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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. Across a wide range of cost and demand assumptions, we find the gains from RTP in high-renewable systems to exceed those in a conventional fossil system by roughly 6 times to 12 times, markedly lowering the cost of renewable 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 unaware of the potential.

In this paper, we develop a novel 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 generation and storage capacities, real-time operation of the system, and a demand system

[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).

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 modelled 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-day-to-serve day over two years (728 days modelled 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 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 and trade 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 our 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 major 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 (Fossil) and a least-cost system with no constraints on the generation mix (Uncon-

[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.

strained). Our model characterizes a full equilibrium in each case, jointly solving for investment, real-time operations with reserves, and 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] Our 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 highly-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% renewable 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% renewable system (up to 62.7% of baseline expenditure). We also find greater benefits of RTP in high renewable systems if, in addition to

[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.

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 a 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.[7] And finally, RTP will provide alternatives to, and ease evaluation of, expensive grid upgrades normally financed by expensive 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.

[7] RTP creates price differences across hours, allowing possibilities for profitable storage for firms and consumers.

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 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 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.[8]

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 engender 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.[9] 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, like electric vehicle charging and appliance use, by developing new flexible sources of demand, or

[8] 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 more extreme.

[9] 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 model we present here, the most difficult day to serve in a high-renewable system over 730 days of high-resolution benchmark weather and demand data is November 22, 2008, which was very cloudy but below-average demand.

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 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 span 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 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 elasticity. 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* ($\sigma_l = 0.1$).

In the computational model, we partition a baseline load profile, drawn from actual historical hourly demand, into three pseudo-customers, each with a different interhour substitutability

parameter, $\sigma \in \{\sigma_l = 0.1, \sigma_m = 1, \sigma_f = 10\}$ and a different baseline demand profile, derived from historic demand. 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, day, and season, to account for time-of-day and weather.

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:

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

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

This demand system provides an intuitive and relatively simple way to embody a range of heterogenous demand responses and inter-temporal substitutability of loads that vary over seasons and weather-related circumstances. The degree of interhour substitutability 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*[10], to respond to real-time variation in prices, or provide contingency or regulating reserves to the balancing authority.[11] 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 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

[10] 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).

[11] *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.

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.

$$\text{Load} = \beta_0 + \beta_1 h + \beta_2 h^2 + \beta_3 h^3 + \beta_4 PV + \beta_5 \text{T}.$$

where h is hour per day, PV 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 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.[12] Some measure of these costs is implicit in the elasticities of substitution. The challenge with explicit 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	Mid	Inflex	High	Mid	Inflex	High	Mid	Inflex
	$\sigma_f = 10$	$\sigma_m = 1$	$\sigma_l = 0.1$	$\sigma_f = 10$	$\sigma_m = 1$	$\sigma_l = 0.1$	$\sigma_f = 10$	$\sigma_m = 1$	$\sigma_l = 0.1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							(1)+(4)	(2)+(5)	(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

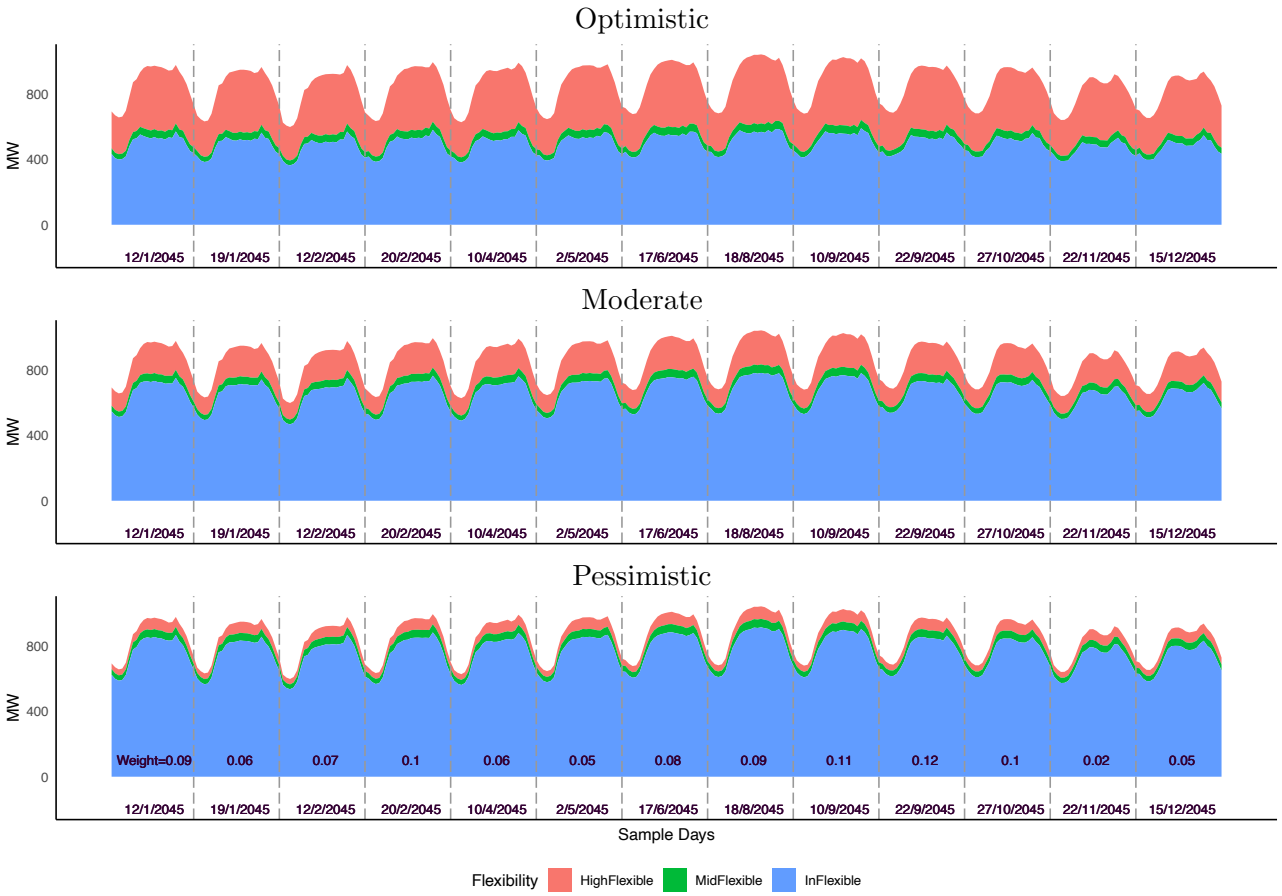
Notes: The table reports assumed shares of flexible, mid-flexible, and inflexible demand in each of the three scenarios. σ denotes the within-day interhour elasticity of substitution. Column 7 is the sum of columns 1 and 4 multiplied by hourly load and weighted by the size of the cluster represented 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

[12] 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)

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.

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 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:

$$\text{Net Cost} = p_h^* x_h^* + p_h^u x_h^u + p_h^d x_h^d \tag{4}$$

$$= p_h^* x_h^* + p_h^u x_h^* + p_h^d \cdot (\max(x_h) - x_h^*) \tag{5}$$

$$= x_h^* \cdot (p_h^* + p_h^u - p_h^d) + p_h^d \max(x_h), \tag{6}$$

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 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*[13] (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. 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). In the supplement to this paper provides the main equations and constraints used in *Switch*.

