer term, storage ought to ameliorate market power, so long as ownership is not too concentrated among those who also own substantial generation capacity (Acemoglu, Kakhbod and Ozdaglar 2017, Fabra and Llobet 2019). Because tax credits for renewable energy can be extended to battery storage only if paired with and charged by renewable energy installations, this may be a concern in some areas (Anderson, Elgqvist and Settle 2018). Like storage, improved transmission pairs well with renewables and would also reduce market power. Careful consideration of market power would depend on the nature of market rules and would be complicated greatly by storage.[32] Regardless, RTP ought to do a lot to abate market power both in conventional and in high-renewable systems that are vulnerable to it, and could otherwise simplify some aspects of regulation.

A practical challenge with RTP in Hawai'i is that there is no market to set real-time prices. The system is managed by an investor-owned utility, Hawaiian Electric Company, that owns the transmission and distribution network and most conventional thermal generation. The PUC typically requires all new generation, including renewables, be purchased from independent via purchase power agreements with fixed or fuel-based prices to limit financing costs. The utility's allowed revenue is set using performance-based regulation and customer tariffs are regulated by the PUC. Time-of-use rates have been introduced, but there is no current appetite for RTP, even though current marginal costs are essentially flat, like those in our conventional fossil scenarios.[33] Since there is no market, real-time prices would need to be set by a regulatory mechanism, such as the marginal cost given by automatic generation control system software that optimize operations in real-time.[34] Such software would need to be modernized to account for storage,

[32] With few exceptions, areas with wholesale markets also have *capacity markets* that ensure sufficient "firm" capacity is installed to meet peak demand and limit market power (Spees, Newell and Pfeifenberger 2013). If such markets lead to excess investment, real-time prices, even if otherwise competitive, may be too low to recover all capital expenses. Rules for what qualifies as "firm" capacity, however, vary widely across wholesale markets, and it is unclear whether any of them ever incentivized an appropriate level and type of generation resources, even before substantial integration of renewable energy and storage (Bushnell et al. 2017). ERCOT, the only exception in the United States, is an "energy only" market that lacks a capacity market and may be more susceptible to price spikes. Texas is also seeing record growth of storage investment to arbitrage price spikes https://www.utilitydive.com/news/texas-drives-record-growth-in-us-energy-storage-market-in-q2-despite-chall/632268/.

[33] See https://www.hawaiianelectric.com/products-and-services/save-energy-and-money/time-of-use-program/time-of-use-rate-history for a history of time-of-use rates, which are scheduled to be made "opt out" sometime in 2023. These rates far exceed marginal costs at all times, but create price differentials large enough to potentially induce significant demand response by residential users over time, but are too high relative to commercial baseline rates to be adopted by large-scale customers.

[34] Most all power systems are operated in real-time using software that minimizes the cost of balancing supply and demand at each moment given fuel and other costs and operating constraints of available generation resources,

supply, and demand, all of which would be linked to weather forecasts and other factors. Other vertically integrated utilities, such as Georgia Power, have implemented RTP without a market, with prices tied to the utility's day-ahead or hour-ahead forecasts of this measure of marginal cost. In other contexts, with well-functioning wholesale markets and location-specific marginal costs, RTP may simply require a sensible way to allocate any necessary fixed charges, such as the inspired suggestion by Borenstein, Fowlie and Sallee (2021) to make such charges progressive.

Relatedly, although Switch is one of only a few models that simultaneously considers investment and real-time operations, chronological decisions do not explicitly consider uncertainty about future demand and weather-linked supply, as actual wholesale markets would. Instead, operations decisions, including plant-specific start/stop decisions and storage adjustments, assume perfect foresight within each day, and account for uncertainty by requiring sufficient up- and down-reserves. The solution, however, finds marginal prices for reserves are zero across all days and scenarios, and real-time prices typically show more variation between days than within them. These results suggest that a more refined treatment of uncertainty using, say, stochastic dynamic programming, would not yield substantially different results. If these results generalize to other settings, as we suspect they will, they also suggest that market power will mainly be a concern on the toughest-to-serve days and/or when inventory of stored energy reaches critical lows.

7.3 Overcoming Resistance to Real-Time Pricing

Despite its potential benefits for consumers and its usefulness for affordably integrating intermittent clean power, there tends to be institutional resistance to real-time pricing tariffs. Part of the resistance likely comes from both utility customers and state public utility commissions that may fear extreme spikes in prices, like those that occasionally arise in Texas (Departo 2019, Cramton 2021). Some of the resistance also comes from the mixed success of past efforts to implement RTP; while some utilities, like Georgia Power, demonstrated remarkable early success, many other studies show weak participation and limited demand response to variable prices (Barbose et al. 2004, Goldman et al. 2006).

At the same time, current regulatory practice often rewards (implicitly) high-cost, centralized solutions that require more capital expenditure, some of which might be avoided with effective demand-side management. Such investments may include centralized storage, peaking power plant investments, and transmission and distribution upgrades. RTP, if both buying and selling from customers is permitted, effectively opens the system to free entry.[35] Major stake-

subject to any reserve requirements or other constraints. The software calculates the cost of the last kilowatt hour in each moment, and this marginal cost is called *system lambda* as it is effectively the multiplier on the balance constraint in the optimization problem that underpins automatic generation control. In a vertically-integrated system like Oahu's, there would presumably need to be some regulatory oversight of this control software and how future forecasts are developed.

[35] While it is beyond the scope of analysis here, location-specific RTP, down to the node or even circuit level,

holders that would benefit from extensive use of RTP mainly include large-scale commercial customers, who may be unaware of the potential, and would-be providers of devices that could enable demand response, like thermal storage. In the long run, much of the benefits would be dispersed to all customers via competition. At the same time, RTP would generally enable lower-cost competitive outcomes that would diminish rents to more established stakeholders that include incumbent providers of energy, grid services, and transmission and distribution services. It is difficult, however, for disparate consumers and potential entrants to parse the details of regulatory options, much less coordinate and effectively engage in regulatory processes like large incumbent stakeholders do. And many disparate consumers would presumably be easy to dissuade from supporting or participating in RTP with accounts of $9,000 per MWh prices faced by Griddy and other RTP customers in Texas during the Winter of 2021.

There are well-known solutions to the problem of extreme price spikes. It would be easy to hedge such extremes, as Griddy was apparently about to do just before extreme cold struck Texas in the winter of 2021, hobbling much of the gas supply network and many gas-fired power plants, ultimately leading to rolling blackouts and crippling high prices (Borenstein 2007, Cramton 2021). Alternatively, and more simply, reasonable price caps could be placed on RTP tariffs. Our model typically indicates a peak price of $500 MWh or less on the hardest-to-serve day when demand is highly inelastic. A price cap at this level or slightly higher would allow enough price variation to engender the needed investments and demand responses and would pose little meaningful risk to customers given how rarely such hours would occur. Sensible price caps would have the added benefit of limiting market power during constrained periods of time that might tempt those with temporary market power from withholding energy and engineering even higher price spikes (Borenstein et al. 2002a, Woerman 2018).

There may be other ways to implement demand response in a manner that captures most of its potential benefits. Since optimal prices tend to vary more between days than within days, time-of-use rates would likely need to be paired with critical "energy drought" pricing on especially difficult-to-serve days, and "discount days" for the considerably more frequent days when there is a substantial surplus of energy and marginal cost approaches zero. Regulators, investors, and the general public may find the simplicity and transparency of such a pricing mechanism more appealing. It is not yet clear how efficient such second-best pricing mechanisms would be in high-renewable settings, but it would be worthwhile investigating if they turn out to be more institutionally viable than RTP.

might save distribution system upgrades, which are normally financed with rate-of-return regulation, even in places with wholesale markets. This possibility may create growing tension between the interests of utilities and customers, as distributed resources—rooftop solar, batteries, thermal storage and other forms of flexible demand—become increasingly common and affordable.

References

Acemoglu, Daron, Ali Kakhbod, and Asuman Ozdaglar, "Competition in electricity markets with renewable energy sources," *The Energy Journal*, 2017, *38* (KAPSARC Special Issue).

Akar, Sertaç, Philipp Beiter, Wesley Cole, David Feldman, Parthiv Kurup, Eric Lantz, Robert Margolis, Debo Oladosu, Tyler Stehly, Gregory Rhodes et al., "2020 annual technology baseline (ATB) cost and performance data for electricity generation technologies," Technical Report, National Renewable Energy Laboratory-Data (NREL-DATA), Golden, CO (United … 2020.

Anderson, Katherine H, Emma M Elgqvist, and Donald E Settle, "Federal Tax Incentives for Energy Storage Systems," Technical Report, National Renewable Energy Lab.(NREL), Golden, CO (United States) 2018.

Barbose, Galen, Charles Goldman, and Bernie Neenan, "A survey of utility experience with real time pricing," Technical Report, Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States) 2004.

Benthem, Arthur Van, Kenneth Gillingham, and James Sweeney, "Learning-by-doing and the optimal solar policy in California," *The Energy Journal*, 2008, *29* (3).

Blonz, Joshua A, "Making the Best of the Second-Best: Welfare Consequences of Time-Varying Electricity Prices," Technical Report Working Paper W275, Energy Institute, Haas School of Business, University of California at Berkeley 2016.

Bollinger, Bryan K and Wesley R Hartmann, "Information vs. Automation and implications for dynamic pricing," *Management Science*, 2020, *66* (1), 290–314.

Borenstein, Severin, "The long-run efficiency of real-time electricity pricing," *The Energy Journal*, 2005, *26* (3), 93–116.

___ , "Customer risk from real-time retail electricity pricing: Bill volatility and hedgability," *The Energy Journal*, 2007, *28* (2).

___ **and James B Bushnell**, "Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency," *American Economic Journal Economic Policy*, 2022.

___ **and Stephen Holland**, "On the efficiency of competitive electricity markets with time-invariant retail prices," *RAND Journal of Economics*, 2005, *36* (3), 469–494.

——, **James B Bushnell, and Frank A Wolak**, "Measuring market inefficiencies in California's restructured wholesale electricity market," *American Economic Review*, 2002, *92* (5), 1376–1405.

