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.

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

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:

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

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

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).

2.3 Reserve Requirements

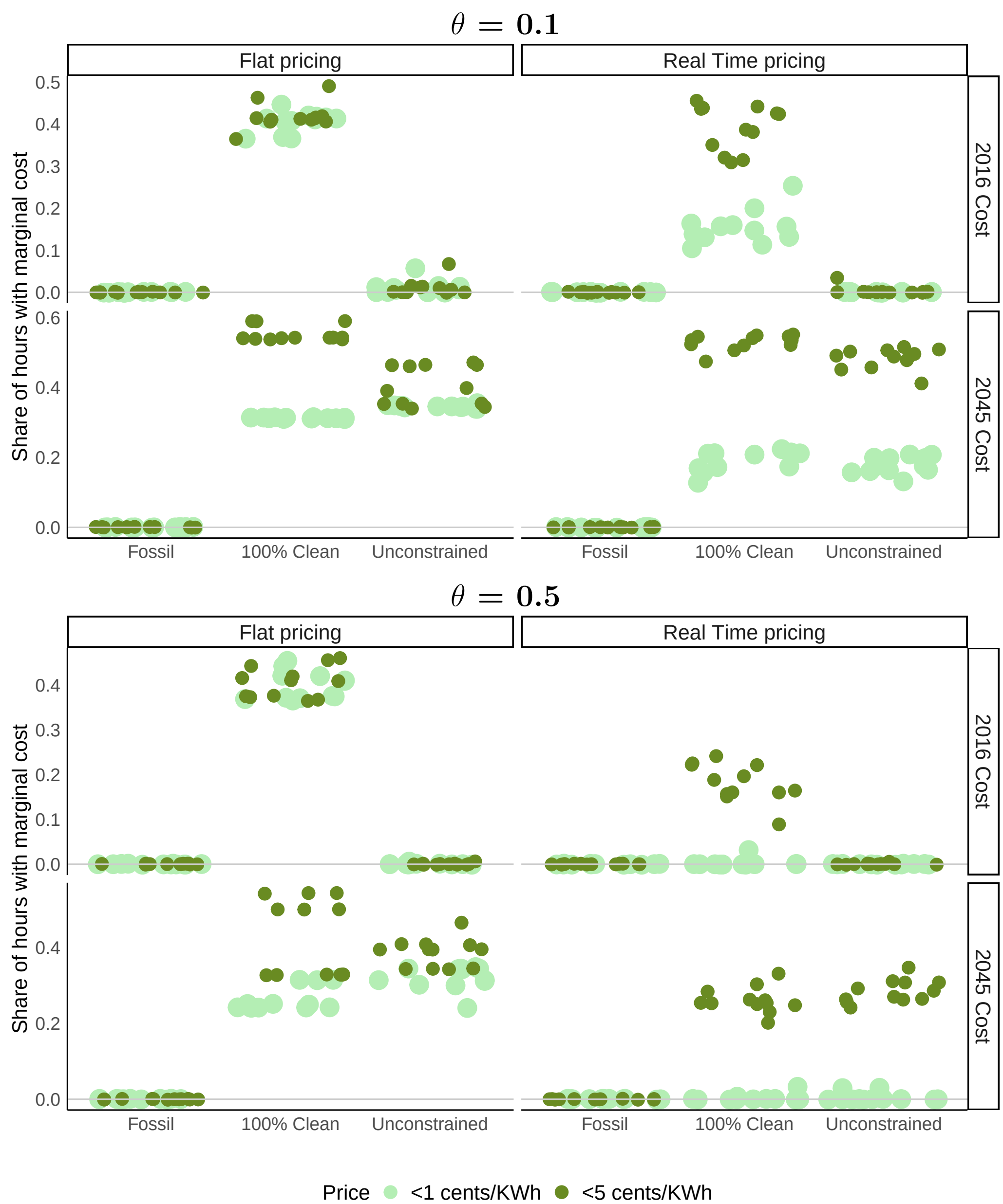
In this implementation of Switch for Oahu, we use the "n-1" criterion for contingency reserves, which means the system always runs with enough capacity to compensate for loss of the largest generator online. In addition, we require regulating reserves equal to 100% of renewable production up to 20% of nameplate capacity rating. For example, if renewables are running at 10% of nameplate capacity, there needs to be battery or fossil backup equal to their production; but if renewables are running at 70% of nameplate rating, we only provide fossil backup equal to 20% of nameplate. These reserve specification match those in an early solar integration study for Oahu (GE Energy Consulting 2012).