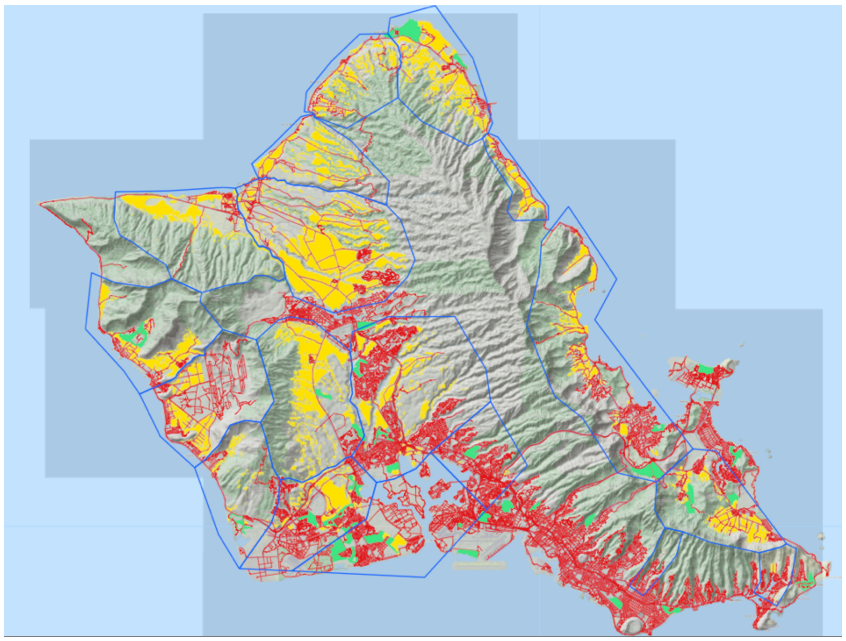
4.0.1 Utility-Scale Solar

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 excluded land with a slope greater than 10%, land within 50 meters of street centerlines, and parcels with any directional dimension less than 60 meters. We assume fixed-panel photovoltaic installations use six acres per MW (AC) of capacity and that tracking photovoltaic installations use 7.5 acres per MW (AC) of capacity. These are roughly in the lower quartile of the national statistics

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

indicated by the National Renewable Energy Laboratory (NREL).[14] Fixed photovoltaic has a ground cover ratio of 0.68 and tracking systems have a 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 irradiance data from the National Solar Radiation Database (NSRDB). The map of lands considered are shown in figure 2.

Figure 2: Land Available for Utility-Scale Solar



The map shows land that is assumed to be available for utility scale solar installations on Oahu given zoning and other technical and legal constraints (shown in yellow). Each area circled in blue is entered as a separate generation project in Switch, with different projects having different capacity limits and hourly production profiles. Red lines indicate roads.

4.1 Rooftop Solar

Rooftop solar potential was estimated from roof area from Google Map images. Visual review of many roofs indicates accurate identification. We assume 40 percent coverage of roofs, which is equivalent to 15 percent of roofs being flat with 70 percent coverage and 85 percent being sloped with 35 percent coverage. We assume 12 percent efficiency with 1000 W/m^2 irradiance (capacity = 120 W/m^2). Hourly output was estimated using PV Watts and the NSRD. Figure 3 shows an image of rooftops on Oahu, including a closeup of the UH Mānoa campus.

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

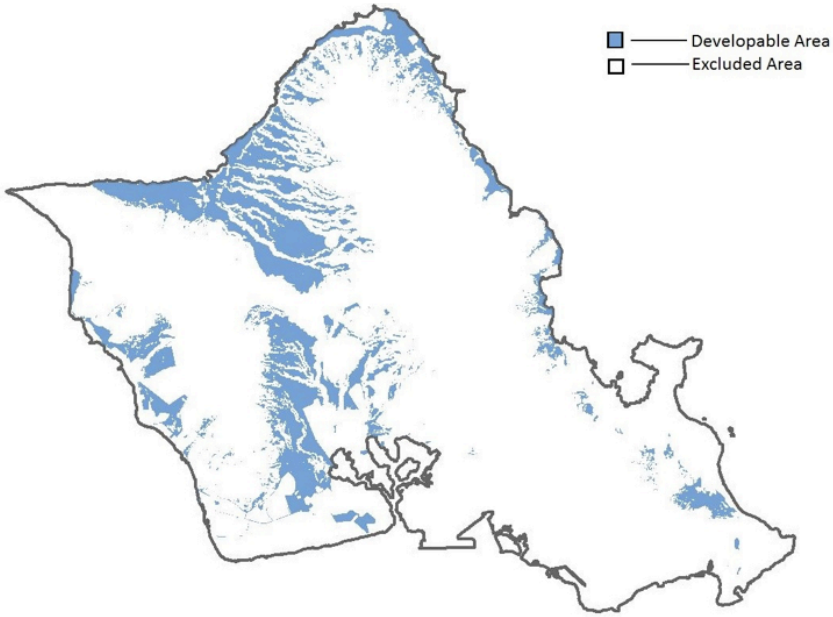
[14] See http://www.nrel.gov/docs/fy13osti/56290.pdf.

Figure 3: Estimating Potential Rooftop Solar

The bottom image shows rooftop space islandwide (in lighted in yellow). The image on top shows a closeup of part of the Mānoa campus to demonstrate accuracy of rooftop identification.

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. A map of areas potentially developable for wind is show in figure 4. 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.

Figure 4: Potential wind farm locations



The map shows land that is assumed to be available for on-shore wind development.

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 13th 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 po-

tential 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 13th 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.[15] 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 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 to

[15] In an earlier version of the paper we sampled the 15th 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.

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. [16] 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.

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 2 and Table 3. 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 5. 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.

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

[16] 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 only report Marshallian consumer surplus.

Table 2: Generators Cost Assumption

Technology	Generators	Year Build	Capital Cost ($/KW)	Fixed Cost ($/Year)	Variable Cost ($/MWh)	Age (Years)	Outage Rate
Fossil-fueled	Airport_DSG	2013	585.67		37.46	61	
	Waiau_10	1973	585.67		3.56	77	
	Waiau_9	1973	585.67		3.37	77	
	Kalaeloa_CC1	1989	2042.05		6	61	
	Kalaeloa_CC2	1991	2042.05		6	61	
	Kalaeloa_CC3	1991	2042.05		6	61	
	CC_152	2045	1667.97	19.08	4.49	30	0.05
	CIP_CT	2009	585.67		40.76	61	
	IC_Barge	2045	1460.71	38.04	20.96	30	0.02
	IC_MCBH	2045	3152.36	38.04	20.96	30	0.02
	IC_Schofield	2018	2706.48	38.04	20.96	30	0.02
	IC_Schofield	2045	2473.99	38.04	20.96	30	0.02
Renewables							
Biomass	H-Power	1989	2042.05		18	61	0.41
Solar PV	CentralTrackingPV	2012	3218.61			30	
	CentralTrackingPV	2016	3218.61			30	
	CentralTrackingPV	2019	1934.12	13.96		30	
	CentralTrackingPV	2045	1934.12	13.96		30	
	FlatDistPV	2016	4644.52			30	
	FlatDistPV	2045	3005.03	18.3		30	
	SlopedDistPV	2016	6762.96			30	
	SlopedDistPV	2045	4492.81	22.19		30	
Wind	OffshoreWind	2045	7476.41	88.9		30	
	OnshoreWind	2011	2417.55			30	
	OnshoreWind	2012	2417.55			30	
	OnshoreWind	2045	2260.75	46.15		30	
Storage	Battery_Bulk	2045	858.62	37.27		15	
	Battery_Conting	2045	989.79	37.27		15	
	Battery_Reg	2045	1120.97	37.27		15	
	DistBattery	2045	858.62	37.27		15	
	Hydrogen Electrolyzer	2045	769.37	46.93	19.92	40	

Note: 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. Assumptions for the fuel cost are in Table 3 in the Appendix.

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.

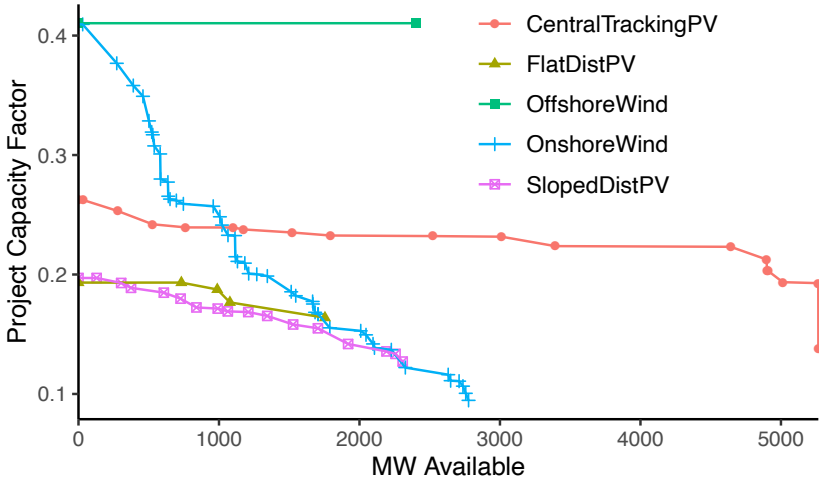
Most of the different sets of assumptions have been detailed above. Overall demand is likely inelastic, so we focus mainly on results with an overall demand elasticity for electricity of 0.1 (the elasticity of substitution between electricity and all other goods); this assumption is somewhat conservative given compelling recent evidence that demand is more elastic over the

Table 3: Fuel Cost Assumption

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

Note: Cost assumptions are derived from Hawaiian Electric Company's Power Supply Improvement Plan from December 2016.