——, **Meredith Fowlie, and James Sallee**, "Designing electricity rates for an equitable energy transition," *Energy Institute at Haas working paper*, 2021, *314.*

——, **Michael Jaske, and Arthur Rosenfeld**, "Dynamic pricing, advanced metering, and demand response in electricity markets," *Journal of the American Chemical Society*, 2002, *128* (12), 4136–45.

Brown, Thomas, Jonas Hörsch, and David Schlachtberger, "PyPSA: Python for Power System Analysis," *Journal of Open Research Software*, January 2018, *6* (1).

Bushnell, James and Kevin Novan, "Setting with the Sun: The impacts of renewable energy on conventional generation," *Journal of the Association of Environmental and Resource Economists*, 2021, *8* (4), 759–796.

——, **Michaela Flagg, and Erin Mansur**, "Capacity markets at a crossroads," *Energy Institute at Hass Working Paper*, 2017, *278.*

Butters, R Andrew, Jackson Dorsey, and Gautam Gowrisankaran, "Soaking up the sun: Battery investment, renewable energy, and market equilibrium," 2021.

Callaway, Duncan S and Ian A Hiskens, "Achieving controllability of electric loads," *Proceedings of the IEEE*, 2010, *99* (1), 184–199.

Consulting, Inc. Navigant, "Demand Response Potential Assessment for the Hawaiian Electric Companies: Final Draft Report," Technical Report, Navigant Consulting, Inc. December 2015.

Corbus, D, M Schuerger, L Roose, J Strickler, T Surles, D Manz, D Burlingame, and D Woodford, "Oahu wind integration and transmission study: Summary report," Technical Report, National Renewable Energy Laboratory (NREL), Golden, CO. 2010.

Cramton, Peter, "Lessons from the 2021 Texas electricity crisis," *Utility Dive*, 2021, *23.*

Dantzig, George B and Philip Wolfe, "Decomposition principle for linear programs," *Operations research*, 1960, *8* (1), 101–111.

Das, Paritosh and Matthias Fripp, "Savings and Peak Reduction Due to Optimally-Timed Charging of Electric Vehicles on the Oahu Power System," Technical Report HI-14-17, Electric Vehicle Transportation Center December 2015.

———, **Deepak Chermakani, and Matthias Fripp**, "Development of SWITCH-Hawaii Model: Loads and Renewable Resources," Technical Report, Florida Solar Energy center 2016.

de Leon Barido, Diego Ponce, Josiah Johnston, Maria V Moncada, Duncan Callaway, and Daniel M Kammen, "Evidence and future scenarios of a low-carbon energy transition in Central America: a case study in Nicaragua," *Environmental Research Letters*, September 2015, *10* (10), 104002.

Denholm, Paul, Maureen Hand, Maddalena Jackson, and Sean Ong, "Land use requirements of modern wind power plants in the United States," Technical Report, National Renewable Energy Laboratory (NREL), Golden, CO. 2009.

Departo, Matt, "Texas' Power Price Spike and Designing Markets for a Carbon-Free Grid," *GreenTech Media*, August 2019.

Deryugina, Tatyana, Alexander MacKay, and Julian Reif, "The long-run dynamics of electricity demand: Evidence from municipal aggregation," *American Economic Journal: Applied Economics*, 2020, *12* (1), 86–114.

Dorfner, Johannes, "Urbs: A Linear Optimisation Model for Distributed Energy Systems — Urbs 0.7.1 Documentation," Technical Report, Chair of Renewable and Sustainable Energy Systems, Technical University of Munich July 2018. available at https://urbs.readthedocs.io/.

Fabra, Natalia and Gerard Llobet, "Auctions with Unknown Capacities: Understanding Competition among Renewables," Technical Report, CEPR Discussion Papers 2019.

———, **David Rapson, Mar Reguant, and Jingyuan Wang**, "Estimating the Elasticity to Real-Time Pricing: Evidence from the Spanish Electricity Market," in "AEA Papers and Proceedings," Vol. 111 2021, pp. 425–29.

FHA, "2009 National Household Travel Survey," Technical Report, U.S. Department of Transportation, Federal Highway Administration, Washington, D.C. 2009.

Fripp, Matthias, "Switch: a planning tool for power systems with large shares of intermittent renewable energy," *Environmental science & technology*, 2012, *46* (11), 6371–6378.

———, "Effect of Electric Vehicles on Design, Operation and Cost of a 100% Renewable Power System," Technical Report Working Paper No. 2017-3, University of Hawaii Economic Research Organization (UHERO), Honolulu, Hawaii March 2017.

Goldman, Charles, Galen Barbose, and Bernie Neenan, "Real-Time Pricing as an Optional Service: It's Alive, But Is It Well?," *The Electricity Journal*, 2006, *19* (1), 18–29.

Gowrisankaran, Gautam, Stanley S Reynolds, and Mario Samano, "Intermittency and the value of renewable energy," *Journal of Political Economy*, 2016, *124* (4), 1187–1233.

He, Gang, Anne-Perrine Avrin, James H Nelson, Josiah Johnston, Ana Mileva, Jianwei Tian, and Daniel M Kammen, "SWITCH-China: A Systems Approach to Decarbonize China's Power System," *Environmental Science & Technology*, 2016.

Heine, Karl, Paulo Cesar Tabares-Velasco, and Michael Deru, "Energy and cost assessment of packaged ice energy storage implementations using OpenStudio Measures," *Energy and Buildings*, 2021, *248*, 111189.

Ito, Koichiro, "Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing," *The American Economic Review*, 2014, *104* (2), 537–563.

Jenkins, Jesse D and Nestor A Sepulveda, "Enhanced Decision Support for a Changing Electricity Landscape: The GenX Configurable Electricity Resource Capacity Expansion Model," Technical Report MITEI-WP-2017-10, MIT Energy Initiative, Cambridge, Massachusetts November 2017. available from http://energy.mit.edu/publication/enhanced-decision-support-changing-electricity-landscape/.

Jha, Akshaya and Gordon Leslie, "Start-up costs and market power: Lessons from the renewable energy transition," *Available at SSRN 3603627*, 2021.

Johnston, Josiah, Rodrigo Henriquez-Auba, Benjamín Maluenda, and Matthias Fripp, "Switch 2.0: A Modern Platform for Planning High-Renewable Power Systems," *SoftwareX*, 2019, *10*, 100251.

Lazard, "Levelized Cost of Energy Analysis Version 15.0," Technical Report, Tech. rep., Lazar Capital Markets Report, version 15 2021.

Liski, Matti and Iivo Vehviläinen, "Gone with the wind? An empirical analysis of the equilibrium impact of renewable energy," *Journal of the Association of Environmental and Resource Economists*, 2020, *7* (5), 873–900.

Mai, Trieu, Yinong Sun, Paige Jadun, Caitlin Murphy, Jeffrey Logan, Matteo Muratori, and Brent Nelson, "Electrification Futures Study: Methodological Approaches for Assessing Long-Term Power System Impacts of End-Use Electrification," Technical Report, National Renewable Energy Lab.(NREL), Golden, CO (United States) 2020.

Mileva, Ana, James H Nelson, Josiah Johnston, and Daniel M Kammen, "SunShot solar power reduces costs and uncertainty in future low-carbon electricity systems," *Environmental Science & Technology*, 2013, *47* (16), 9053–9060.

Nelson, James, Josiah Johnston, Ana Mileva, Matthias Fripp, Ian Hoffman, Autumn Petros-Good, Christian Blanco, and Daniel M Kammen, "High-resolution modeling of the western North American power system demonstrates low-cost and low-carbon futures," *Energy Policy*, 2012, *43*, 436–447.

Nweke, Charles I, Frank Leanez, Glenn R Drayton, and Mohan Kolhe, "Benefits of chronological optimization in capacity planning for electricity markets," in "Power System Technology (POWERCON), 2012 IEEE International Conference on" IEEE 2012, pp. 1–6.

oemof Developer Group, "Open Energy Modelling Framework (oemof) - A modular open source framework to model energy supply systems. Version v0.1.4," March 2017.

O'Neill, Richard P, Eric A Krall, Kory W Hedman, and Shmuel S Oren, "A model and approach to the challenge posed by optimal power systems planning," *Mathematical Programming*, 2013, *140* (2), 239–266.

Pacala, Stephen, Colin Cunliff, Danielle Deane-Ryan, Julia H. Haggerty, Chris T. Hendrickson, Jesse Jenkins, Roxanne Johnson, Timothy C. Lieuwen, Vivian E. Loftness, Clark A. Miller, William Pizer, Varun Rai, Ed Rightor, Kelly Sims Gallagher, Esther S. Takeuchi, Susan F. Tierney, and Jennifer Wilcox, "Accelerating Decarbonization in the United States: Technology, Policy, and Societal Dimensions," Technical Report, National Academy of Sciences 2021.

Palmintier, B.S. and M.D. Webster, "Impact of Operational Flexibility on Electricity Generation Planning With Renewable and Carbon Targets," *IEEE Transactions on Sustainable Energy*, 2015, *7* (99), 1–13.

Reguant, Mar, "The efficiency and sectoral distributional impacts of large-scale renewable energy policies," *Journal of the Association of Environmental and Resource Economists*, 2019, *6* (S1), S129–S168.

Roberts, Michael J., Sisi Zhang, Eleanor Yuan, James Jones, and Matthias Fripp, "Using Temperature Sensitivity to Estimate Shiftable Electricity Demand: Implications for power system investments and climate change," 2021.

Sanchez, Daniel L, James H Nelson, Josiah Johnston, Ana Mileva, and Daniel M Kammen, "Biomass enables the transition to a carbon-negative power system across western North America," *Nature Climate Change*, February 2015, *5* (3), 230–234.

Sengupta, Manajit, Yu Xie, Anthony Lopez, Aron Habte, Galen Maclaurin, and James Shelby, "The national solar radiation data base (NSRDB)," *Renewable and sustainable energy reviews*, 2018, *89*, 51–60.

Spees, Kathleen, Samuel A Newell, and Johannes P Pfeifenberger, "Capacity markets—Lessons learned from the first decade," *Economics of Energy & Environmental Policy*, 2013, *2* (2), 1–26.

Sullivan, Patrick, Kelly Eurek, and Robert Margolis, "Advanced methods for incorporating solar energy technologies into electric sector capacity-expansion models: Literature review and analysis," Technical Report, National Renewable Energy Laboratory (NREL), Golden, CO. 2014.