3 Supplementary Results

3.1 Frequency of Especially Low Marginal Cost

The graphs in Figure S1 show the share of hours with marginal cost less than 1 cent and 5 cents per kWh (\$10/MWh and \$50/MWh) across the range of scenarios. The top panel shows scenarios with an overall demand elasticity $\theta = 0.1$ and the bottom panel shows $\theta = 0.5$. Because this share is not much influenced by the degree of interhour flexibility, the share of EVs, or the baseline demand profile (actual 2007 or projected 2045), all of these variations are shown with the same dot type.

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



3.2 Chronological Production and Consumption Profiles

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

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

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

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

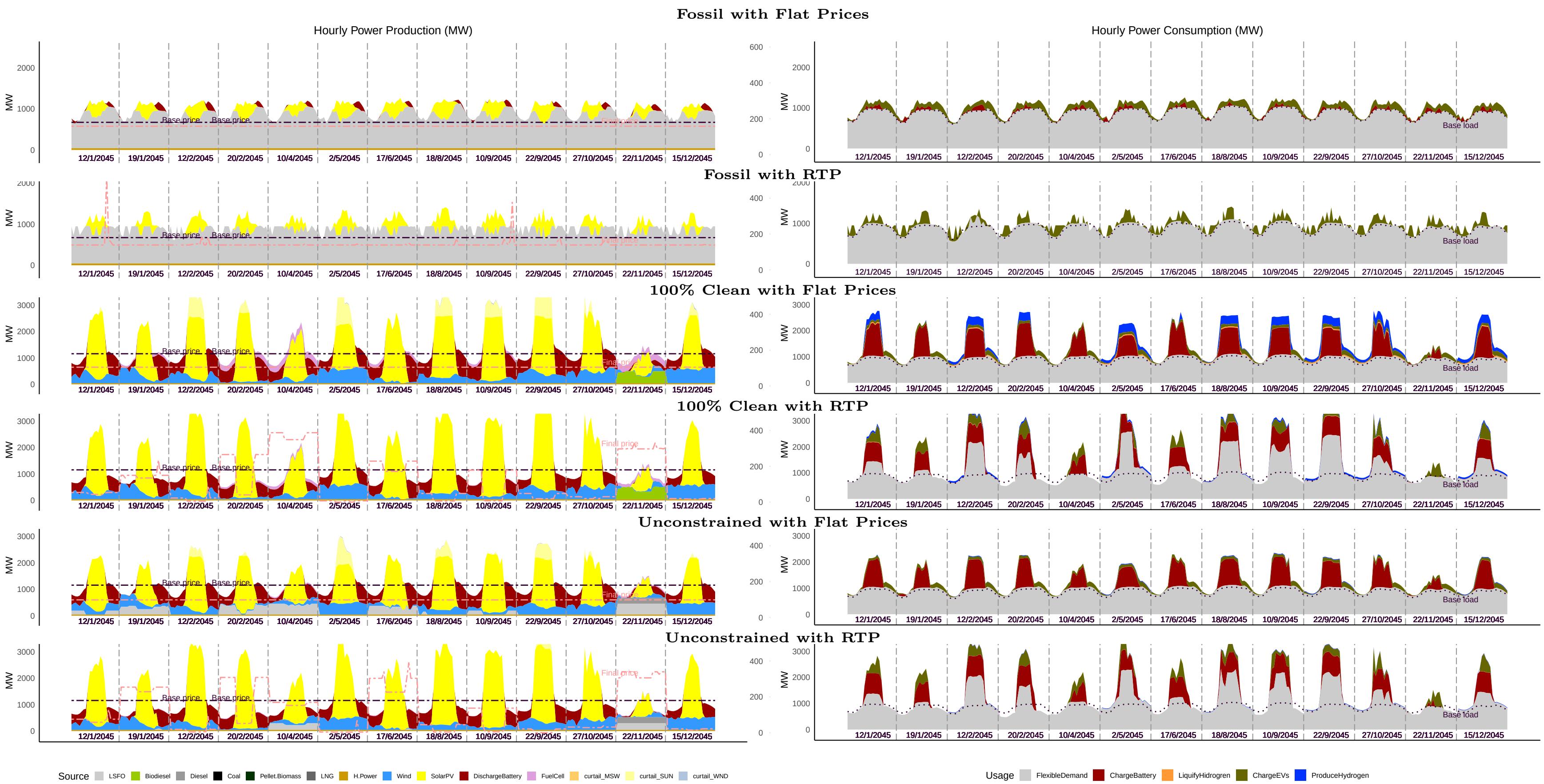
Except for these difficult low-sun and low-wind days, it is generally most economic to simply use renewables and batteries, although the unconstrained model with flat prices will use a conventional plant with LSFO to a limited extent on other days.