Figure 5: 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.

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% Renewable, 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.

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.[17]

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.[18] Because seasonal variability may be more costly to manage than intraday variability, comparison of these scenarios provides some sense of this cost of seasonality.[19]

Much of our discussion focuses on cost differences between flat and variable, marginal-cost

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

[18]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.

[19]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.

pricing (RTP), and those scenarios are crossed with all 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% renewable, 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. This exercise added over a thousand additional 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.[20] 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

[20] 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.

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.

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

Table 5 reports 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, 100% renewable, or unconstrained generation mixes); (2) Technology cost (2016 or projected 2045); (3) Demand flexibility (optimistic or pessimistic); and (4) Pricing (flat or RTP). Comparing different rows from this table, one can infer the welfare implications. The value of RTP, holding all else the same, can be inferred by comparing two adjacent rows. Outcomes reported include the share of renewable energy, average price, average quantity (MW of load), the standard-deviation of price, and welfare metrics measured as a percent of baseline expenditure (future fossil-based system with flat prices). The last column gives the change in total surplus from RTP versus flat pricing holding all else the same.[21]

Many findings can be parsed from this table, including our 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 or dynamic pricing is employed. These gains are only slightly less than the unconstrained optima which increase surplus by 35.0 to 45.8 percent,especially under RTP. Indeed, the unconstrained optima with RTP has 97 percent renewable energy in 2045, and the cost of increasing renewable share beyond these levels is modest. We elaborate upon and refine this point below.

We present a larger set of results in figures 6 and 7. Figure 6 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 profile make RTP more valuable. The value of RTP in the unconstrained model is more similar

[21] 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.

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 7) shows the same results from from a different vantage point; it shows the social cost of a 100% renewable 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% renewable 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% renewable 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.

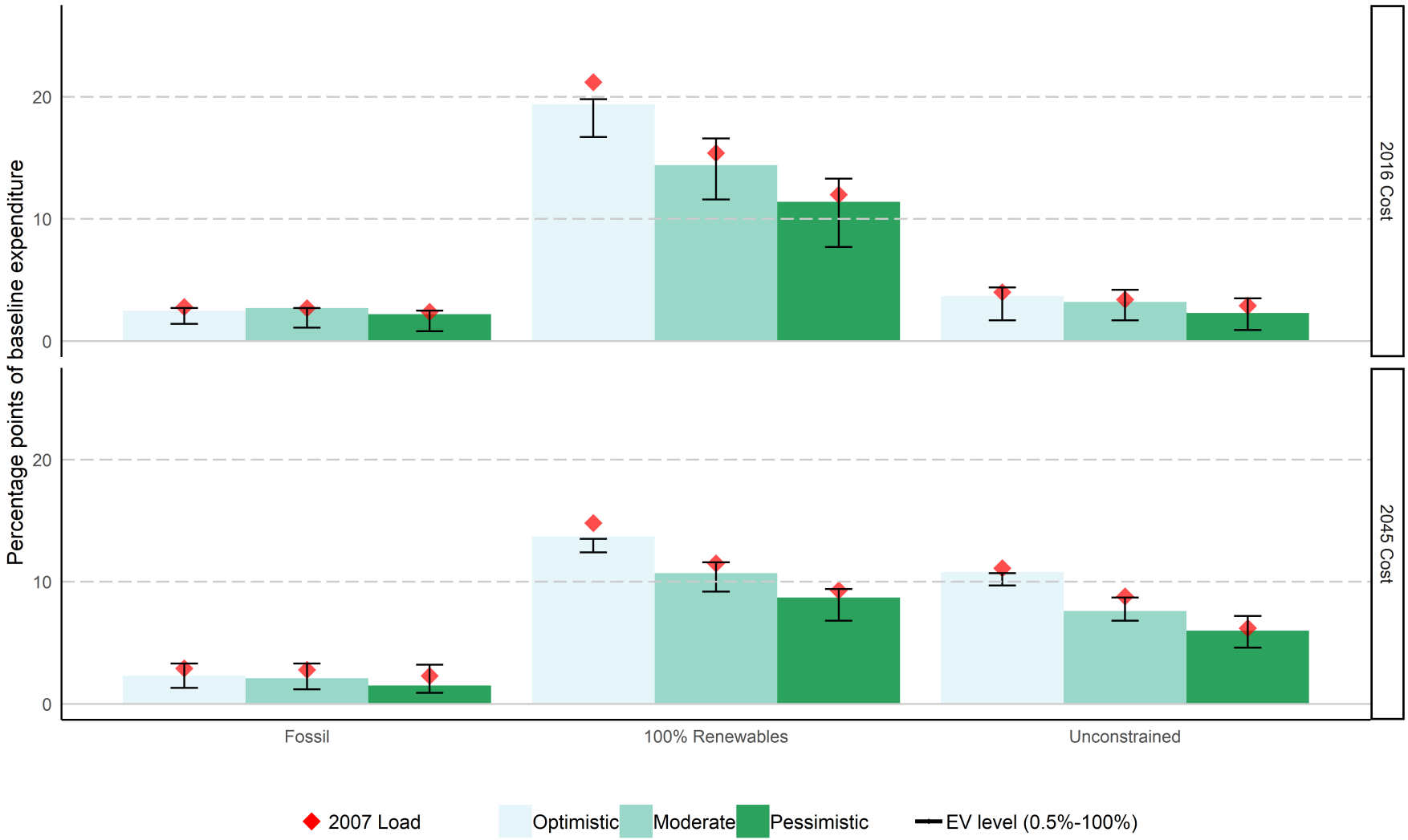
Figure 8 shows how the social cost of renewable energy rises as the share of renewable energy increases from the optimal portfolio (greatest surplus, excluding pollution externalities) to 100 percent renewable. The graphs juxtapose how costs rise with flat vs RTP, with both pessimistic and optimistic 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 5: 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% Renewable	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	

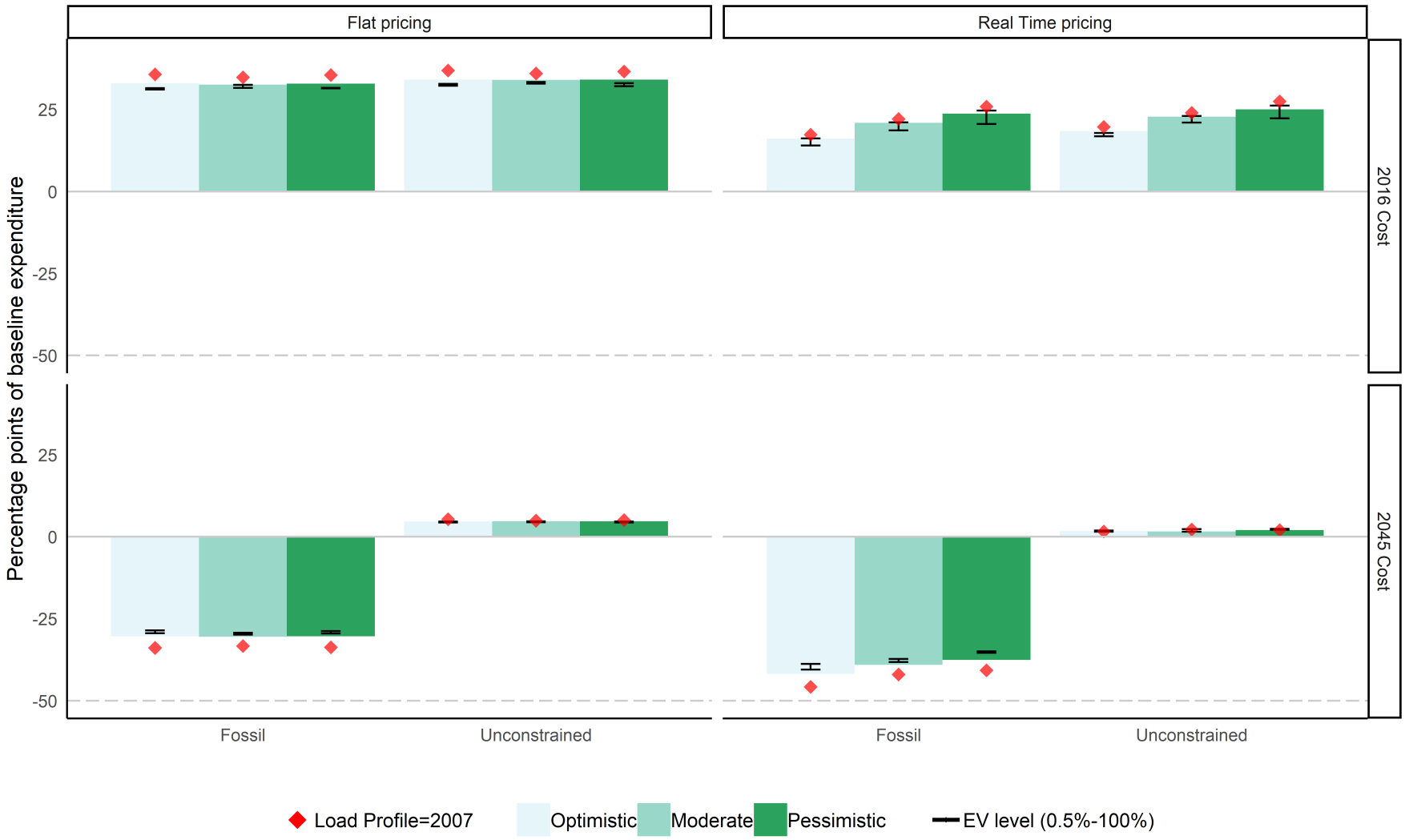
Notes: In all scenarios shown here, the overall demand elasticity (θ) equals 0.1, the baseline load profile is that projected for 2045, and electric vehicles are assumed to comprise 50% of the fleet. Each scenario (row in the table) is defined by assumptions delineated in the first four columns. The first column (Policy Objective) indicates exogenous constraints determined by policy: Fossil prohibits any new renewable energy, but is otherwise least cost; 100% Renewable 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.