Takayama, Akira, "On consumer's surplus," *Economics Letters*, 1982, *10* (1-2), 35–42.

van Stiphout, A., K. De Vos, and G. Deconinck, "The Impact of Operating Reserves on Investment Planning of Renewable Power Systems," *IEEE Transactions on Power Systems*, Jan 2017, *32* (1), 378–388.

Wei, Max, James H Nelson, Jeffery B Greenblatt, Ana Mileva, Josiah Johnston, Michael Ting, Christopher Yang, Chris Jones, James E McMahon, and Daniel M Kammen, "Deep carbon reductions in California require electrification and integration across economic sectors," *Environmental Research Letters*, 2013, *8* (1), 014038.

Woerman, Matt, "Market size and market power: Evidence from the Texas electricity market," Technical Report, Energy Institute at Haas December 2018.

Woodford, Dennis, "Oahu Wind Integration and Transmission Study (OWITS): Hawaiian Islands Transmission Interconnection Project," Technical Report, National Renewable Energy Lab.(NREL), Golden, CO (United States) 2011.

Online Appendix:
Real Time Pricing and the Cost of Clean Power

Imelda, Matthias Fripp, & Michael J. Roberts

Contents

1 Nested CES Demand System

Each pseudo-customer possessing a different interhour elasticity is assumed to maximize utility $U(x_1, x_2, \dots, x_h, \dots, x_{24}, Y|\sigma, \theta, \alpha, \beta_1, \beta_2, \dots, \beta_h, \dots, \beta_{24})$ subject to their budget constraint, $\sum_{h=1}^{24} p_h x_h + Y = M$, where x_h is electricity consumed in hour h, Y represents expenditure on all other goods with a constant price equal to 1 (i.e., money); α and β_h are share parameters that weight all other goods relative to electricity and electricity in each hour relative to other other hours; and M is total income. M is calibrated by dividing total baseline electricity expenditure of a particular pseudo-customer in a day by the share of aggregate income spent on electricity. The α and β_h parameters are calibrated from the statewide share of income spent on electricity expenditure, and by baseline load shares allocated to each pseudo-customer.

Following Rutherford (2008), suppose there exists a unit expenditure function or an ideal price index (the minimum expenditure required to achieve baseline utility) in the "calibrated share form," a measure relative to baseline values. The expenditure function is:

$$e(p_h, p_{(-h)}, \bar{p_h}, \bar{p_{(-h)}}, \bar{U}) = \bar{U}\left(\alpha\left(\frac{p_Y}{\bar{p_Y}}\right)^{1-\theta} + (1-\alpha)\left(\sum_{h=1}^{n}\beta_h\left(\frac{p_h}{\bar{p_h}}\right)^{1-\sigma}\right)^{\frac{1-\theta}{1-\sigma}}\right)^{\frac{1}{1-\theta}} \tag{1}$$

where $\bar{U}$, $\bar{p_Y}$, $\bar{p_h}$ indicate baseline values for respective parameters, α is the calibrated share given the baseline value of $\bar{Y} = M - \sum_h \bar{x}_h \bar{p_h}$, $\alpha = \bar{Y}/M$, and β_h are calibrated shares of each day's electricity consumed by the pseudo-customer in each hour at the associated baseline prices $\bar{p}_h$.

Consumer welfare is measured by the indirect money metric utility function. That is, we can write indirect utility in terms of the income required at baseline prices to achieve the level of utility achievable at prices p and income M, as:

$$V(p_h, \bar{p}_{-h}, M) = \frac{M}{e(p_h, p_{(-h)}, \bar{p_h}, \bar{p}_{-h}, \bar{U})} \tag{2}$$

From Roy's Identity, Marshallian demand is given by:

$$x_h(e(p_h, p_{-h}, \bar{p_h}, \bar{p}_{-h}), M) \quad = \quad -\frac{\partial V/\partial p_h}{\partial V/\partial M} = \frac{M}{e}\frac{\partial e}{\partial p_h}$$

The closed form solution of demand functions then can be written as a function of calibrated share parameters derived from a baseline load profile and the share of income spent on electricity at baseline prices.

$$\frac{x_h(p|\bar{p}, \sigma, \beta, M)}{\bar{p}} =$$

$$M\left(\alpha + (1-\alpha)\left(\sum_{j=1}^{24}\beta_j\left(\frac{p_j}{\bar{p_j}}\right)^{1-\sigma}\right)^{\frac{1-\theta}{1-\sigma}}\right)^{-1} \times (1-\alpha)\left(\sum_{j=1}^{24}\beta_j\left(\frac{p_j}{\bar{p_j}}\right)^{1-\sigma}\right)^{\frac{\sigma-\theta}{1-\sigma}} \times \beta_h\left(\frac{\bar{p_h}}{p_h}\right)^{\sigma} \tag{3}$$

Total demand is given by the sum of demand from each pseudo customer, as indicated in the main paper.

2 Mathematical Formulation of Switch

Here we provide a brief overview of the core equations used by Switch. A more complete documentation of the software can be found in Johnston, Henriquez-Auba, Maluenda and Fripp (2019).

Switch 2.0 has a modular architecture that reflects the modularity of actual power systems. Most power system operators follow rules that maintain an adequate supply of power, and most individual devices are not concerned with the operation of other devices. Similarly, core modules in Switch define spatially and temporally resolved balancing constraints for energy and reserves, and an overall social cost. Separate modules represent components such as generators, batteries or transmission links. These modules interact with the overall optimization model by adding terms to the shared energy and reserve balances and the overall cost expression. They can also define decision variables and constraints to govern operation of each technology. This approach makes it possible for users to add, remove or alter modules, representing different system components and formulations without unexpected interactions with other parts of the model. Consequently, Switch 2.0 can be readily customized to address the needs of a given study or region.

In the treatment below, we have omitted elements that define regional load zones and power transfers between these zones, since our model of Oahu has only a single zone. However, transmission constraints would be of critical importance for applications to larger geographical areas that are connected, such as the continental United States. We have similarly omitted definitions for multiple investment periods, since we use a single stage for this study.

2.1 Objective Function

The objective function minimizes the net present value of all investment and operation costs:

$$\min \sum_{c^{\mathrm{f}} \in \mathcal{C}^{\mathrm{fixed}}} c^{\mathrm{f}} + \sum_{t \in \mathcal{T}} w_t^{\mathrm{year}} \sum_{c^{\mathrm{v}} \in \mathcal{C}^{\mathrm{var}}} c_t^{\mathrm{v}} \tag{4}$$

Function (4) sums over sets of fixed costs $\mathcal{C}^{\mathrm{fixed}}$ and variable costs $\mathcal{C}^{\mathrm{var}}$. Each fixed cost component $c^{\mathrm{f}} \in \mathcal{C}^{\mathrm{fixed}}$ is a model object, specified in units of dollars per year. This object may be a variable, parameter or expression (calculation based on other components). Variable cost components c^{v} are indexed by timepoint (t) among all study timepoints ($\mathcal{T}$) and specified in units of dollars per hour. The term c_t^{v} is the element with index t from component c^{v}, i.e., a variable cost that occurs during timepoint t. The weight factor w_t^{year} scales costs from a sampled timepoint to an annualized value. For this study, we select one 24 hour day from each month of the year, so that the time points t specify actual hours. The weights multiply the individual days by about 30 such that the accounting reflects costs over an entire year.

Plug-in modules add components to the fixed and variable cost sets to represent each cost that they introduce. For example, the generator-building module adds the total annual fixed cost for all generators and batteries (capital repayment and fixed operation and maintenance) to the $\mathcal{C}^{\mathrm{fixed}}$ set, and the generator-dispatch module adds variable costs (fuel and variable O&M) for these facilities to $\mathcal{C}^{\mathrm{var}}$. The specification is generic so that models of different granularity may be considered depending on the needs of a particular problem and computational expense.

2.2 Operational Constraints

Power Balance: Specifies that power injections and withdrawals must balance during each time point. Injections are mainly output from power plants and battery storage, and withdrawals are mainly customer loads and battery charging. As with the objective function, plug-in modules add model objects to $\mathcal{P}^{\text{inject}}$ and $\mathcal{P}^{\text{withdraw}}$ to show the amount of power injected or withdrawn by each system component during each timepoint. For this study, production components were defined by the standard generation modules, and withdrawal components were defined by the standard electric vehicle model and a purpose-built responsive demand module.

$$\sum_{p^{\text{i}} \in \mathcal{P}^{\text{inject}}} p_t^{\text{i}} = \sum_{p^{\text{w}} \in \mathcal{P}^{\text{withdraw}}} p_t^{\text{w}}, \qquad \forall t \in \mathcal{T} \tag{5}$$

Dispatch: Power generation from a source (e.g., a power plant) must fall below its committed (turned on) capacity $W_{g,t}$ during time point t multiplied by a capacity factor $\eta_{g,t}$, that may vary with exogenous factors like solar radiation or wind speed.

$$P_{g,t} \leq \eta_{g,t} W_g, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{6}$$

Additional constraints further limit operation:

$$W_{g,t} \leq K_g, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{7}$$

$$d_g^{\min} W_{g,t} \leq P_{g,t}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{8}$$

Equation 7 constrains the commitment choice to fall below the installed capacity K_g (possibly multiple identical units); equation 8 limits dispatch by a minimum-load constraint that applies to many power plants.