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

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

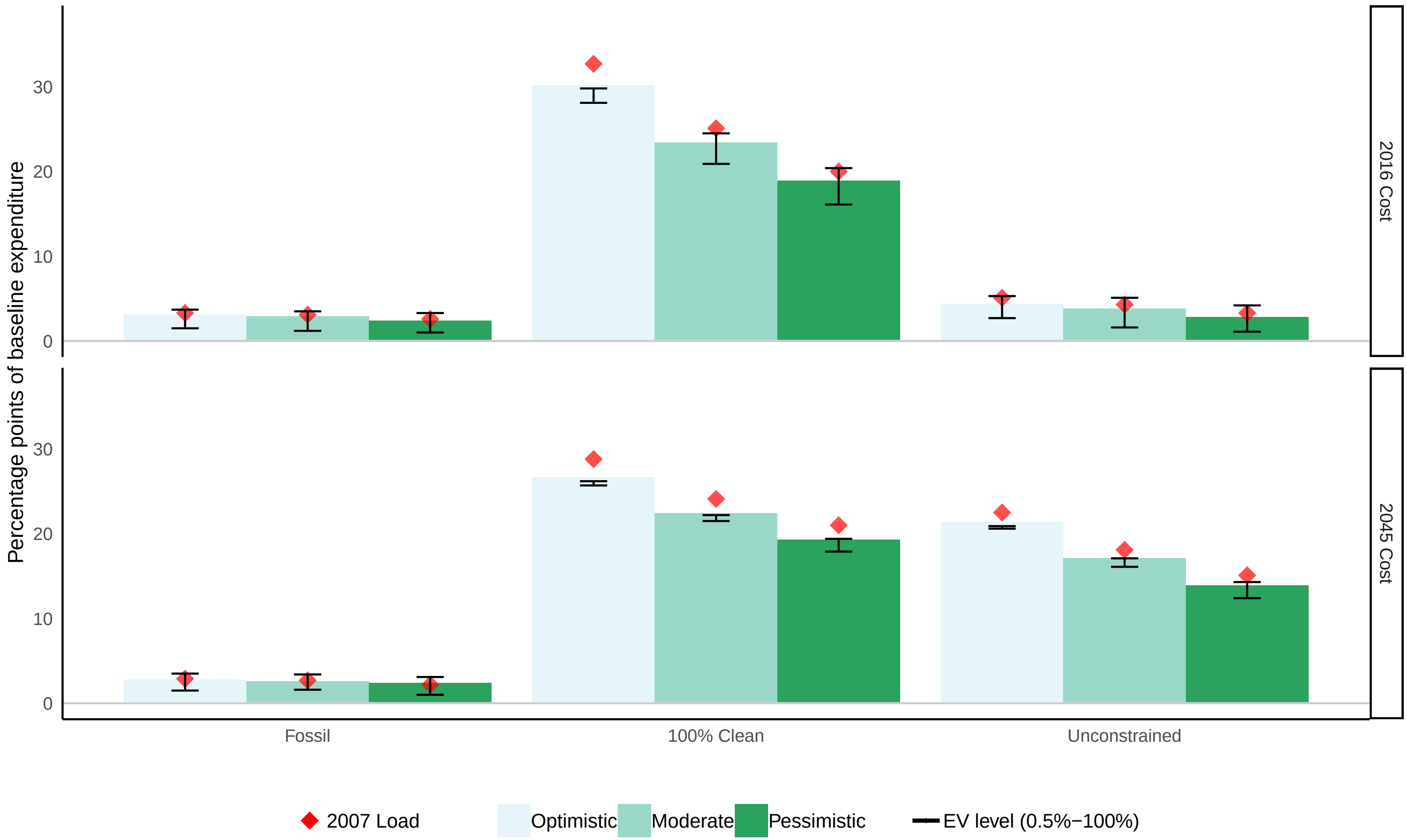
These comparisons indicate some subtle tradeoffs involved with co-optimizing intermittent renewables, short- and long-term storage, and traditional thermal generation, either with biofuels or conventional fossil fuels. The general lesson that we draw from these comparisons is that large shares of clean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