Figure 6: Surplus gain from real time pricing under different policy, cost and demand flexibility scenarios.



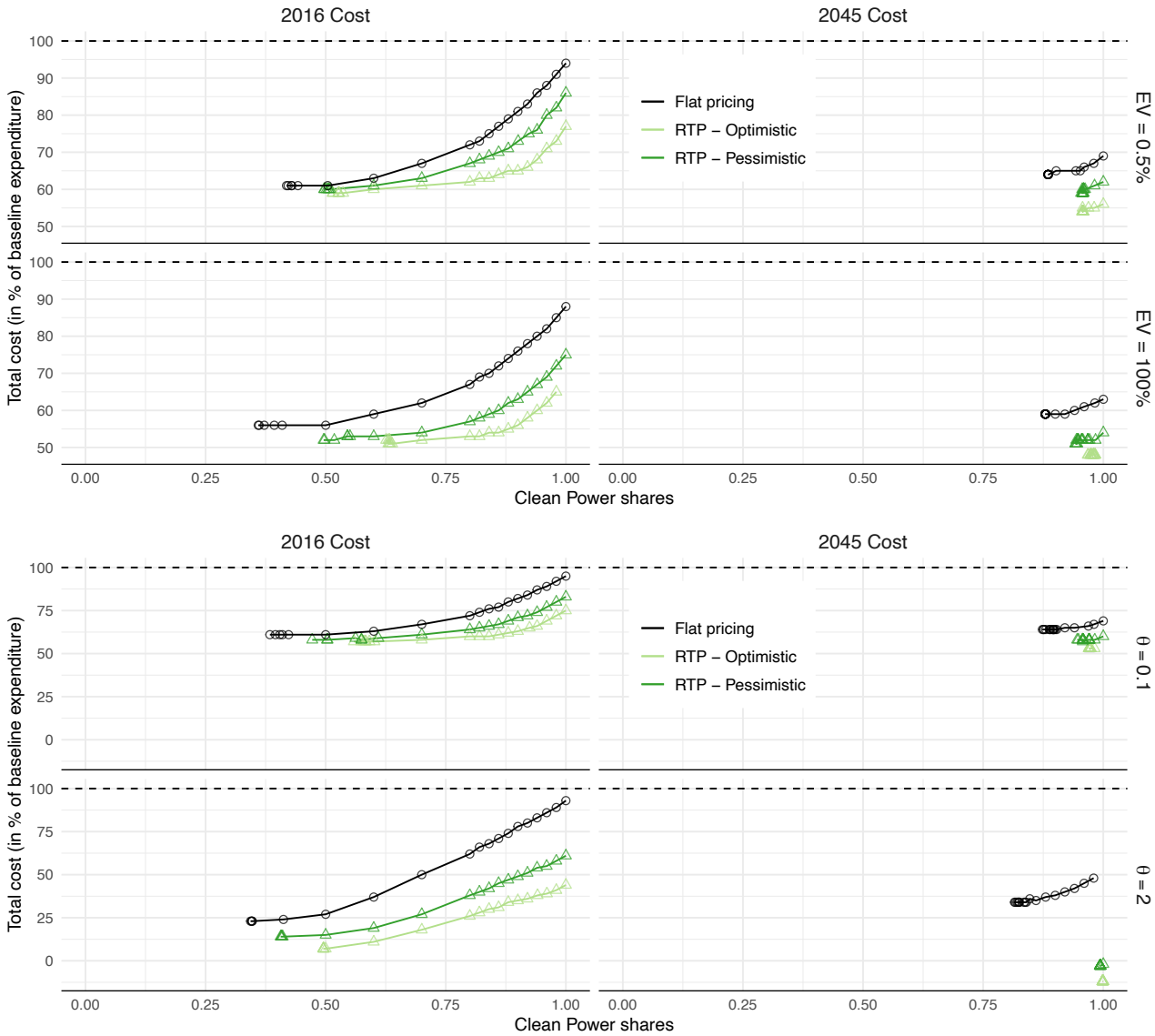
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an 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% renewable 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 7: 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% renewable 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 8: 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 renewable electricity rises above the least-cost share, holding all else the same. Social cost is measured as percent of expenditure (excluding externalities) in the baseline scenario, which is a predominantly fossil system with flat pricing in the year 2045. Graphs on the left assume current (2016) costs, while graphs on the right assume projected future (2045) costs. 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 $\theta = 0.1$. 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.

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 8). 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.

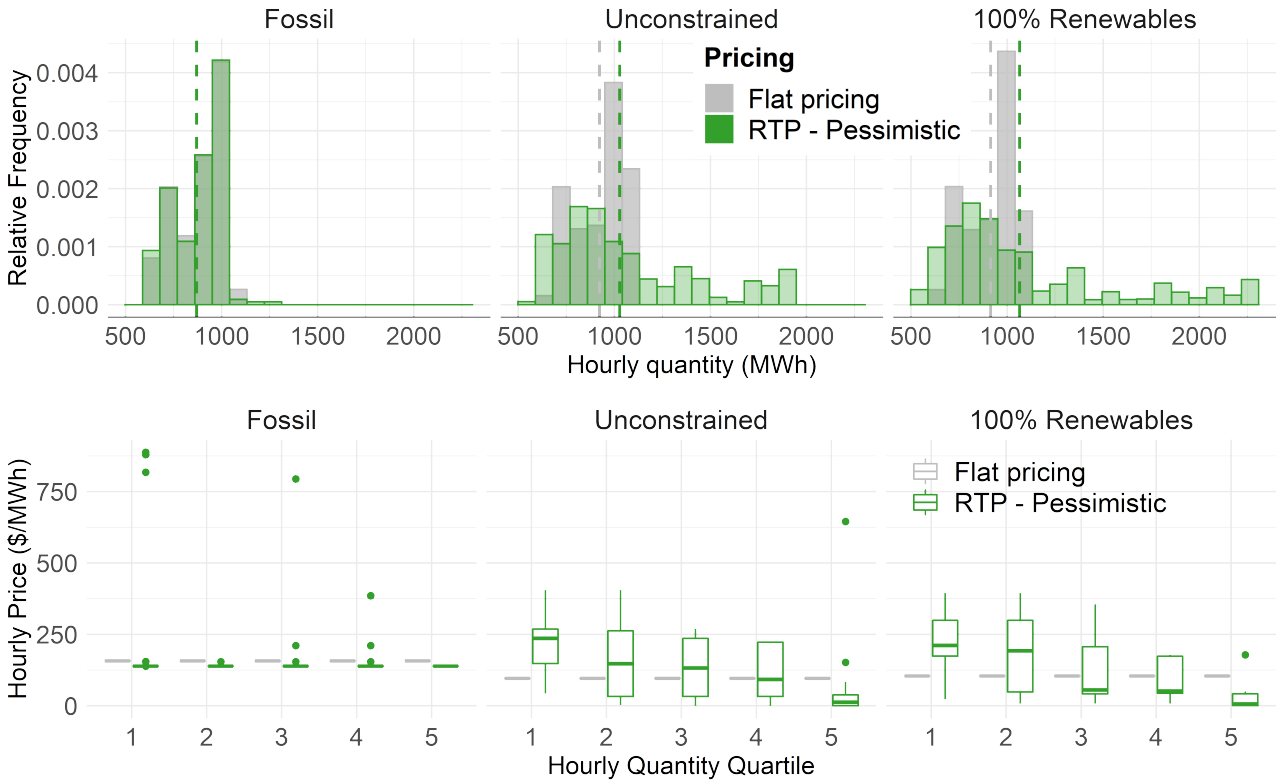
6.2 Equilibrium Prices and Quantities

We show the full distributions of equilibrium quantities and prices for a few scenarios in Figure 9. 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 unconstrained and high-renewable 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 markedly, with considerably 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. These are times when renewable energy is plentiful and there may be curtailment and zero or near-zero prices. [22] Thus, RTP helps in high-renewable systems because it can act to increase quantity demanded when power is unusually plentiful, not just curb demand when power is especially scarce. The scenarios depicted in Figure 9 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. [23]

[22] 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.