Minimum up and down times: The amount of capacity started up ($U_{p,t}$) or shut down ($V_{p,t}$) during each hour in each generation project is calculated via

$$W_{g,t} - W_{g,t-1} = U_{g,t} - V_{g,t}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{9}$$

Additional constraints require that all capacity that was started up during an uptime look back window ($\hat{\tau}_g^{\text{u}}$, defined for each project technology) is still online, and that all capacity that was shutdown during the downtime look back window ($\hat{\tau}_g^{\text{d}}$) remains uncommitted.

$$W_{g,t} \geq \sum_{t'=t-\hat{\tau}_g^{\text{u}}}^{t} U_{g,t'}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{10}$$

$$W_{g,t} \leq K_g^{\text{G}} - \sum_{t'=t-\hat{\tau}_g^{\text{d}}}^{t} V_{g,t'}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{11}$$

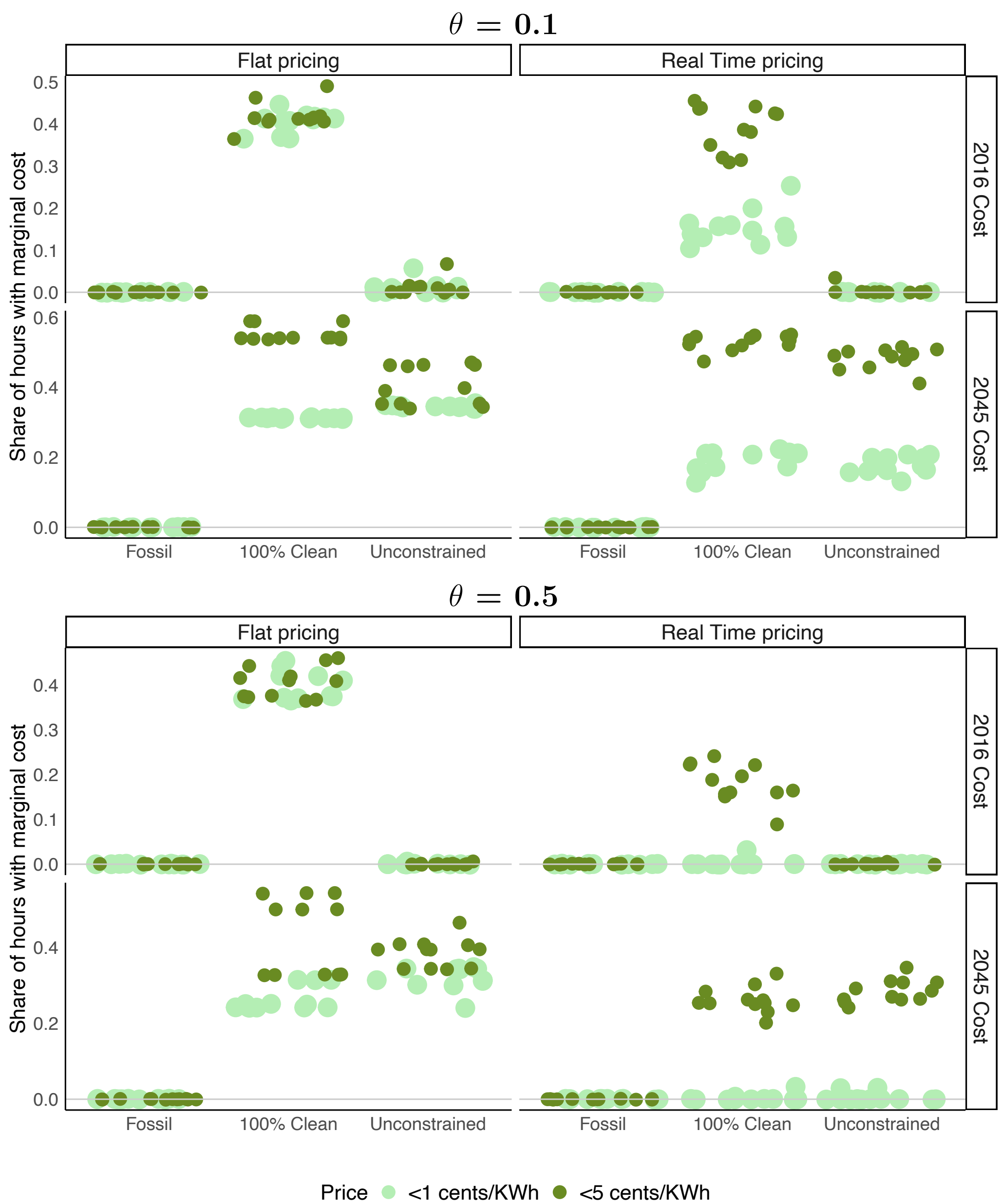
The variable $U_{g,t}$ is also used to determine startup costs for each plant (not shown).

3 Supplementary Results

3.1 Frequency of Especially Low Marginal Cost

The graphs in Figure S6 show the share of hours with marginal cost less than 1 cent and 5 cents per kWh ($10/MWh and $50/MWh) across the range of scenarios. The top panel shows scenarios with an overall demand elasticity $\theta = 0.1$ and the bottom panel shows $\theta = 0.5$. Because this share is not much influenced by the degree of interhour flexibility, the share of EVs, or the baseline demand profile (actual 2007 or projected 2045), all of these variations are shown with the same dot type.

Figure S1: Share of hours with marginal cost less than 1 cent and 5 cents per kWh.



3.2 Chronological Production and Consumption Profiles

The following graphs in Figure S2 show chronological production and consumption profiles for all 13 sample days, selected to span a maximally diverse set of possible wind, solar, and demand possibilities. The main paper shows only three of these days from these baseline scenarios. Careful inspection of these graphs reveals how Switch balances various constraints to achieve general optimization. Profiles for other scenarios can be accessed from the online website. Here we elaborate on some of these details.

The fossil scenarios show a mostly conventional and contemporary system with pre-existing renewable energy. Variation in net demand (demand minus renewable supply, mostly solar) is partly balanced from ramping existing thermal power plants that use low-sulfur fuel oil (LSFO). In time, however, batteries will be a more economical way to serve peak loads, at least under flat pricing. Batteries are typically charged midday when renewable supply is ample and demand is somewhat below peak. RTP benefits this conventional system by allowing peak demands to be shaved, some of which comes from shifting EV charging to lower-cost times. As a result, RTP eliminates use of batteries. The days look remarkably similar, however, which is emblematic of conventional systems, wherein system design is governed mainly by peak demand; in Hawaii demand does not vary much across days due to the relatively mild climate.

The 100% clean and unconstrained scenarios appear strikingly different even at first glance due to the very large role of solar generation. Wind generation (in light blue) is also prevalent, but is relatively resource constrained on Oahu, except for off-shore resources. The model never selects off-shore wind, however, due to its high cost. All 100% clean and unconstrained scenarios also employ substantial use of batteries, but visibly less under RTP. The 100% clean system with flat prices also makes ample use of hydrogen, and to a lesser degree in other scenarios.

More subtle differences between the scenarios come from comparison of the relatively constrained days, especially 4/10 (the fifth day from the left) and 11/22 (the second day from the right), the later of which was the 13th "most-difficult-to-serve" day added after the initial 12 were selected from k-means clustering. These two days, which have frequency weights of 0.06 and 0.02, respectively, employ the use of traditional thermal power plants due to low supply of wind and sun. In the unconstrained scenarios, a conventional power plant using LSFO operates all day on both days, due to the minimum operating and ramping constraints of the plants. On 11/22, a second peaking diesel power plant operates in the unconstrained scenario and burns biodiesel in the 100% clean scenarios. Interestingly, however, no thermal power plant operates on 4/10 in the 100% clean scenarios, with demand balance achieved by a combination of greater renewable capacity, hydrogen-powered fuel cell, plus higher prices in the case of RTP to stave off demand. On this day, prices turn out higher on 11/4 than on 11/22 in the clean-RTP case, but not in the unconstrained case, owing mainly to the fact that no thermal plant operates. If it were to operate, its minimum operating level would drive prices down to a point that would not be economic given the high startup costs, especially with expensive biodiesel. In larger regions operating at considerably greater scale, such start-stop constraints would not be binding and we might see some limited use of biofuel on days like 4/10. With flat prices, the clean scenarios must employ additional power from hydrogen in a fuel-cell plant on both difficult days, since demand cannot be staved with higher prices.

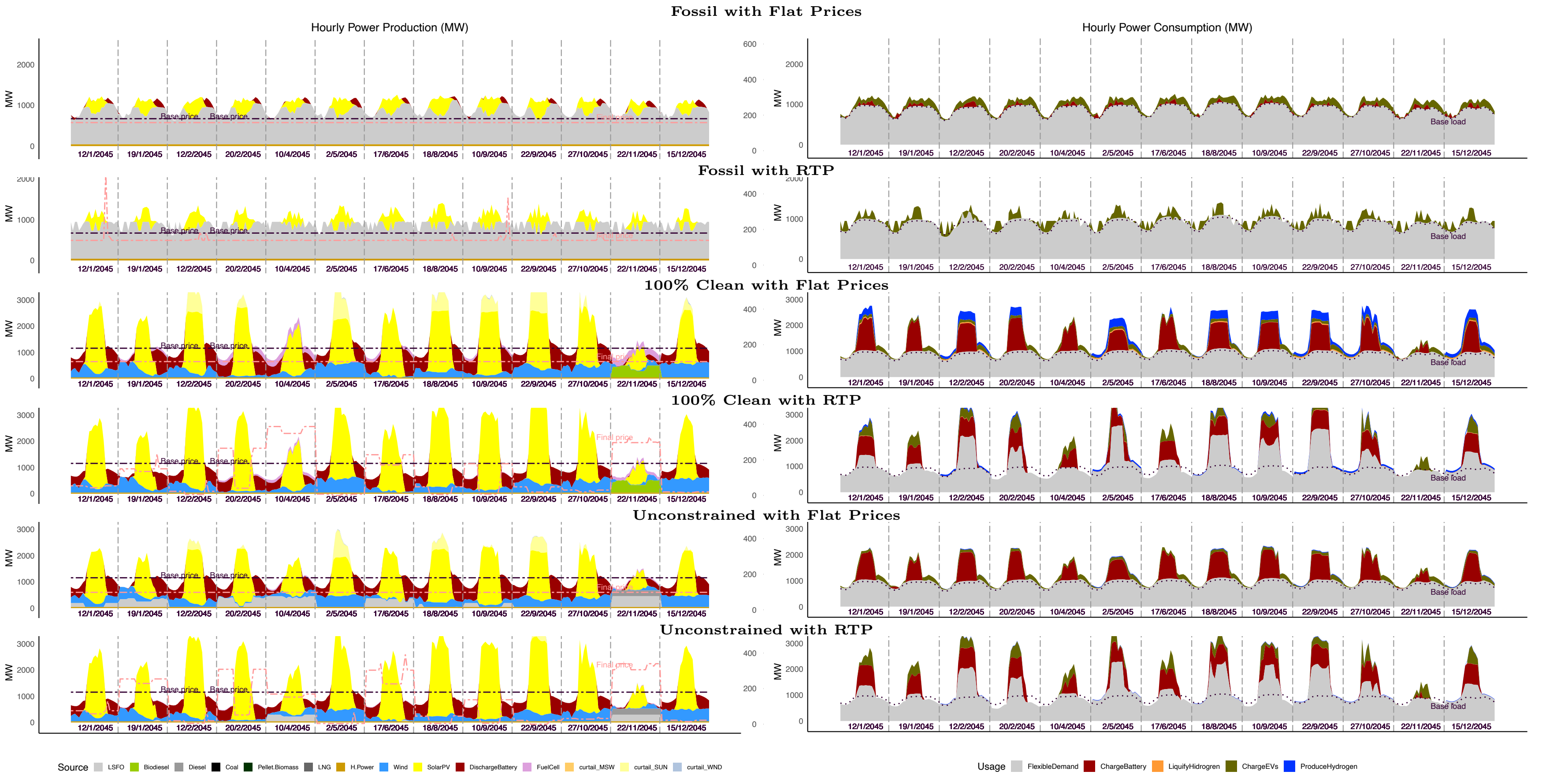
Except for these difficult low-sun and low-wind days, it is generally most economic to simply use renewables and batteries, although the unconstrained model with flat prices will use a conventional plant with LSFO to a limited extent on other days.