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



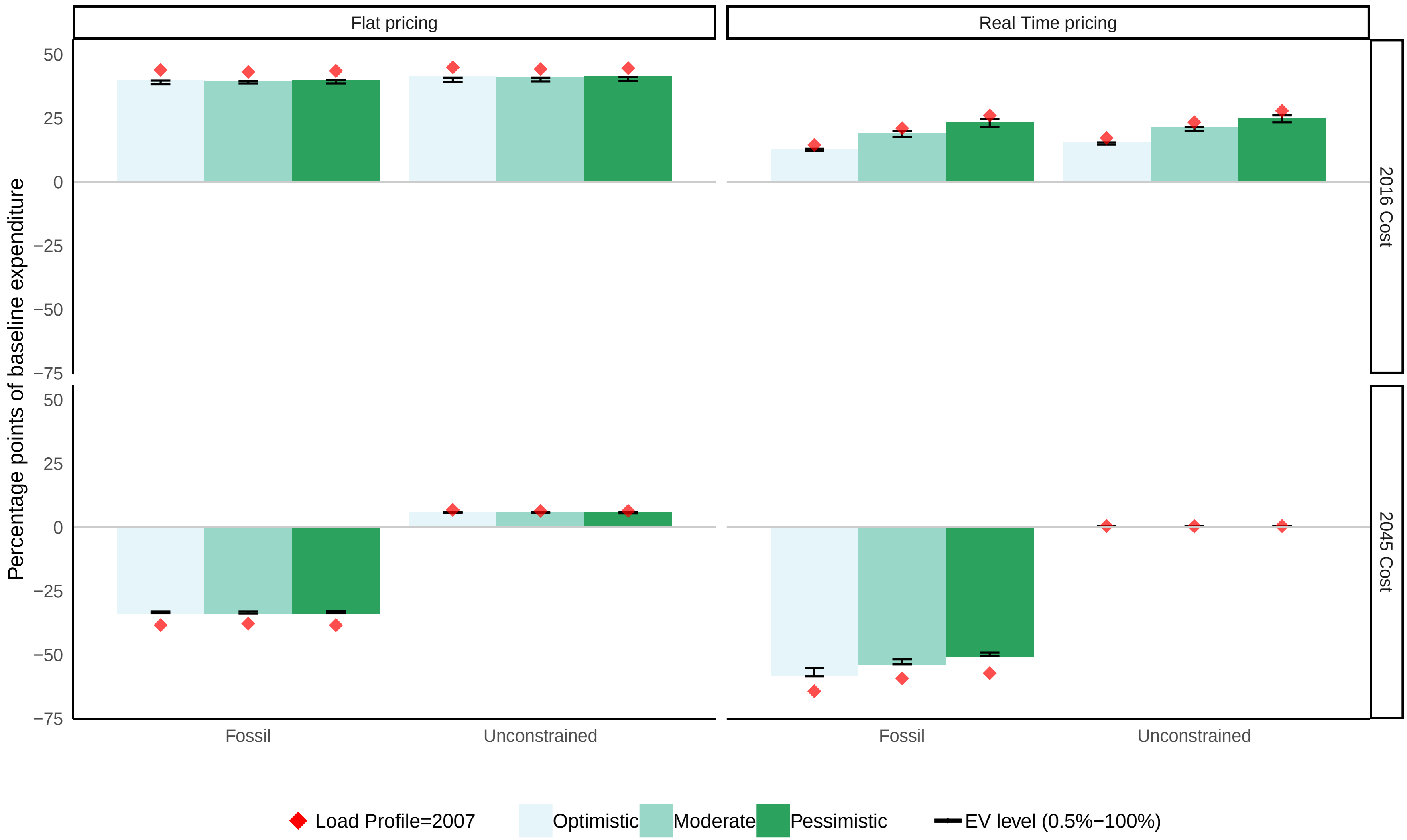
The scenarios presented above assume the moderate scenario for interhour substitutability of demand, an inelastic overall demand elasticity for electricity equal to 0.1, a baseline demand profile projected for 2045, a vehicle fleet with 50% electric vehicles, and costs of production as projected for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