[23] 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 (provided in Figure 1); the plotted distributions take

Figure 9: 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 10 we show hourly generation, storage, and use profiles for three sample days in a few scenarios. Fossil, 100% renewable, 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 are for 2045 technology and fuel costs, and pessimistic demand flexibility.[24] 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 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% renewable 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% renewable case. The 100% renewable scenario also makes use of hydrogen for long-run storage.

- With flat prices, both unconstrained and 100% renewable systems have significant curtailment of solar on the high-weight day (the middle day shown). In the RTP scenarios,

these weights into account.

[24] 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.

the price falls to zero or somewhat less than zero during on this day, and extra demand is shifted into these hours.

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

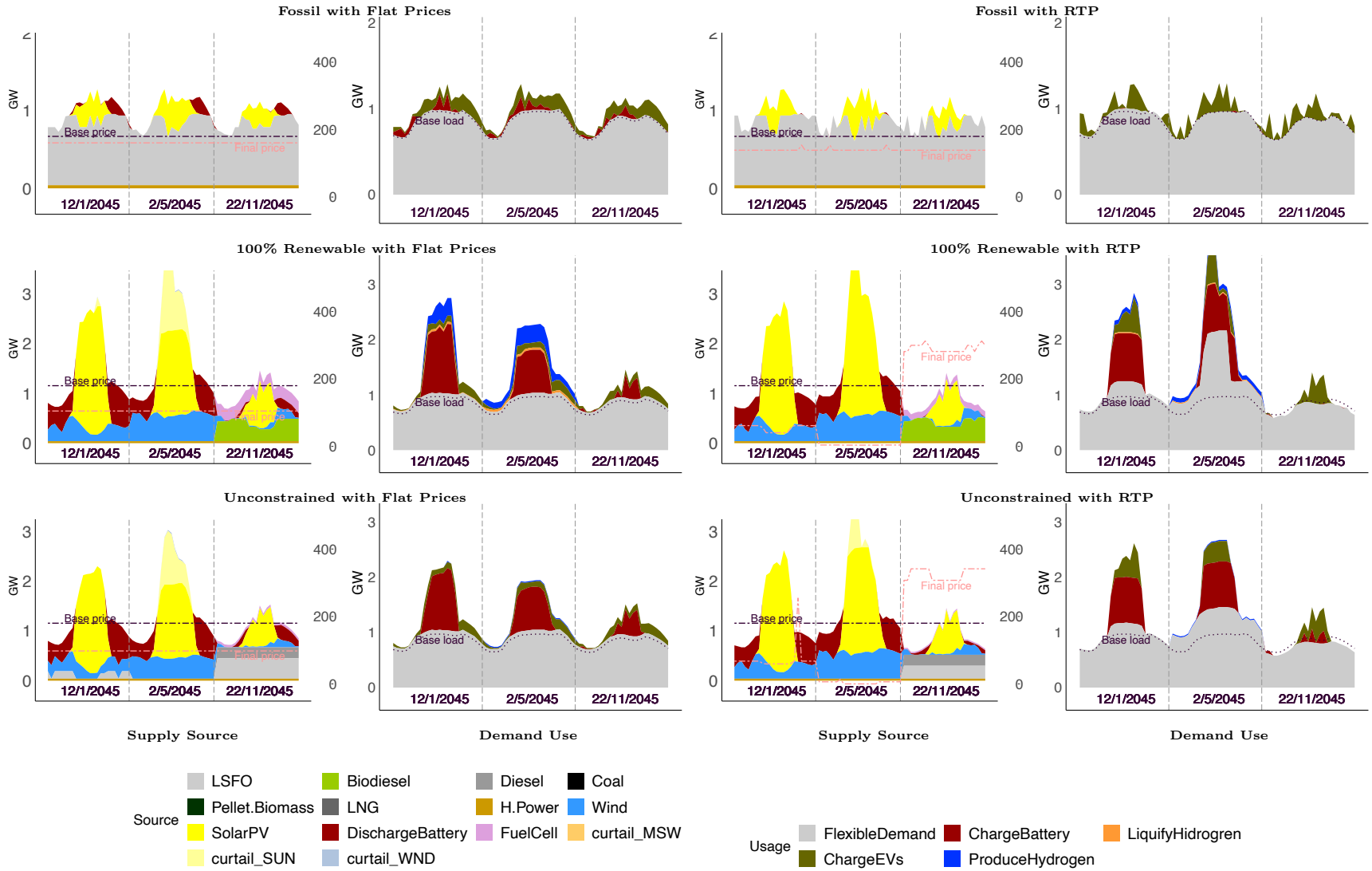
- Although prices vary widely in the high-renewable RTP scenarios, they vary much more *between* days than *within* days. In both unconstrained and 100% renewable scenarios (bottom and middle rows, respectively), the high-renewable days (which are common) have zero or negative prices all day long, not 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 element not evident in the graphs or tables concerns the cost and prices associated with provision of reverses. While adequate reserves and equilibrium prices 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.

6.4 Generation Mix

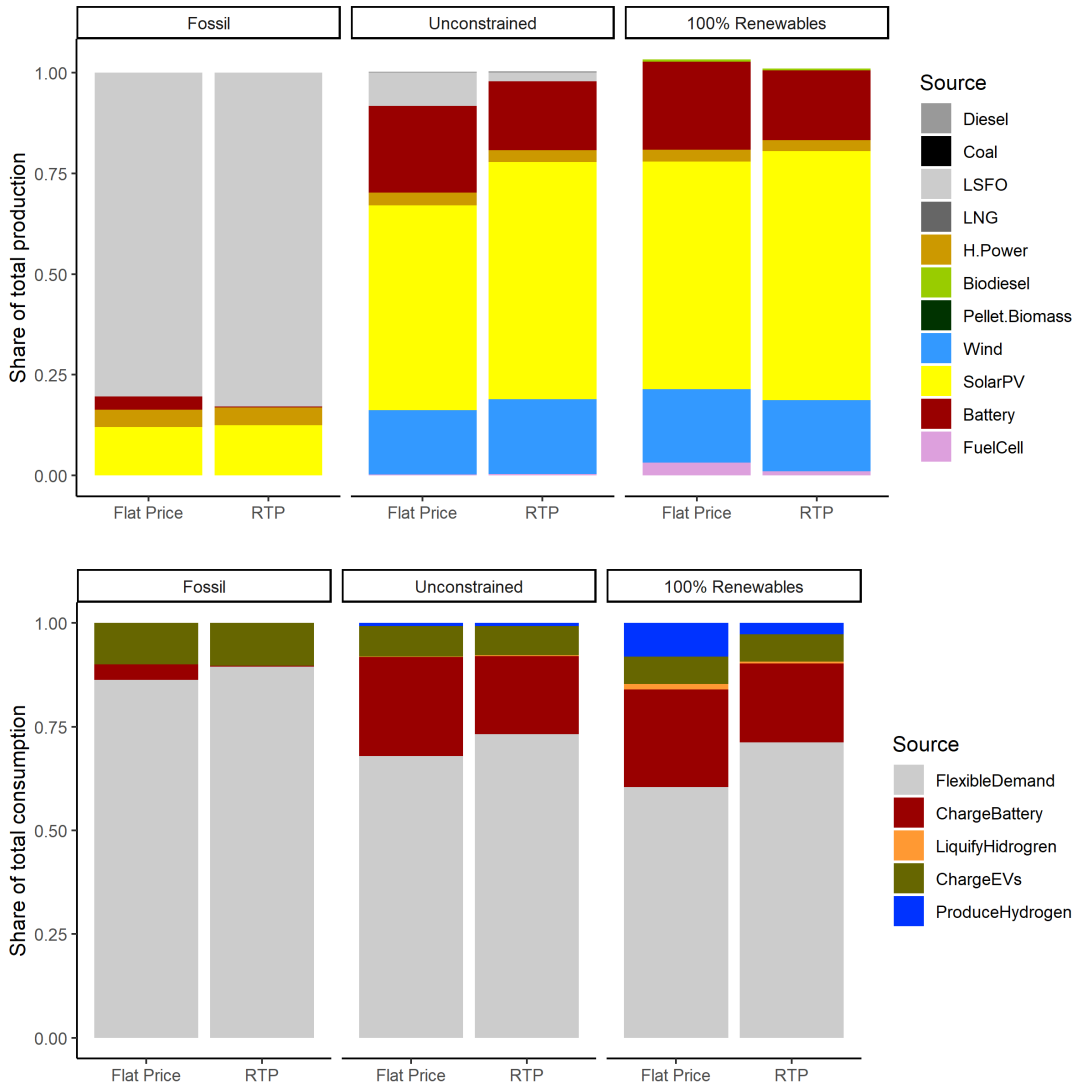
Aggregating across sample days we show in Figure 11 how the whole generation and consumption portfolios differ in RTP versus flat-price environments. In the fossil scenario, we see that RTP nearly eliminates use of batteries overall, not just in the sample days depicted above. In unconstrained and high-renewable 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. This is also greater *overall* electricity use in the RTP scenarios, not directly apparent in the shares. These results are clear in Table 5.