It is also interesting to compare days that are less constrained. Consider, for example, how prices differ between the 100% clean and unconstrained RTP scenarios on the first two sample days, 1/12 and 1/19. On these days, prices are actually lower in the 100% clean scenario than the unconstrained case. This occurs because the 100% clean scenario has more over-building of renewables to achieve adequate supply on the difficult days, which makes for more abundance and lower prices on other days. Thus, there are compensating benefits associated with the extra cost of meeting supply on tough-to-serve days, but these are only realized with RTP. This is a key reason why the cost of increasing the share of clean energy above the least-cost share is relatively inexpensive with RTP.

Finally, we note the evident demand reshaping on the right-side panels of Figure S2. This reshaping generally shows considerable growth in demand during supply-rich mid-day times and moderate reductions during early morning and evening times. One interpretation of this kind of shifting would be marked growth of air conditioning paired with thermal storage such that benefits of mid-day cooling could be transferred to evening, nighttime, and early morning use. Some of the more extreme shifts derive from extended periods of very low prices where the CES demand system might imply larger demand response than might be realized in practice. Note, however, that there is relatively little surplus associated with these shifts given how low prices and marginal utility are when prices are very near zero. These shifts and benefits associated with shifting can be larger in scenarios with a larger overall demand elasticity, but such benefits are only speculative at present–they would require new flexible sources of demand. These scenarios can be viewed on the interactive website developed for this paper.

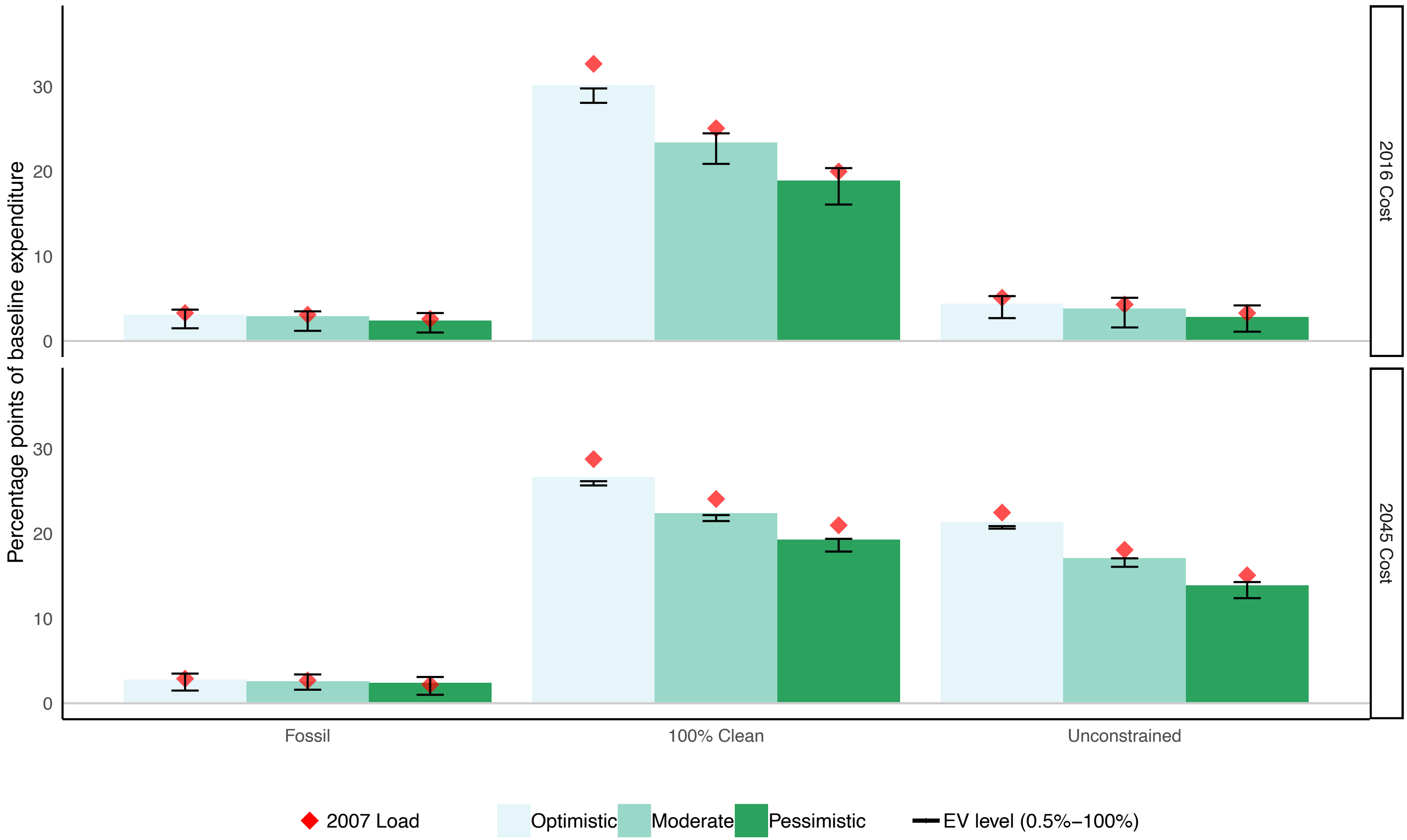
These comparisons indicate some subtle tradeoffs involved with co-optimizing intermittent renewables, short- and long-term storage, and traditional thermal generation, either with bio-fuels or conventional fossil fuels. The general lesson that we draw from these comparisons is that large shares of clean wind and solar power will soon be least cost regardless of the policy environment, and that while some days will be challenging, there are a number of ways to achieve balance on such days, all of which are made considerably less costly with RTP. A key benefit of RTP is the way it encourages more overbuilding of renewables to better serve resource constrained days, because it creates additional benefits on less-resource-constrained days under RTP; under flat pricing the extra power would simply be curtailed. This potential value of RTP is likely to be far greater in regions with more seasonality than Hawai'i.

Figure S2: Hourly production and consumption profiles for several scenarios with moderate interhour demand flexibility.



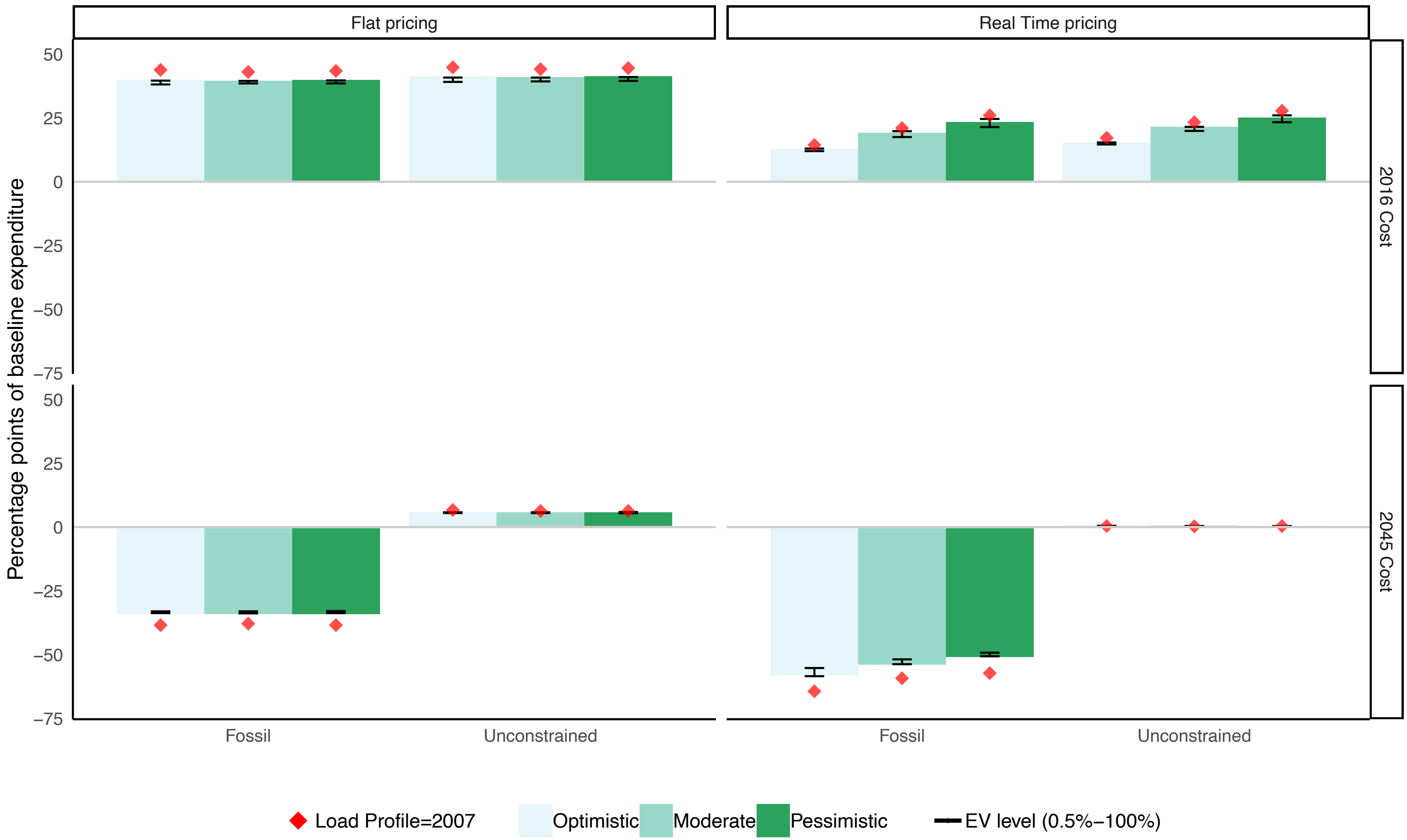
The scenarios presented above assume the moderate scenario for interhour substitutability of demand, an inelastic overall demand elasticity for electricity equal to 0.1, a baseline demand profile projected for 2045, a vehicle fleet with 50% electric vehicles, and costs of production as projected for 2045 in HECO's Power Supply and Improvement Plan. The first two rows show fossil-fuel systems with flat and dynamic, real-time pricing; the next two rows show 100% clean systems with flat pricing and RTP; and the last two rows show the welfare-maximizing systems (resource unconstrained) with flat pricing and RTP.