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



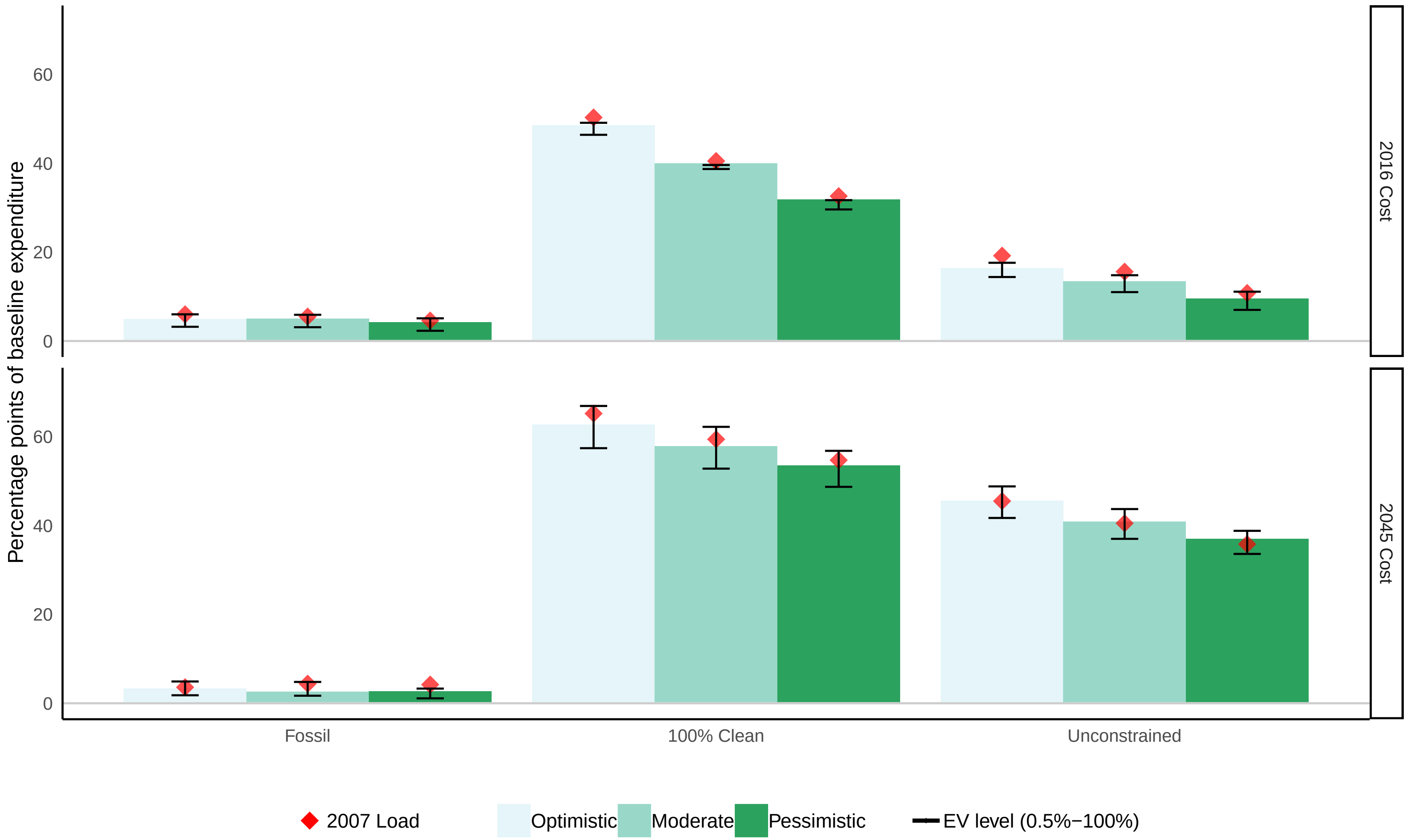
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an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