Figure 10: 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% renewable 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 11: 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 columns 13-15 of Table 5. For example, in the 100% renewable, 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, not 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 inequality 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 6 and 7 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 with a higher overall demand elasticity.

7 Conclusions

7.1 Contribution and Summary of Findings

We developed the first 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 poor times, using high-cost biofuels in traditional power plants while increasing prices to limit demand. In some 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 significant in high-renewable scenarios with flat pricing.[25]

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 more remarkable 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

[25]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.

Renewable Energy Laboratory (NREL) assessed demand response potential for a large number of end uses and customer types (Mai, Sun, Jadun, Murphy, Logan, Muratori and Nelson 2020). While that study assumed that a potentially 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 our findings for flat-pricing scenarios appear remarkably 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 that the technology cost assumptions used in this analysis are fairly conservative, especially in light of rapid technological advancement in the last few years. By some estimates, such as Bloomberg New Energy Finance and Lazard,[26] current renewable energy and battery technology costs already rival Hawaiian Electric Company's projections for 2045 that we used in this analysis (Lazard 2017). Currently, renewable technology costs are far less, and fossil fuel costs far greater, than those assumed for 2016.

Note that 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 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

[26] See https://about.bnef.com/blog/ and https://www.lazard.com/perspective/levelized-cost-of-energy-2020/

demand response may be less valuable in continental regions as compared to Hawai'i, recent 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.

A complete answer to the question of why our model shows clean power systems to be so affordable would require study of more locations, and careful inter-comparison of models, data inputs, and other assumptions. For this reason, we make all of the input data and model code publicly available. We also make the findings as transparent as possible by solving many scenarios and building graphical displays that can be scrutinized for inconsistencies by subject experts. We hope these steps serve to open the "black box" of this complex model so as to better inform decision makers and the public.

7.2 Overcoming Obstacles to Real-Time Pricing

Despite its potential benefits for consumers and its usefulness in affordably integrating intermittent clean power, there tends to be institutional resistance to real-time-pricing tariffs. Part of the resistance likely comes from reticence of both utility customers and state public utility commissions that may fear public backlash from 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.[27] Major stakeholders 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

[27] While it is beyond the scope of analysis here, location-specific RTP, down to the node or even circuit level, might do a lot to save on distribution system upgrades, which are almost universally financed with rate-of-return regulation. 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.

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 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).

A practical challenge with RTP in Hawai'i is that there is no market. Instead, real-time prices would need to be set by a regulatory mechanism, such as the "system lambda" of the automatic generation control system software that optimizes operations in real time. Such software would need to be modernized to account for storage, 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 real-time-prices, 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.

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 more frequent days when there is a substantial surplus of energy. 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.

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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 $U(x_1, x_2, \ldots, x_h, \ldots, x_{24}, Y|\sigma, \theta, \alpha, \beta_1, \beta_2, \ldots, \beta_h, \ldots, \beta_{24})$ 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.

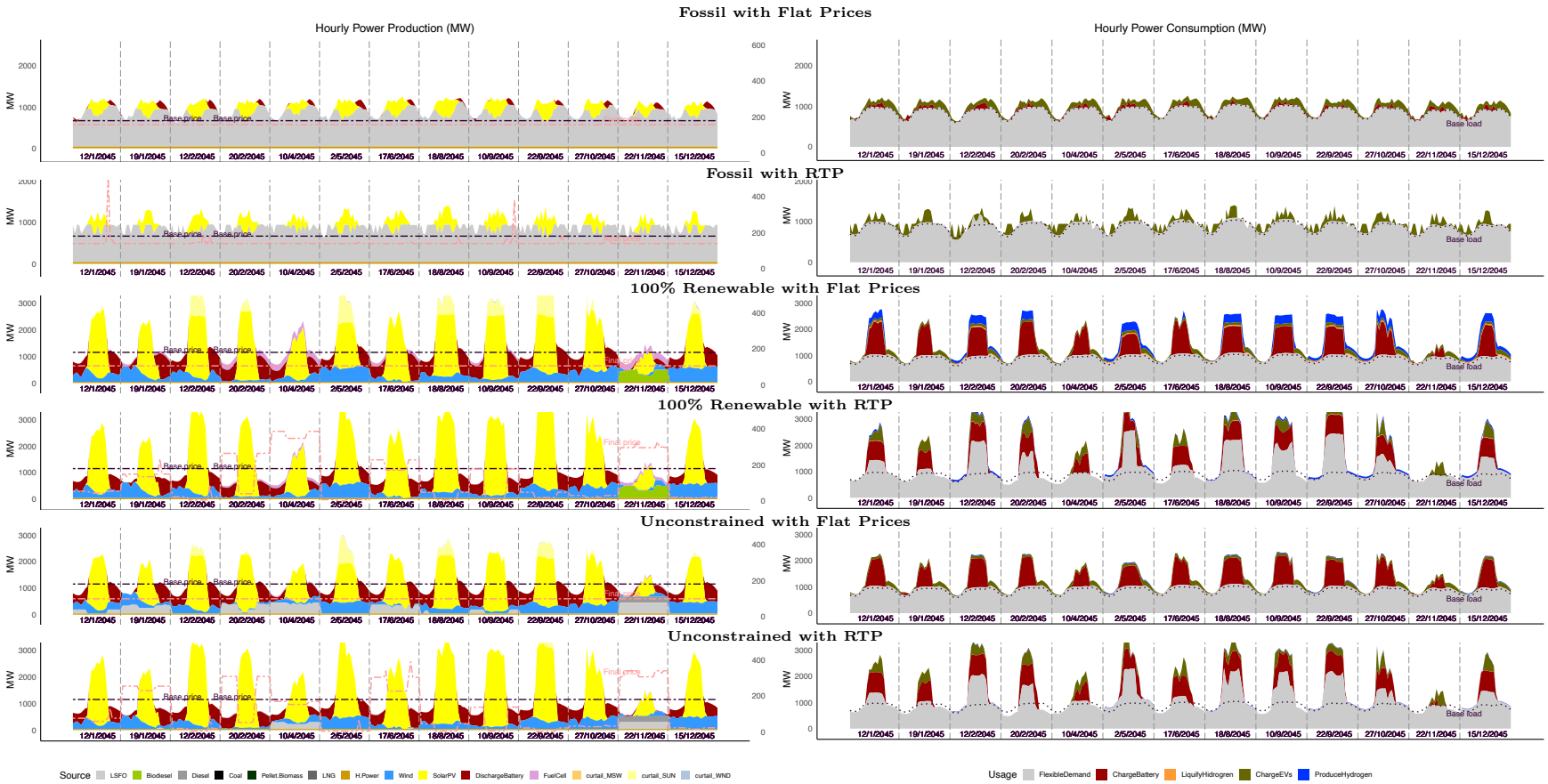
$$W_{g,t} \geq \sum_{t'=t-\hat{\tau}_g^{\text{u}}}^{t} U_{g,t'}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{10}$$