Figure S3: Surplus gain from real time pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.5.



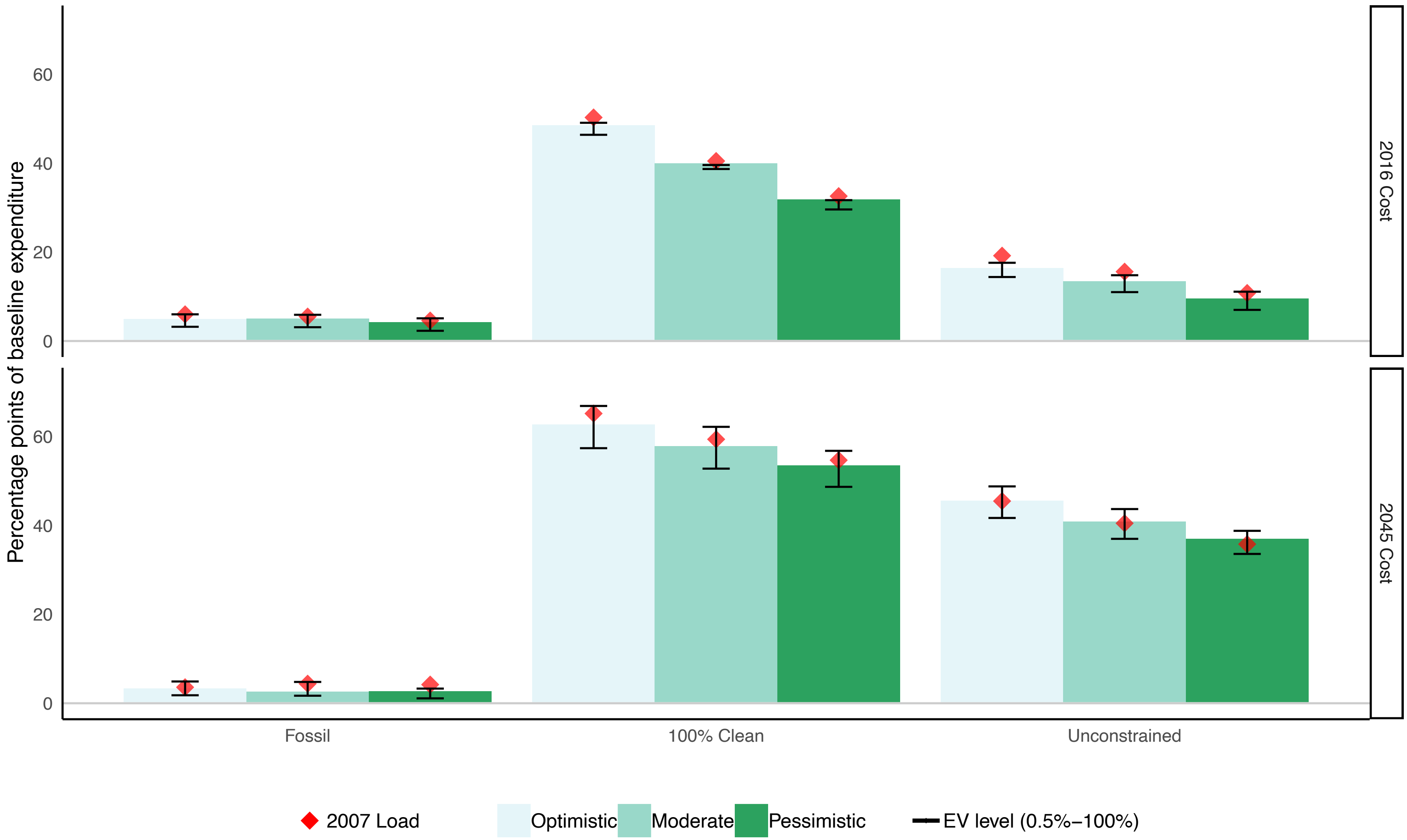
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.5 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% clean or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure S4: Cost of 100 percent renewable energy system relative to fossil and unconstrained systems under different cost and demand flexibility scenarios when the overall demand elasticity equals 0.5.



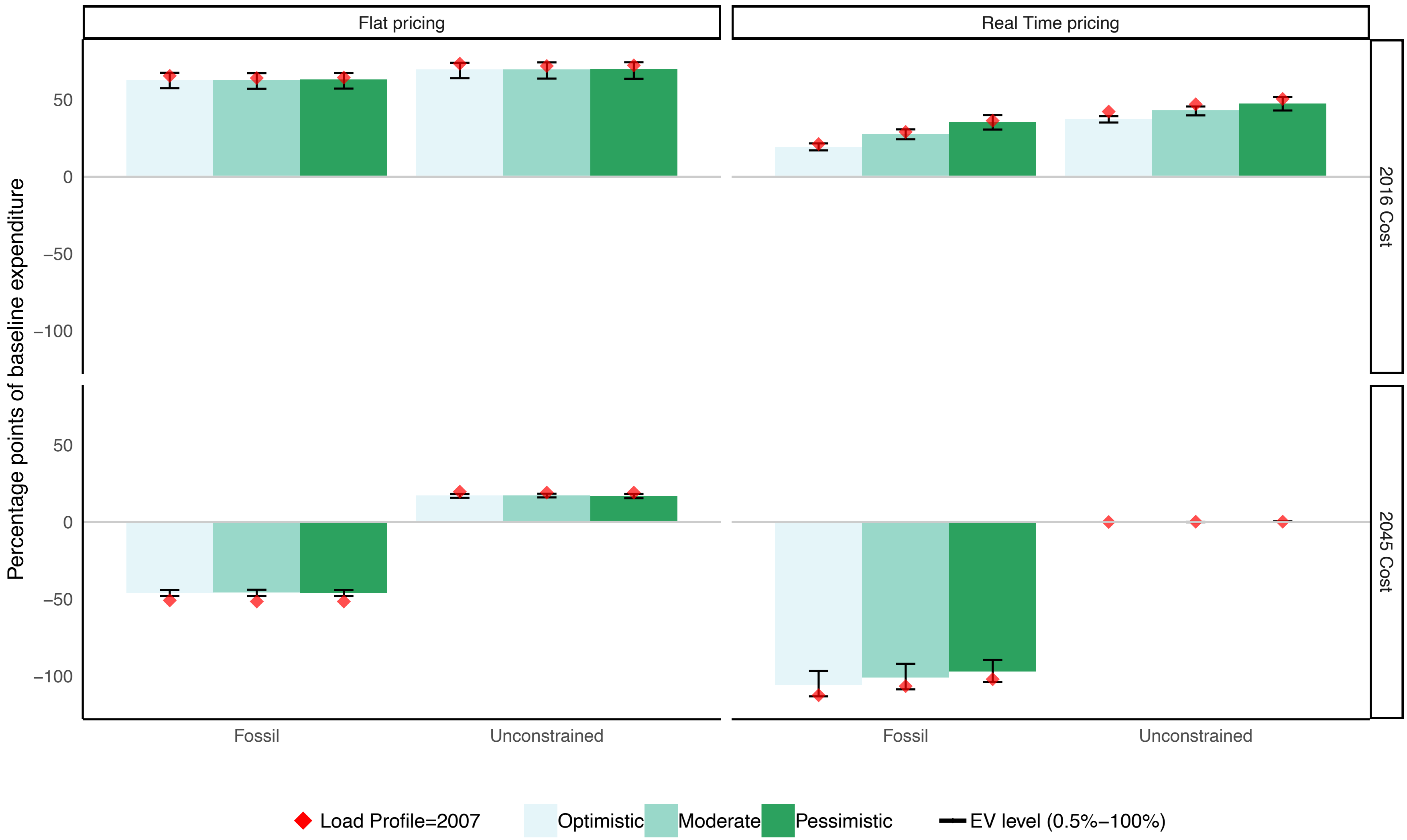
The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.5 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% clean or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure S5: Surplus gain from real time pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 2.



The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 2 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% Clean or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure S6: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 2.



The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 2 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% Clean or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Table S1: Main Results: Comparison of prices, quantities, and surplus with flat and RTP pricing.