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



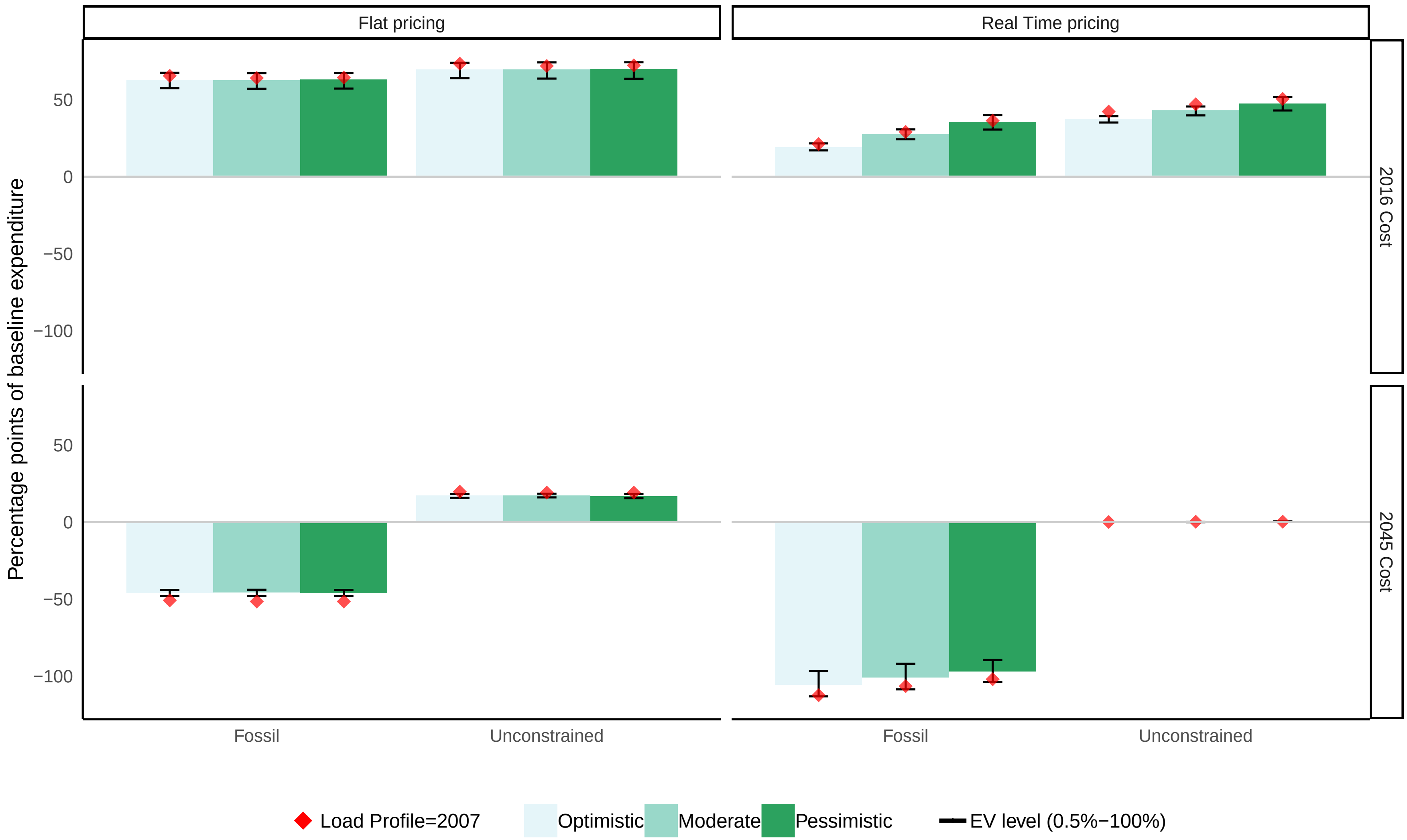
The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with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

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



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

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



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

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

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

Notes: This is a more complete version of Table 5 in the main paper. In all scenarios shown here, the overall demand elasticity (θ) equals 0.1, the baseline load profile is that projected for 2045, and electric vehicles are assumed to comprise 50% of the fleet. Each scenario (row in the table) is defined by assumptions delineated in the first four columns. The first column (Policy Objective) indicates exogenous constraints determined by policy: Fossil prohibits any new renewable energy, but is otherwise least cost; 100% Clean reflects the intended outcome of the State's Renewable Portfolio Standard, and Unconstrained maximizes welfare without constraints on the generation mix. The second column indicates whether current costs (2016) or the present value of future costs projected for 2045 from HECO's Power Supply and Improvement Plan are assumed. The third column indicates the degree of demand flexibility, as detailed in table 1. The fourth column indicates whether retail prices are flat or RTP. The remaining columns summarize the outcomes of the conditionally optimized system: average price, average quantity, standard deviation of price, and changes in surpluses from the baseline case (fossil system, future costs, and flat pricing). All changes in welfare are reported as the percent difference relative to the baseline level of expenditure on electricity. %ΔEV is the percent change in charging costs for electric vehicles from the base case. Note that ΔCS includes changes in EV charging costs. We also examine changes in welfare for different demand flexibilities, which only matters for RTP pricing scenarios. The last column reports the social value of RTP holding all else the same. The supplement provides additional results that consider more elastic demand or more EVs.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

References

GE Energy Consulting, *Hawaii Solar Integration Study: Final Technical Report for Oahu* Apr 2012.

Imelda, Matthias Fripp, and Michael J Roberts, "Data and Code for: Real-Time Pricing and the Cost of Clean Power [Data set]," Technical Report 2023. https://doi.org/10.5281/zenodo.7228323.

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

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