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

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

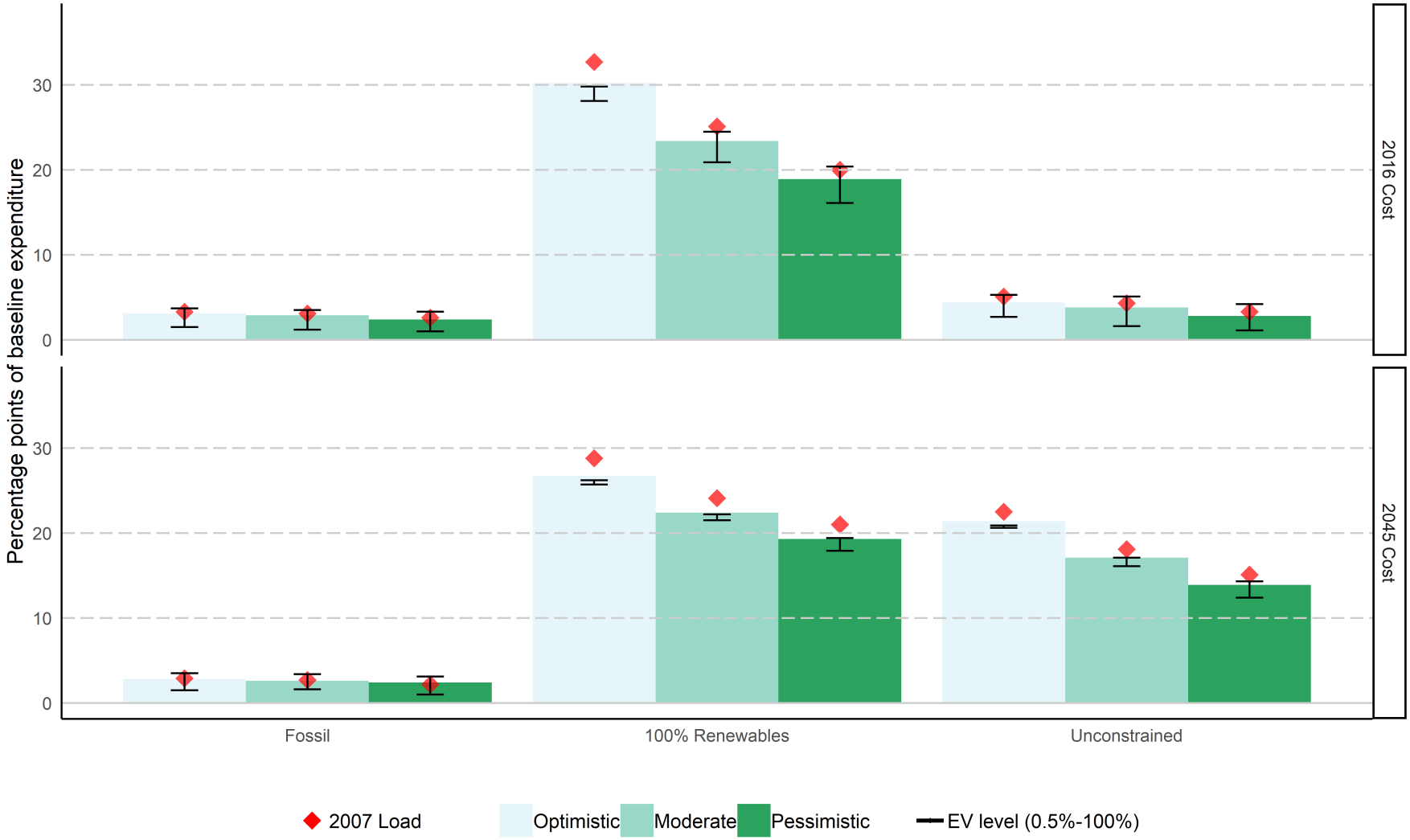
3 Supplementary Results

Figure S1: Hourly production and consumption profiles for several scenarios with moderate interhour demand flexibility.



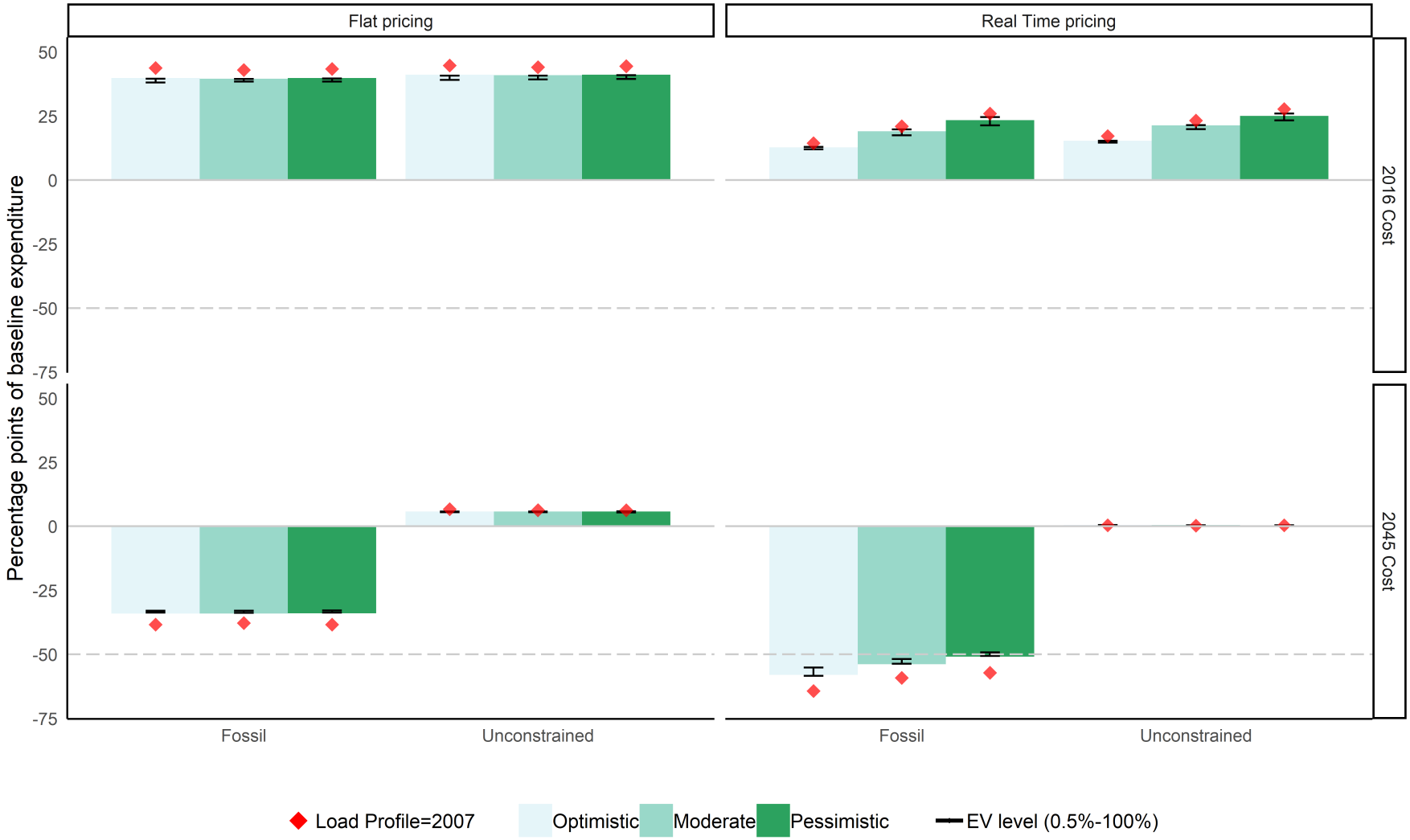
The scenarios presented above assume the moderate scenario for interhour substitutability of demand, an inelastic overall demand elasticity for electricity equal to 0.1, a baseline demand profile projected for 2045, a vehicle fleet with 50% electric vehicles, and costs of production as projected for 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% renewable systems with flat pricing and RTP; and the last two rows show the welfare-maximizing systems (resource unconstrained) with flat pricing and RTP.

Figure S2: Surplus gain from real time pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.5.