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) Clean (%)	(6) Price ($/MWh)	(7) Mean Q (MWh/hr)	(8) SD of Price ($/MWh)	(9) Δ CS (%)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS RTP (%)
Fossil	2016	Optimistic	Flat	16	90	930	0	48.3	-54.9	-11.1	37.2	37.2	37.2	37.2	2.5
			Dynamic	16	82	952	21	53.0	-69.5	-13.3	39.7	44.4	42.6	42.4	
		Pessimistic	Flat	16	90	930	0	44.3	-51.3	-7.2	37.1	37.2	37.2	37.2	2.2
			Dynamic	16	94	939	41	45.5	-62.2	-6.2	39.3	41.7	36.8	34.7	
	2045	Optimistic	Flat	17	158	870	0				Baseline				2.3
			Dynamic	17	148	884	87	12.5	-23.8	-10.2	2.3	8.9	8.0	7.0	
		Pessimistic	Flat	17	158	870	0				Baseline				1.5
			Dynamic	17	150	869	81	9.3	-20.5	-7.8	1.5	9.5	7.5	5.4	
100% Clean	2016	Optimistic	Flat	100	150	876	0	7.6	-10.9	-3.4	4.2	4.3	4.3	4.3	19.4
			Dynamic	100	158	1,006	153	27.5	-52.3	-4.0	23.6	35.8	20.5	9.1	
		Pessimistic	Flat	100	147	878	0	2.3	-6.4	1.9	4.2	5.9	5.9	5.9	11.4
			Dynamic	100	189	984	197	14.0	-47.1	1.6	15.6	35.5	21.7	5.2	
	2045	Optimistic	Flat	100	105	914	0	37.2	-45.5	-6.8	30.4	28.9	28.9	28.9	13.7
			Dynamic	100	123	1,062	133	52.2	-68.9	-8.1	44.1	51.7	42.0	35.9	
		Pessimistic	Flat	100	105	914	0	34.6	-42.2	-4.2	30.4	28.8	28.8	28.8	8.7
			Dynamic	100	119	1,054	125	44.2	-68.1	-5.1	39.1	54.3	44.4	34.3	
Unconstrained	2016	Optimistic	Flat	39	81	941	0	51.9	-60.1	-13.5	38.3	42.4	42.4	42.4	3.7
			Dynamic	57	86	958	21	52.0	-73.3	-10.0	42.0	43.8	41.6	41.2	
		Pessimistic	Flat	40	81	936	0	46.2	-47.7	-7.8	38.3	42.3	42.3	42.3	2.3
			Dynamic	50	79	961	36	52.7	-71.9	-12.1	40.6	52.2	46.2	44.0	
	2045	Optimistic	Flat	90	101	918	0	38.5	-46.4	-3.5	35.0	31.0	31.0	31.0	10.8
			Dynamic	97	116	1,041	127	54.0	-71.2	-8.1	45.8	52.5	43.9	37.8	
		Pessimistic	Flat	89	96	923	0	39.0	-45.1	-3.9	35.1	33.7	33.7	33.7	6.0
			Dynamic	97	118	1,021	124	46.2	-67.4	-5.0	41.1	53.2	45.4	36.5	

Notes: This is a more complete version of Table ?? in the main paper. In all scenarios shown here, the overall demand elasticity (θ) equals 0.1, the baseline load profile is that projected for 2045, and electric vehicles are assumed to comprise 50% of the fleet. Each scenario (row in the table) is defined by assumptions delineated in the first four columns. The first column (Policy Objective) indicates exogenous constraints determined by policy: Fossil prohibits any new renewable energy, but is otherwise least cost; 100% Clean reflects the intended outcome of the State's Renewable Portfolio Standard, and Unconstrained maximizes welfare without constraints on the generation mix. The second column indicates whether current costs (2016) or the present value of future costs projected for 2045 from HECO's Power Supply and Improvement Plan are assumed. The third column indicates the degree of demand flexibility, as detailed in table 1. The fourth column indicates whether retail prices are flat or RTP. The remaining columns summarize the outcomes of the conditionally optimized system: average price, average quantity, standard deviation of price, and changes in surpluses from the baseline case (fossil system, future costs, and flat pricing). All changes in welfare are reported as the percent difference relative to the baseline level of expenditure on electricity. %ΔEV is the percent change in charging costs for electric vehicles from the base case. Note that ΔCS includes changes in EV charging costs. We also examine changes in welfare for different demand flexibilities, which only matters for RTP pricing scenarios. The last column reports the social value of RTP holding all else the same. The supplement provides additional results that consider more elastic demand or more EVs.

Table S2: Supplementary Results: Surplus changes relative to baseline if actual loads from 2007.

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) Clean (%)	(6) Price ($/MWh)	(7) Mean Q (MWh/hr)	(8) SD of Price ($/MWh)	(9) Δ CS (%)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS RTP (%)
Fossil	2016	Optimistic	Flat	14	89	1,031	0	52.7	-50.0	-11.8	40.9	57.2	57.2	57.2	2.8
			Dynamic	14	81	1,057	17	57.9	-60.0	-14.2	43.7	63.8	61.8	61.6	
		Pessimistic	Flat	14	89	1,031	0	50.4	-44.4	-9.8	40.6	57.2	57.2	57.2	2.4
			Dynamic	14	85	1,049	41	54.0	-54.3	-11.0	43.0	67.7	62.0	59.7	
	2045	Optimistic	Flat	16	185	947	0	Baseline							2.9
			Dynamic	15	167	963	34	-0.6	-9.2	3.5	2.9	8.6	6.9	6.6	
		Pessimistic	Flat	16	185	947	0	Baseline							2.3
			Dynamic	15	163	964	56	-2.4	-7.9	4.7	2.3	18.5	13.8	11.3	
100% Clean	2016	Optimistic	Flat	100	150	969	0	9.7	-9.2	-4.5	5.2	20.3	20.3	20.3	21.2
			Dynamic	100	164	1,112	153	30.9	-45.8	-4.6	26.4	54.4	37.9	25.1	
		Pessimistic	Flat	100	152	968	0	7.0	-3.2	-1.9	5.1	19.3	19.3	19.3	12.0
			Dynamic	100	160	1,085	149	20.6	-42.2	-3.6	17.1	57.6	39.4	26.1	
	2045	Optimistic	Flat	100	105	1,011	0	41.1	-39.0	-7.2	33.9	47.2	47.2	47.2	14.8
			Dynamic	100	122	1,177	133	57.5	-59.3	-8.8	48.7	72.5	62.2	55.4	
		Pessimistic	Flat	100	105	1,011	0	39.2	-34.2	-5.5	33.7	47.2	47.2	47.2	9.3
			Dynamic	100	134	1,144	160	48.1	-55.4	-5.1	43.0	74.7	63.8	53.2	
Unconstrained	2016	Optimistic	Flat	38	82	1,029	0	53.2	-46.9	-11.1	42.1	61.3	61.3	61.3	4.0
			Dynamic	60	100	1,047	42	53.8	-63.1	-7.7	46.1	59.6	56.2	55.5	
		Pessimistic	Flat	38	82	1,039	0	52.0	-44.6	-10.3	41.7	61.2	61.2	61.2	2.9
			Dynamic	53	85	1,055	49	54.2	-58.7	-9.6	44.6	71.2	62.6	58.6	
	2045	Optimistic	Flat	87	93	1,025	0	47.3	-42.4	-8.1	39.2	54.4	54.4	54.4	11.1
			Dynamic	98	120	1,156	134	58.4	-60.0	-8.1	50.3	72.5	63.4	56.6	
		Pessimistic	Flat	87	95	1,023	0	47.3	-39.3	-8.5	38.8	53.4	53.4	53.4	6.2
			Dynamic	97	121	1,154	146	50.8	-55.3	-5.7	45.0	75.2	65.7	55.8	

Notes: Like table S1, except baseline demand is tied to actual 2007 loads, not projected loads for 2045; actual 2007 load profile is somewhat more variable across the season.

Table S3: Supplementary Results: Surplus changes relative to baseline if fewer electric vehicles (0.5 percent).

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) Clean (%)	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS RTP (%)
Fossil	2016	Optimistic	Flat	18	89	930	0	43.3	-51.8	-7.5	35.8	43.3	43.3	43.3	1.4
			Dynamic	18	98	937	19	36.1	-65.1	1.0	37.2	38.2	36.2	36.0	
		Pessimistic	Flat	18	90	930	0	43.7	-49.0	-7.8	35.9	43.2	43.2	43.2	0.8
			Dynamic	17	81	953	40	48.7	-64.0	-12.0	36.7	55.5	50.2	48.2	
	2045	Optimistic	Flat	19	161	868	0				Baseline				1.3
			Dynamic	19	154	880	21	2.9	-20.3	-1.6	1.3	5.2	3.0	2.8	
		Pessimistic	Flat	19	161	868	0				Baseline				0.9
			Dynamic	19	156	877	52	1.3	-17.4	-0.4	0.9	9.5	3.4	0.8	
100% Clean	2016	Optimistic	Flat	100	149	876	0	3.4	-13.9	0.9	4.3	6.7	6.7	6.7	16.7
			Dynamic	100	174	1,007	180	21.5	-50.5	-0.5	21.0	40.9	24.9	10.4	
		Pessimistic	Flat	100	146	879	0	4.1	-2.3	0.2	4.3	8.6	8.6	8.6	7.7
			Dynamic	100	171	989	165	11.3	-54.7	0.7	12.0	46.6	22.5	7.4	
	2045	Optimistic	Flat	100	104	914	0	34.3	-42.2	-4.9	29.4	34.1	34.1	34.1	12.4
			Dynamic	100	124	1,067	139	47.7	-68.1	-5.8	41.8	59.7	47.3	41.3	
		Pessimistic	Flat	100	104	914	0	34.7	-39.3	-5.2	29.5	34.2	34.2	34.2	6.8
			Dynamic	100	127	1,054	142	41.5	-68.6	-5.2	36.3	66.8	47.7	40.0	
Unconstrained	2016	Optimistic	Flat	43	84	937	0	49.9	-57.1	-12.8	37.1	46.7	46.7	46.7	1.7
			Dynamic	53	81	957	29	48.5	-73.7	-9.7	38.8	50.9	48.6	48.0	
		Pessimistic	Flat	40	81	935	0	46.5	-43.7	-9.2	37.3	48.9	48.9	48.9	0.9
			Dynamic	50	90	953	58	43.7	-70.4	-5.5	38.2	57.4	46.7	43.7	
	2045	Optimistic	Flat	88	95	924	0	40.7	-46.4	-6.7	34.0	39.6	39.6	39.6	9.7
			Dynamic	96	102	1,041	100	51.2	-71.1	-7.4	43.7	61.4	53.2	45.9	
		Pessimistic	Flat	88	96	923	0	41.1	-43.5	-6.9	34.1	39.4	39.4	39.4	4.6
			Dynamic	96	111	1,029	108	40.5	-70.3	-1.8	38.7	65.8	51.7	43.1	

Notes: Like table S1 in the main paper, except the share of electric vehicles is 0.5% (the current share of the fleet) instead of 50%.