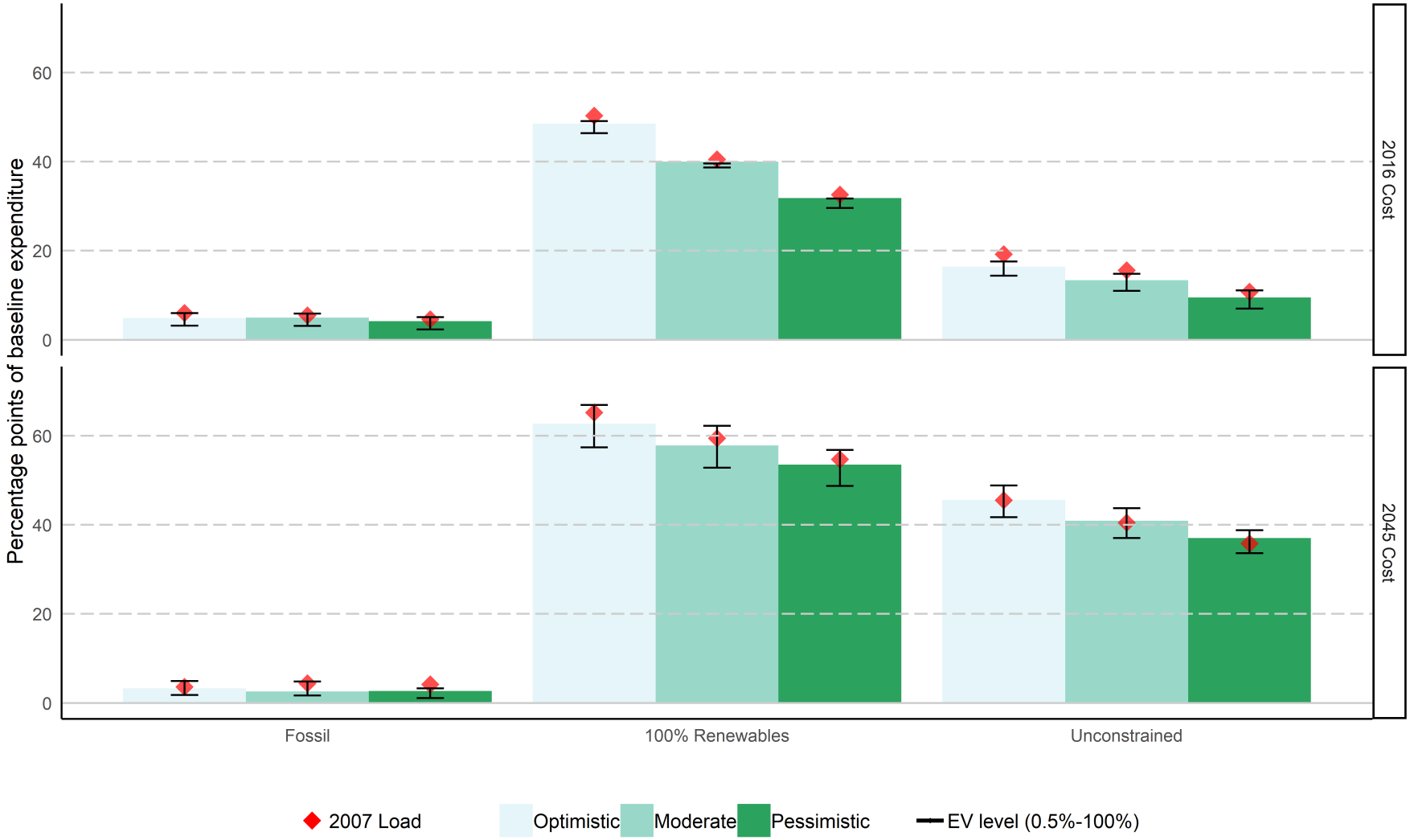
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an 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% renewable 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 S3: 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.



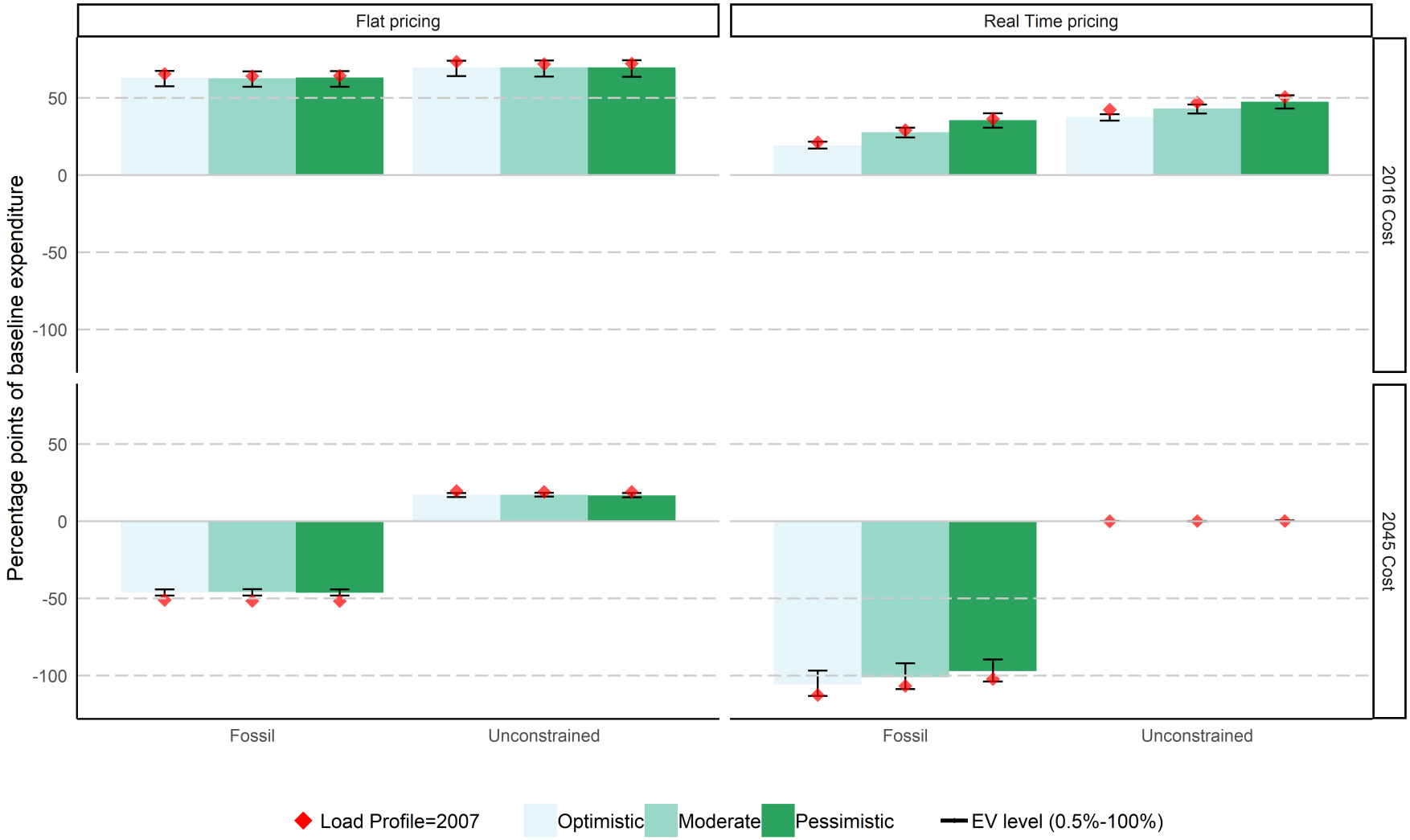
The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with 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% renewable 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: 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% renewable 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: 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% renewable 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: 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% Renewable	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	84	1,078	52	57.2	-61.2	-12.5	44.6	170.1	193.0	62.5	
	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 5 in the main paper, 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 S2: 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% Renewable	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	44.6	-70.3	-6.0	38.7	65.8	51.7	43.1	

Notes: Like table 5 in the main paper, except the share of electric vehicles is 0.5% (the current share of the fleet) instead of 50%.

Table S3: 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% Renewable	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 5 in the main paper, except the share of electric vehicles is 100% instead of 50%.

Table S4: 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% Renewable	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	1,121	0	36.3	-42.9	-2.2	34.1	39.0	147.7	33.1	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 5 in the main paper, except the the overall demand elasticity (θ) equals 0.5 instead of 0.1

Table S5: 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% Renewable	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 5 in the main paper, except the the overall demand elasticity (θ) equals 2 instead of 0.1

References

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