Table S4: Supplementary Results: Surplus changes relative to baseline if more electric vehicles (100 percent).

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) Clean (%)	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS RTP (%)
Fossil	2016	Optimistic	Flat	14	92	927	0	60.0	-48.8	-25.1	34.9	64.3	64.3	64.3	2.7
			Dynamic	14	67	957	0	73.3	-60.2	-35.6	37.6	76.5	76.5	76.5	
		Pessimistic	Flat	14	92	930	0	35.4	-27.4	-0.2	35.3	64.2	64.2	64.2	2.5
			Dynamic	14	67	957	0	46.4	-36.4	-8.6	37.8	76.4	76.4	76.4	
	2045	Optimistic	Flat	15	236	856	0	Baseline							3.3
			Dynamic	16	178	860	34	9.0	-13.1	-5.7	3.3	25.3	23.9	23.5	
		Pessimistic	Flat	16	236	856	0	Baseline							3.2
			Dynamic	16	194	861	74	-19.1	11.4	22.3	3.2	17.9	16.6	15.4	
100% Clean	2016	Optimistic	Flat	100	153	873	0	25.8	-21.1	-22.0	3.8	36.1	36.1	36.1	19.8
			Dynamic	100	163	1,016	157	45.9	-48.5	-22.3	23.6	64.2	50.9	41.7	
		Pessimistic	Flat	100	149	877	0	-2.0	3.3	6.0	3.9	38.0	38.0	38.0	13.3
			Dynamic	100	164	989	148	12.6	-26.2	4.6	17.2	65.3	53.2	40.8	
	2045	Optimistic	Flat	100	107	912	0	52.4	-43.7	-23.8	28.6	57.5	57.5	57.5	13.5
			Dynamic	100	119	1,067	125	67.1	-59.2	-25.0	42.1	77.5	69.4	64.4	
		Pessimistic	Flat	100	107	912	0	25.5	-19.8	3.3	28.8	57.3	57.3	57.3	9.4
			Dynamic	100	120	1,052	127	35.5	-35.7	2.6	38.2	78.7	70.2	62.4	
Unconstrained	2016	Optimistic	Flat	36	85	930	0	62.0	-47.1	-26.0	36.0	67.5	67.5	67.5	4.4
			Dynamic	64	89	957	30	67.6	-60.1	-27.2	40.4	71.2	68.7	68.2	
		Pessimistic	Flat	36	88	932	0	34.3	-21.9	1.7	36.0	66.1	66.1	66.1	3.5
			Dynamic	50	84	942	55	42.2	-37.6	-2.7	39.5	75.8	72.1	69.6	
	2045	Optimistic	Flat	88	95	924	0	58.5	-47.3	-25.6	32.9	63.0	63.0	63.0	10.7
			Dynamic	98	124	1,052	140	67.7	-59.3	-24.1	43.6	77.0	69.6	64.8	
		Pessimistic	Flat	88	95	924	0	31.8	-23.5	1.3	33.1	62.8	62.8	62.8	7.2
			Dynamic	95	104	1,022	90	39.5	-37.5	0.7	40.3	79.5	73.7	66.6	

Notes: Like table S1 in the main paper, except the share of electric vehicles is 100% instead of 50%.

Table S5: Supplementary Results: Surplus changes if overall demand elasticity = 0.5

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) Clean (%)	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS RTP (%)
Fossil	2016	Optimistic	Flat	12	93	1,218	0	49.3	-49.5	-5.3	44.1	33.9	33.9	33.9	3.1
			Dynamic	12	82	1,278	10	55.8	-63.5	-8.6	47.2	40.2	39.0	38.9	
		Pessimistic	Flat	12	94	1,221	0	50.2	-50.4	-6.2	44.1	33.4	33.4	33.4	2.4
			Dynamic	12	93	1,216	29	48.7	-58.5	-2.2	46.5	40.0	35.1	33.6	
	2045	Optimistic	Flat	16	154	928	0				Baseline				2.8
			Dynamic	16	148	957	15	9.5	-17.9	-6.7	2.8	4.6	2.9	2.7	
		Pessimistic	Flat	16	155	925	0				Baseline				2.4
			Dynamic	16	151	947	41	7.7	-19.1	-5.3	2.4	7.0	3.0	1.2	
100% Clean	2016	Optimistic	Flat	100	154	926	0	5.7	-4.0	-1.5	4.2	-0.3	-0.3	-0.3	30.2
			Dynamic	100	158	1,179	117	33.7	-52.0	0.7	34.4	34.6	18.3	8.3	
		Pessimistic	Flat	100	152	934	0	3.3	-2.3	1.0	4.2	1.6	1.6	1.6	18.9
			Dynamic	100	165	1,072	125	20.2	-51.6	3.0	23.1	36.0	17.8	5.0	
	2045	Optimistic	Flat	100	109	1,108	0	35.8	-38.2	-1.7	34.1	24.8	24.8	24.8	26.7
			Dynamic	100	108	1,409	90	63.6	-68.3	-2.8	60.8	50.2	41.0	35.9	
		Pessimistic	Flat	100	109	1,108	0	36.8	-39.3	-2.8	34.0	25.3	25.3	25.3	19.3
			Dynamic	100	110	1,361	89	58.5	-71.3	-5.3	53.3	53.1	42.2	35.8	
Unconstrained	2016	Optimistic	Flat	32	89	1,221	0	46.6	-39.5	-1.1	45.4	35.9	35.9	35.9	4.4
			Dynamic	48	82	1,312	11	59.4	-68.9	-9.7	49.8	42.6	40.9	40.6	
		Pessimistic	Flat	32	89	1,224	0	52.0	-54.6	-6.7	45.4	36.4	36.4	36.4	2.8
			Dynamic	41	81	1,320	34	59.5	-69.1	-11.3	48.2	49.2	43.2	41.1	
	2045	Optimistic	Flat	88	102	1,148	0	44.0	-43.2	-4.1	39.9	28.8	28.8	28.8	21.4
			Dynamic	100	103	1,415	80	64.6	-69.2	-3.3	61.3	51.0	42.0	37.0	
		Pessimistic	Flat	88	102	1,144	0	45.0	-44.3	-5.2	39.8	28.9	28.9	28.9	13.9
			Dynamic	100	108	1,346	83	58.7	-70.4	-5.1	53.7	53.7	42.6	35.9	

Notes: Like table S1 in the main paper, except the the overall demand elasticity (θ) equals 0.5 instead of 0.1

Table S6: Supplementary Results: Surplus changes if overall demand elasticity = 2

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) Clean (%)	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS RTP (%)
Fossil	2016	Optimistic	Flat	8	115	2,061	0	40.4	-22.5	26.9	67.4	25.6	25.6	25.6	4.9
			Dynamic	7	111	2,222	6	49.9	-46.7	22.4	72.3	28.1	27.5	27.5	
		Pessimistic	Flat	8	116	2,015	0	41.3	-21.2	26.0	67.4	23.5	23.5	23.5	4.2
			Dynamic	7	113	2,141	24	47.9	-46.7	23.7	71.6	30.1	25.5	24.6	
	2045	Optimistic	Flat	14	162	1,074	0				Baseline				3.3
			Dynamic	14	158	1,112	12	3.1	-14.5	0.1	3.3	3.3	2.0	1.9	
		Pessimistic	Flat	14	160	1,083	0				Baseline				2.7
			Dynamic	14	159	1,111	39	0.6	-13.6	2.1	2.7	5.7	1.3	-0.2	
100% Clean	2016	Optimistic	Flat	100	160	1,103	0	3.4	-6.4	1.2	4.6	1.5	1.5	1.5	48.5
			Dynamic	100	160	1,541	59	25.6	-48.0	27.5	53.1	23.5	10.0	5.9	
		Pessimistic	Flat	100	166	1,171	0	5.3	-6.4	-1.0	4.3	-3.2	-3.2	-3.2	31.8
			Dynamic	100	160	1,465	79	22.3	-50.9	13.8	36.1	35.5	15.0	6.2	
	2045	Optimistic	Flat	100	123	1,816	0	36.5	-31.3	9.8	46.2	21.3	21.3	21.3	62.7
			Dynamic	100	112	2,757	34	68.0	-57.2	40.9	108.9	35.8	30.9	29.9	
		Pessimistic	Flat	100	123	1,816	0	36.8	-29.7	9.5	46.3	19.9	19.9	19.9	53.5
			Dynamic	100	118	2,574	53	62.8	-54.5	37.0	99.8	40.0	30.5	26.8	
Unconstrained	2016	Optimistic	Flat	35	103	2,561	0	62.1	-38.4	12.2	74.2	32.5	32.5	32.5	16.4
			Dynamic	50	100	2,857	14	74.8	-70.2	15.8	90.6	37.6	34.9	34.3	
		Pessimistic	Flat	34	98	2,481	0	65.5	-43.6	8.7	74.1	33.7	33.7	33.7	9.5
			Dynamic	41	104	2,663	39	66.1	-64.6	17.5	83.6	44.2	33.7	30.5	
	2045	Optimistic	Flat	81	109	2,499	0	57.0	-40.2	6.4	63.4	29.3	29.3	29.3	45.6
			Dynamic	100	111	2,771	31	68.2	-57.4	40.8	109.0	35.9	31.1	30.1	
		Pessimistic	Flat	84	99	2,321	0	49.0	-35.1	14.0	63.0	33.0	33.0	33.0	37.0
			Dynamic	99	114	2,601	49	62.6	-55.1	37.4	100.0	40.6	31.0	27.5	

Notes: Like table S1 in the main paper, except the the overall demand elasticity (θ) equals 2 instead of 0.1

References

Johnston, Josiah, Rodrigo Henriquez-Auba, Benjamín Maluenda, and Matthias Fripp, "Switch 2.0: A Modern Platform for Planning High-Renewable Power Systems," *SoftwareX*, 2019, *10*, 100251.

Rutherford, Thomas F, "Calibrated CES Utility Functions: A Worked Example," Technical Report, Mimeo, ETH Zürich 2008.